Successful Project Portfolio Management Delivery: A Novel Strategic Portfolio Decision-Making Model

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Successful Project Portfolio Management Delivery: A Novel Strategic Portfolio Decision-Making Model

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ABSTRACT

Project Portfolio Management (PPM) is an essential component of an organisation's strategic procedures which requires considering several factors to envisage a range of long-term outcomes that support strategic project portfolio decisions. The success of PPM is closely associated with the degree of understanding of its issues and the quality of decisions made at the portfolio level as poor judgement reduces efficiency and increases portfolio costs. Although several Multi-criteria Decision-making (MCDM) methods have been introduced in support of PPM decision-making functions, there has been little assessment of their performances, particularly regarding which one works best for PPM.

This study identifies the key PPM challenges, proposes a new framework for classifying PPM MCDM-related methods and undertakes a literature review of the application of MCDM approaches to PPM. Of over 100 methods identified in over 1400 publications, eight (AHP, ANP, DEA, DSRA, ELECTRE, PROMETHEE, TOPSIS and VIKOR) that best suit PPM are selected and compared. Although two standard methods (AHP and DEA) are shown to be the most appropriate for application to PPM, each has its own shortcomings.

To overcome the challenges, this study proposes a novel method for portfolio selection/decision making that combines the Portfolio Theory (PT), AHP and a DEA cross-efficiency technique and considers the profit, risks and proficiency of the portfolio. It is demonstrated that this method can be useful for selecting a portfolio with positive and negative data and, subsequently, measuring efficiency using the AHP. To test the applicability of the proposed model, it is used to determine the efficiency levels of ten of the largest companies in Australia in 2014 and 2015, with two criteria, namely, the expected return and variance, used to identify the preference status of each company. A consistency test conducted to assess the objectivity of the results indicates that this application of the proposed model, which simultaneously analyses profits, risks and proficiency, is feasible and adoptable for a contemporary industrial scenario. Furthermore, an executive management system is proposed as an alternative decision support tool for decision makers.

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ABBREVIATIONS AND DESCRIPTIONS

Abbreviation	Description
AM	Additive Model
ARAS	Additive Ratio Assessment
AVF	Additive Value Function
AIRM	Aggregated Indices Randomisation Method
AMP	AMP Ltd
ANP	Analytic Network Process
AHP	Analytic Hierarchy Process
ANZ	ANZ Banking Group Ltd
AI	Artificial Intelligence
ANN	Artificial Neural Network
AR	Assurance Region
AD	Axiomatic Design
BSC	Balance Score Card
BCC	Banker-Charnes-Cooper
BWM	Best Worst Method
BHP	BHP Billiton Ltd
CCGA	Chance Constrained and Genetic Algorithm
CCDEA	Chance Constraint DEA
COMET	Characteristic Objects METhod
CCR	Charnes-Cooper-Rhodes
CBA	Choosing by Advantages
CBA	Commonwealth Bank of Australia
COPRAS	COmplex Proportional ASsessment
CA	Comprehensive Algorithm
CP	Compromise Programming
CI	Consistency Index
CR	Consistency Ratio
CRS	Constant Returns to Scale
CGT	Cooperative Game Theory
COLS	Corrected Ordinary Least Squares
CEM	Cost Efficiency Models
COS	Cost of Safety
CWs	Criteria Weights
CE	Cross-efficiency

DEA	Data Envelopment Analysis
DEA CE	DEA Cross-efficiency Model
DAME	Decision Analysis Module for Excel
DEX	Decision EXpert
DMs	Decision Makers
DM	Decision Matrix
DSS	Decision Support System
DMUs	Decision-Making Units
DIER	Dependence-based Interval-valued ER
DRSA	Dominance-based Rough Set Approach
ELECTRE	ELimination and Choice Translating REality
ERP	Enterprise Resource Planning
ER	Evidence Reasoning
ERA	Evidential Reasoning Approach
FMEA	Failure Mode and Effect Analysis
FDHM	Free Disposal Hull Models
FST	Fuzzy Set Theory
GA	Genetic Algorithm
GP	Goal Programming
GSCM	Green Supply Chain Management
GRA	Grey Relation Analysis
GDSSs	Group Decision Support Systems
HDT	Hasse Diagram Technique
HOQ	House of Quality
IDA	Index Decomposition Analysis
IPV	Inner Product of Vectors
I	Input-oriented
ILP	Integer Linear Programming
IMRP	Interactive Minimax Reference Point
ISM	Interpretive Structural Modelling
LGP	Lexicographic Goal Programming
LP	Linear Programming
LINMAP	Linear Programming Techniques for Multidimensional Analysis of Preference
MQG	Macquarie Group Ltd
MP	Mathematical Programming
MACBETH	Measuring Attractiveness by a Categorical-Based Evaluation Technique

MH	Meta-Heuristics
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
MSBM	Modified Slack-based Measure
MCS	Monte Carlo Simulation
MADM	Multi-attribute Decision Making
MCDA	Multi-criteria Decision Analysis
MCDM	Multi-criteria Decision Making
MODM	Multi-objective Decision Making
MAGIQ	Multi-attribute Global Inference of Quality
MAUT	Multi-attribute Utility Theory
MAVT	Multi-attribute Value Theory
MAPPAC	Multi-criterion Analysis of Preferences by means of Pair-wise Alternatives and Criterion comparisons
MCQA	Multi-criterion Q-Analysis
MULTIMOORA	Multi-objective Optimisation by Ratio Analysis plus Full Multiplicative Form
MOORA	Multi-objective Optimisation on basis of Ratio Analysis
MOP	Multi-objective Programming
MEW	Multiplicative Exponent Weighting
NAB	National Australia Bank Ltd
NLP	Nonlinear Programming Model
NAIDE	Novel Approach to Imprecise assessment and Decision Environment
NT	Numerical Taxonomy
OWA	Ordered Weighted Averaging
OECD	Organization for Economic Co-operation and Development
ORESTE	Organisation, Rangement Et Synthese De Donnes Relationnelles
O	Output-oriented
OT	Outranking Techniques
PT	Portfolio Theory
PAPRIKA	Potentially All Pair-wise Rankings of all possible alternatives
PGP	Pre-emptive Goal Programming
PRAGMA	Preference RAnking Global frequencies in Multi-criterion Analysis
PROMETHEE	Preference Ranking Organisation METHod for Enrichment Evaluation
PCA	Principal Component Analysis
PPM	Project Portfolio Management
PEM	Pugh Evaluation Matrix

QFD	Quality Function Deployment
RSEM	Radial Super-efficiency Model
RI	Random Indices
RDM	Range Directional Measure
RIO	Rio Tinto Ltd
RSA	Rough Set Approach
SEM	Scale Efficiency Measure
SORM	Semi-oriented Radial Measure
SR	Sharpe Ratio
SAW	Simple Additive Weighting
SMART	Simple Multi-attribute Rating Technique
SBM	Slack-based Measure
SMAA	Stochastic Multi-criteria Acceptability Analysis
SP	Stochastic Programming
SPMT	Strategic Portfolio Management Tool
SWOT	Strengths, Weaknesses, Opportunities and Threats
SIR	Superiority and Inferiority Ranking
TOPSIS	Technique for Order Performance by Similarity to Ideal Solution
TLS	Telstra Corp Ltd
TRIZ	Theory of Inventive Problem Solving
TCO	Total Cost of Ownership
TDS	Total Diet Studies
TACTIC	Tratement des Actions Compte Tenu de l'Importance des Crite'res
UBT	Utility-Based Techniques
UTA	Utility Theory Additive
VA	Value Analysis
VE	Value Engineering
VRS	Variable Return to Scale
VRM	Variant of Radial Model
VIKOR	VlseKriterijumska Optimizacija I Kompromisno Resenje
WLAM	Weighted Linear Assignment Method
WPM	Weighted Product Model
WSM	Weighted Sum Model
WBC	Westpac Banking Corporation
WOW	Woolworths Ltd
ZOGP	Zero-One Goal Programming

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Darius Danesh

June 2017

SUMMARY OF APPENDED PAPERS

The research work presented in this thesis has been accepted and acknowledged by the project portfolio management and multi-criteria decision-making communities through its presentation at two international conferences and the submission of three journal papers to an internationally recognised journal. The following publications and conference presentations have arisen from this research:

<u>Publication I</u>

(Related Thesis Chapters: I and II. Full paper available at ANNEX J)

Danesh, D., Ryan, M. J., & Abbasi, A. Multi-criteria Decision-making Methods for Project Portfolio Management: A Literature Review. International Journal of Management and Decision Making, [Accepted].

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<u>Publication II</u>

(Related Thesis Chapters: I-III and Annexes A, C, E. Full paper available at ANNEX K)

Danesh, D., Ryan, M. J., & Abbasi, A. (2017). A Systematic Comparison of Multi-criteria Decision Making Methods for the Improvement of Project Portfolio Management in Complex Organisations. International Journal of Management and Decision Making. 16(3), 280-320.

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Publication III

(Related Thesis Chapters: II and IV. Full paper available at ANNEX L)

Danesh, D., Ryan, M. J., & Abbasi, A. (2015). Using Analytic Hierarchy Process as a Decision-Making Tool in Project Portfolio Management. World Academy of Science, Engineering and Technology: International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering, 9(12), 3751-3761.

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Publication IV

(Related Thesis Chapters: I and IV-VII. Full paper available at ANNEX M)

Danesh, D., Ryan, M. J., & Abbasi, A. (2017). A Novel Integrated Strategic Portfolio Decision-Making Model. International Journal of Strategic Decision Sciences (IJSDS), 8(3), 1-44. doi:10.4018/IJSDS.2017070101

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Publication V

(Related Thesis Chapters: I and V-VII. Full paper available at ANNEX N)

Danesh, D., & Ryan, M. J. (2017). Complex Portfolio Decision Making: An Innovative Strategic Portfolio Management Tool. 2nd International Conference on Advances in Economics, Management and Innovation (ICAEMI), [Accepted].

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CHAPTER I

1.1. INTRODUCTION

Management activities, such as improving public services, implementing new policies and introducing new management systems, are conducted through projects and portfolios, with their poor performances and, in particular, their failures to deliver targeted benefits, having a negative effect on national growth, not to mention the waste of public assets and taxpayers' money (Chih & Zwikael, 2013).

The increasing difficulty of delivering capital programs in large organisations has also led to a focus on the more comprehensive and effective management of programs and portfolios (Prieto, 2008). The successful delivery of organisational objectives is significantly linked to the effective collection of projects in portfolios (Better & Glover, 2006; Bridges, 1999; Cooper, Edgett, & Kleinschmidt, 2000; Project Management Institute, 2006; Radulescu & Radulescu, 2001; Sommer, 1999). However, evaluating and comparing the performances of portfolios are complex tasks (Closs, Jacobs, Swink, & Webb, 2008) which usually require multiple criteria or targets with many requirements and a technique that could suggest correct decision options to Decision Makers (DMs) is required.

Comprehensive and effective Project Portfolio Management (PPM) is a key element of an organisation's strategic concepts (Dietrich & Lehtonen, 2005; Grundy, 2000) for selecting and maintaining proper portfolio choices. Since the achievement of organisational strategic goals often depends on the outcomes of projects (Aubry, Hobbs, & Thuillier, 2007), it is essential to identify the projects or portfolio of projects (and/or programs) which align well with these goals without exceeding the limitations of the available resources (Blichfeldt & Eskerod, 2008). The role of PPM is to evaluate, select and prioritise projects, as well as revise priorities, and possibly eliminate and reduce projects currently in progress (Cooper, Edgett, Kleinschmidt, & Elko, 1998). By managing and analysing all projects and their inter-relationships at a portfolio level, the goal of PPM is to enhance the overall efficiency of a project portfolio.

"Project Portfolio management is a dynamic decision process, whereby a business's list of active new products (and R&D) projects are constantly up-dated and revised. In this process, new

projects are evaluated, selected and prioritized; existing projects may be accelerated, killed or de-prioritized; and resources are allocated and reallocated to the active projects. The portfolio decision process is characterized by uncertain and changing information, dynamic opportunities, multiple goals and strategic considerations, interdependence among projects, and multiple decision-makers and locations" (Cooper et al., 2001b).

PPM is an essential part of strategic management practice which involves decisions concerning the actions a business needs to undertake to successfully achieve its strategic targets. PPM is basically a strategic decision-making method that involves determining, reducing and diversifying risk, identifying and addressing variations, and recognising and accepting the need for trade-offs (Kester, Griffin, Hultink, & Lauche, 2011; Levine, 2005). As an essential factor in PPM is assessing which group of projects maximises the success and achievement of strategic targets, PPM has become an active decision practice in which new items for analysis and improvements are constantly updated.

To be able to confirm the possible implementation of a portfolio, PPM needs to visualise the options for, and potential outcomes of, project decisions across it, with the quality of decision making a key element of a successful project portfolio (Matheson & Menke, 1994). Project interconnections and relationships among activities that increase the complexity of PPM decision making need to be considered along with financial, strategic, risk, resource and other elements. As portfolios of complex and interdependent projects are common, there is certainly a clear need for advanced methods that can recognise and handle their associations. To analyse a portfolio's performance, it is important to aggregate the overall performances of its projects in a mathematically meaningful way that implies their strategic impacts at different levels of abstraction.

These challenges can be addressed using various Multi-criteria Decision-making (MCDM) methods which aim to maintain decisions (Roy, 1996) with often conflicting criteria by rating the options; categorising the decisions into a number of classifications; and/or identifying a preferred option (Gomes, 1989). MCDM is a structure for analysing decision issues with complex multiple targets (Nijkamp, Rietveld, & Voogd, 2013; Zeleney, 1984) and can handle long-term options, unknown aspects, risks and complicated values. The practice of MCDM generally defines targets, selects the requirements for determining them, specifies options, modifies the measurement values, assigns weights to the requirements, and uses a mathematical algorithm to score options and choose them (Hajkowicz & Prato, 1998; Howard, 1991; Keeney & Keeney, 2009; Massam, 1988). MCDM also incorporates several methods that enable estimations of various requirements to assist DMs to select, rank and evaluate various options (Belton & Stewart, 2002), and examine decision problems specified by various difficult goals (Nijkamp et al., 2013).

The evaluation of a portfolio's performance requires selecting an appropriate portfolio assessment method(s). Several studies have highlighted that using unsuitable and poor assessment methods could result in the selection of particular sorts of projects in a portfolio and the rejection of the rest (Brun, Sætre, & Gjelsvik, 2008; Kester, Hultink, & Lauche, 2009) with, consequently, certain projects possibly being rejected if they just fail to match the relevant model (Corso & Pellegrini, 2007; Sandstrom & Bjork, 2010).

Although PPM is currently a widely researched subject, specifically in the area of product development (Bible & Bivins, 2011; Cooper, Edgett, & Kleinschmidt, 2001c), few studies have addressed the use of MCDM in PPM decision making. There are many decision-making techniques that can support PPM, with organisations which use structured ones to manage and implement their portfolios more successful due to their capability to reduce the gap between PPM and MCDM (Müller, Martinsuo, & Blomquist, 2008). However, in order to use appropriate decision-making methods, it is necessary to understand the challenges of PPM decision making.

Although a few studies discuss PPM challenges (e.g., Cooper et al., 2001c; Elonen & Artto, 2003) and relevant decision-making issues (e.g., Manos, Papathanasiou, Bournaris, & Voudouris, 2010), there is no framework for properly linking them, in particular, using MCDM in PPM decision making.

While many experts considered ways of selecting appropriate techniques for analysing decision problems (Cooper, Edgett, & Kleinschmidt, 2001b), most selection factors were based on technical assumptions without considering the specificities of a PPM assessment and the reasons for a PPM's failure. Most studies did not provide clear reasons for choosing any single technique and often only a few were compared. Moreover, each assessment was confined mainly to a specific industry which resulted in the elimination of some useful PPM-related MCDM methods. Although some research has been conducted in both the private and public sectors to determine the effects of different MCDM techniques on the success or failure of a decision (Coles, 2012; Cooper, 1980; Defence & Black, 2011), little attention has been paid to usability issues in a real PPM experiment. Furthermore, while various MCDM techniques and tools have been studied for either ranking or classification purposes, only a few have actually been used for PPM (Ehrgott, Klamroth, & Schwehm, 2004). As current methods have their own advantages and disadvantages, a constructive review and comparison of existing MCDM methods is required to identify the most suitable one(s) for PPM decision making. Properly understanding PPM and its decision-making challenges also helps to correctly identify the factors required to develop a structured framework for selecting the ideal MCDM method(s) as a tool(s) in PPM decision making.

This study aims to present a logical structure by which to determine the projects that need to be performed by a corporation and obtain the highest likely return on an asset with the least potential risk. This study aims to propose a decision-making model that supports individuals in setting specific, measurable, achievable and relevant decision outcomes.

This study also aims to propose an integrated MCDM method for PPM that provides the appropriate information to the DMs responsible for decision making that can be simply used without any limitations or data restriction. It aims to propose a new tool that provides a clear and timely understanding of emerging issues and risks in the delivery of a portfolio by highlighting them so that organisations can respond in an effective, efficient and coordinated manner to guide remedial actions. This will provide organisations with the capability to receive timely and specific identification of significant exceptions, make suitable decisions and then manage effective remediation with the support of senior management. In keeping with the primary goal of this study, the focus is on highlighting underperforming projects/programs/investments in a portfolio. By identifying and remediating issues early in its life cycle, the proposed tool aims to prevent a portfolio from becoming a matter of concern. To achieve this goal, a comprehensive literature review needs to be conducted to identify the key challenges of PPM first and use them to develop a comparison model for selecting useful MCDM techniques for PPM. After they are analysed, those preferred for overcoming the challenges of PPM are specified and compared to identify any possible shortcomings.

Based on the observed knowledge gaps, the primary concerns of this study are the 14 questions posed in Figure 1 which are addressed in the following chapters.

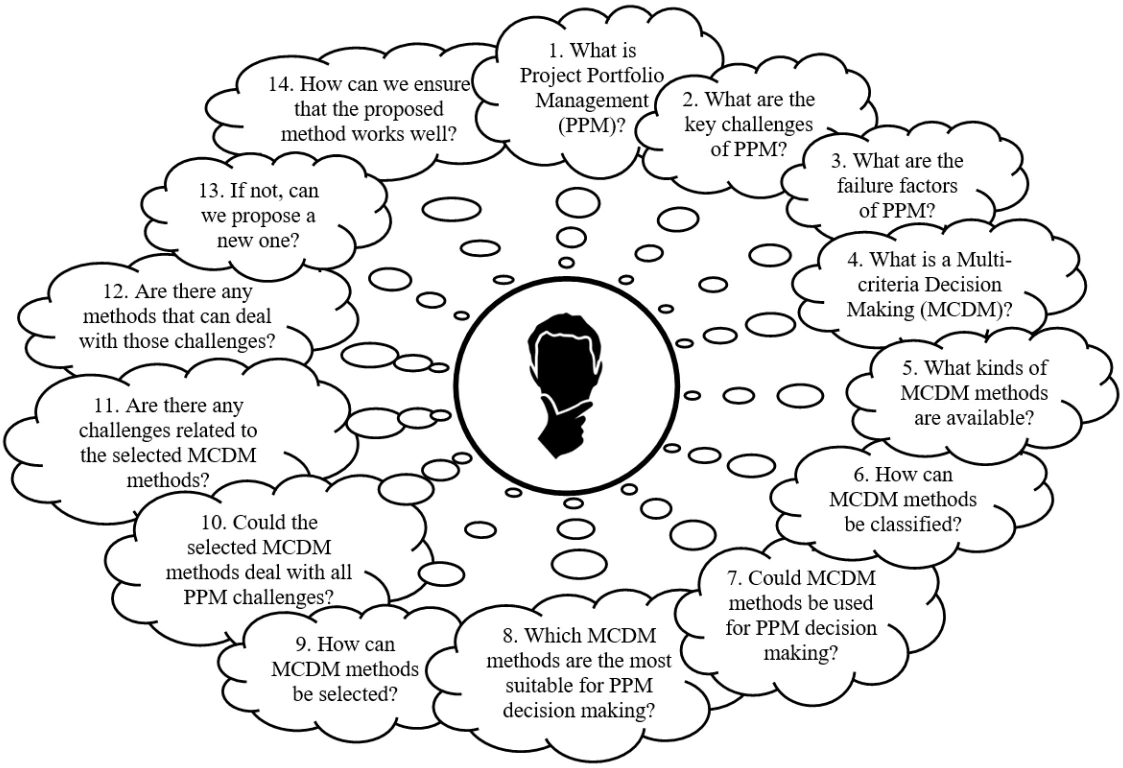

Figure 1. Research Questions Considered In This Work

In this study, a comprehensive review of the literature is conducted to analyse the challenges of PPM decision making. Then, MCDM techniques are classified to improve knowledge of their assessment and decision-making approaches, with their strengths and weaknesses in relation to PPM decision making analysed to determine any constraints and limitations on applying them, and identify how PPM challenges can be overcome using a preferred MCDM method(s). Accordingly, a systematic comparison of MCDM techniques and development of a solid structure that improves knowledge of the assessment and selection techniques for projects in complex organisations are presented.

As PPM and MCDM are broad fields and many researchers from different backgrounds have been involved in these fields, presenting generic research questions may have led to irrelevant questions or misdirection as to the purpose of the study or what is to be achieved. For the same reason, this study presented detailed questions that provide a clear pathway to our research direction and the purpose of the questions. This approach made the information flow better without losing sight of the main goal and research points.

1.2. METHODOLOGY

The initial purpose of this study is to uncover the key factors behind the failures of PPM and use them to develop a comparison model for selecting useful MCDM techniques for PPM. Moreover, it aims to build a reliable and operational model for examining the overall efficiency and success of a portfolio with regard to its comparative efficiencies determined by the quality of its outcomes. It aims to increase an organisation's knowledge of MCDM methods and PPM challenges and, thereby, improve its capability to make strategic portfolio decisions.

The selection of publications considered is restricted based on the following factors. The review covers the literature on decision making, and organisational and portfolio management published between 1860 and 2016, with Google Scholar used to retrieve the relevant articles accessed using the following search phrases: ["Project Portfolio Management" OR "Portfolio Management" OR "Project and Program Management"] AND ["Multi-criteria Decision Making" OR "Complex Decision Making"] which produces more than 1400 extracted publications.

This thesis is organised in six chapters following this introductory one. PPM and its challenges are highlighted in CHAPTER II accompanied by a step-by-step investigation through which various MCDM techniques and applications for both ranking and classification are recognised.

In CHAPTER III, the key reasons behind the failures of PPM are used to develop a PPM MCDM classification model for analysing and comparing several MCDM techniques. An extensive examination of the literature on more than 100 MCDM techniques is conducted to identify the most suitable for PPM. To the best of our knowledge, this is probably the first research study to benchmark PPM MCDM methods on this scale. MCDM techniques from various groups are classified according to their specifications. Then, an examination of them in terms of their different classifications as well as differences among those belonging to the same group is carried out. After they are analysed, those preferred for overcoming the challenges of PPM selection, which this study aims to resolve, are specified.

The academic perspectives of the DEA and AHP concepts are introduced in CHAPTER IV through a literature review of the works related to their methodologies. Their shortcomings and the issues involved in using them are described. Then, an overview of an integrated AHP/DEA model, which compensates for their deficiencies, as well as a discussion of cross-efficiency and other methods that can deal with negative variables are presented.

In CHAPTER V, a new model for dealing with the abovementioned drawbacks is proposed and, based on observations, a model of indicators is developed as an alternative decision support tool for DMs.

CHAPTER VI discusses three real case studies to clearly demonstrate how well the newly proposed method and Strategic Portfolio Management Tool (SPMT) tool work compared with existing standard models. The results show the capability of this approach to be used in a predictive manner when dealing with PPM problems in different portfolio scenarios. Case Study 1 presents a decision scenario in a project portfolio environment for estimating the efficiency levels of more than 120 major projects/programs in the Australian Resources and Energy sector in 2015. Case Study 2, which consists of the portfolios of Australia's ten largest firms for the financial year 2014-15, illustrates how the proposed model is applied in relatively large portfolios. The results from the standard models presented in the literature review are then compared with those from the proposed model (in both case studies) which shows how well they agree. Moreover, the simplicity of the proposed decision support system (i.e., SPMT) is tested in Case Study 3 to demonstrate how it can calculate a portfolio's efficiency level in only one click considering the existing challenges of portfolios and PPM requirements.

This study concludes its investigation with a discussion in CHAPTER VII of the requirements for operationalising the proposed method. Finally, its limitations are presented and recommendations for future work identified.

The work in this study extends the sensitivity analysis frameworks introduced by Barron and Schmidt (1988), Insua and French (1991), Wolters and Mareschal (1995), and Ringuest (1997). The difficulties of PPM decision making can be identified in different project situations, such as the selection of projects, prioritisation and balancing of resources (e.g., cost and time) or financial management. Since selecting and prioritising of projects in PPM are our areas of interest, this research is undertaken from a management decision-making rather than mathematical point of view.

1.3. RESEARCH ROADMAP

A research roadmap, which is referred to throughout this thesis, provides a framework for this study by: summarising existing knowledge and information regarding the topics considered; demonstrating the intent behind this exercise through specific questions about the research challenges; describing the methodological strategy adopted to simply analyse these challenges;

outlining the possible final results that may be obtained; and presenting the remainder of the structure of this thesis.

This roadmap, which is the basis of the strategic plan for this research, highlights the knowledge gaps as well as actions needed to deal with any shortcomings. It describes the questions and ideas that led to the selection of this study's subject such as what needs to be known for the investigation to proceed, how this study plans to answer these questions, why the subject warrants further consideration and research, and some of the best ways of approaching its specific topics.

The proposed roadmap consists of seven sections, each of which is focused on a specific chapter and the relevant research questions and topics addressed throughout this thesis. These sections are designed to provide the reader with an overview of the aim and structure of this research and assist in exploring the wealth of information collectively presented in each chapter.

As each question may be interpreted differently by each person depending on their knowledge and background, we presented our questions specifically and in detail to avoid any potential misunderstanding.

Figure 2 shows the roadmap that outlines the key priority research elements required to be investigated in the next chapters which are further developed before the completion of this study is discussed in CHAPTER VII.

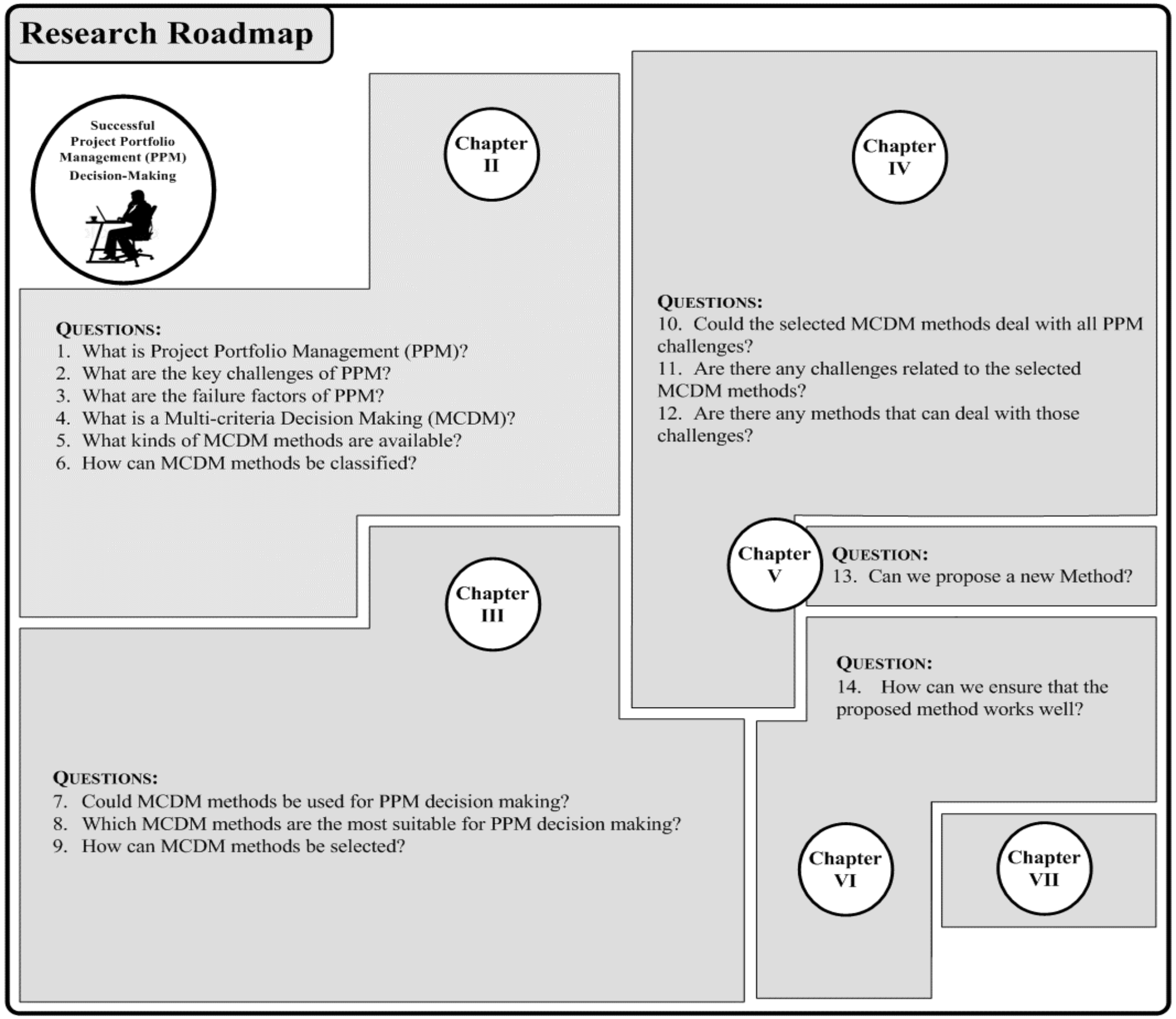

Figure 2. RESEARCH ROADMAP

CHAPTER II

2. EXECUTIVE SUMMARY

Project Portfolio Management (PPM) has become a key element of large organisations' service delivery due to the close attention inherently paid to numerous issues in the discipline of project management. Its success is closely associated with the degree of understanding of its issues and the quality of decisions made at the portfolio level which can be addressed using Multi-criteria Decision-making (MCDM) methods. Although several of these methods have been introduced to support decision-making functions as part of PPM, there has been little assessment of their performances, particularly when combining some of them. This chapter identifies the key challenges of PPM, proposes a new framework for classifying PPM MCDM-related methods and presents a literature review of applications of MCDM methods to PPM.

2.1. PROJECT PORTFOLIO MANAGEMENT (PPM)

2.1.1. PPM Overview

As organisations progressively transform their activities into project-based forms, projects tend to be the key tools for delivering their strategies (Artto, Dietrich, & Nurminen, 2004; Dietrich & Lehtonen, 2005; Dietrich, Poskela, & Artto, 2003; Meskendahl, 2010; Turner, 1993). These projects are influenced by several drivers, such as competitive demands, complex organisational plans and the increasing accessibility of resources and software products (Cleland, 1999; Webb, 1994).

Businesses managing various projects at the same time are usually regarded as multi-project organisations, with Zika-Viktorsson, Sundström, and Engwall (2006) mentioning that they are typically known as project-based organisations (Engwall & Jerbrant, 2003; Payne, 1995). In many cases, these projects are managed as a project portfolio, that is, "*a group of projects to be carried out under the sponsorship of a particular organisation*" (Archer & Ghasemzadeh, 2004). Project investment decisions play essential strategic roles in the majority of businesses, particularly project-based ones (Maylor, Brady, Cooke-Davies, & Hodgson, 2006; Thiry & Deguire, 2007), with approximately 90% of projects in any organisation conducted or started in a multi-project environment (Payne, 1995).

The role of PPM is to evaluate, select and prioritise projects, as well as revise priorities, and possibly eliminate and reduce projects currently in progress (Cooper, Edgett, Kleinschmidt, & Elko, 1998). By managing and analysing all projects and their inter-relationships at a portfolio level, the goal of PPM is to enhance the overall efficiency of a project portfolio.

Portfolio management seems to have been first employed in the 1950s to determine inventory portfolios (Markowitz, 1952). There are several definitions of PPM as individuals often regard portfolio management in different ways based on their backgrounds (Cooper et al., 2001c). In this study, we focus on the following.

"Project Portfolio management is a dynamic decision process, whereby a business's list of active new products (and R&D) projects are constantly up-dated and revised. In this process, new projects are evaluated, selected and prioritized; existing projects may be accelerated, killed or de-prioritized; and resources are allocated and reallocated to the active projects. The portfolio decision process is characterized by uncertain and changing information, dynamic opportunities,

multiple goals and strategic considerations, interdependence among projects, and multiple decision-makers and locations" (Cooper et al., 2001b).

Most studies acknowledge that PPM is generally considered as an active decision-making procedure whereby a set of projects is modified (Martinsuo & Lehtonen, 2007). Project and program management are focused on 'performing the project/program right' while portfolio management refers to 'carrying out the right project' (Cooke-Davies, 2002; PMI, 2006). PPM is viewed as the connection between strategy and procedure that allows a business to convert its ideas into reality and apply its strategies (Dey, 2006; Peter & Ashley, 2004). In particular, an improvement in any business is a result of its effective projects that produce new products (Englund & Graham, 1999). These projects are also the main component of planning and applying organisational strategies (Cleland, 1999). Wheelwright and Clark (1992a) determined the significance of selecting the right projects in a project portfolio for an organisation's future.

PPM is an essential part of strategic management practice which involves decisions concerning the actions a business needs to undertake to successfully achieve its strategic targets. In other words, it is an organisational function for increasing the value of a particularly challenging project concept (Cicmil, Williams, Thomas, & Hodgson, 2006; Jonas, 2010; Levine, 2005). The literature emphasises that PPM is basically a strategic decision-making method that involves determining, reducing and diversifying risk, identifying and addressing variations, and recognising and accepting the need for trade-offs (Kester, Griffin, Hultink, & Lauche, 2011; Levine, 2005). The importance of the position of a project portfolio in both public and private sector strategies has been emphasised more frequently as being an essential activity for organisations, leading PPM to assume a significant role in a competitive strategy and present itself as an element that impacts on the long-term outcomes of a business (Cooper et al., 2001b). As an essential factor in PPM is assessing which group of projects maximises the success and achievement of strategic targets, PPM has become an active decision practice in which new items for analysis and improvements are constantly updated.

The systematic control of a portfolio's outcomes can enhance benefits for businesses (Platje, Seidel, & Wadman, 1994). As PPM can handle several projects as a single program, it is more popular with practitioners (Artto et al., 2004). Many studies emphasise the significance of PPM for assessing, prioritising and choosing the right projects and programs according to organisational policies (e.g., Cooper et al., 2001b). Also, as the main critical studies of PPM concentrate on its practices of project selection and prioritisation (Artto et al., 2004; Elonen & Artto, 2003; PMI, 2006), choosing the most appropriate project is a significant aspect of organisational management. There are various meanings of a portfolio's operations of screening, examining and selecting projects (Blichfeldt & Eskerod, 2008). Also, Bible and Bivins (2011) divide PPM processes into the following three stages: 1) strategic, which sets the PPM's foundation for explaining the aim, vision and objectives of a business; 2) tactical, which consists of the screening and selection phases when the number of projects is restricted to a manageable level to determine the most beneficial ones for an organisation (Bible & Bivins, 2011), with a project's contribution to each goal able to be assessed using a variety of MCDM techniques (Bible & Bivins, 2011); and 3) operational, which refers to monitoring, assessing and managing the project portfolio in a way that confirms it is heading in the right direction. The goals of PPM are maximising a portfolio's value, developing its strategic arrangement and balancing its assignments (Cooper, Edgett, & Kleinschmidt, 2002) which this research uses to determine whether a PPM is successful. The key elements for obtaining a stable portfolio are the financial benefits related to the procedures used to gain a maximised value of it, strategic features associated with its objective(s) and risks. Through establishing a business plan for the elements, a decision maker (DM) is able to review the opportunities and, thereby, make judgements that can be verified by information (Maylor, 2010).

Various analyses have suggested that PPM and its performance results need to be assessed at the project, portfolio and organisational levels (Müller et al., 2008), with an effective PPM required to promote an organisation's overall goals. Therefore, an organisation's short- and long-term success factors are taken into account in the work of Shenhar, Dvir, Levy, and Maltz (2001) and applies the measurements of Maylor et al. (2006) on Cooper's three PPM goals (i.e., maximising a portfolio's value, developing its strategic arrangement and balancing its assignments) (Cooper et al., 2002) to discover their relationships.

Although PPM is not directly focused on ensuring good result for the key elements of obtaining a stable portfolio when aiming for strategic goals and objectives, its effective practice is capable of increasing the probabilities of choosing and then completing the assignments that best achieve an organisation's goals and promote its perspective. The fundamental aspects involved in obtaining such targets are (1) selecting the projects that best promote strategic targets, (2) analysing efficiency throughout the execution of a project to ensure that the portfolio remains on target while obtaining strategic advantages and (3) being able to modify a strategy and/or the portfolio whenever adjustments are required. To examine efficiency at the portfolio level, it is essential to identify the capabilities of individual projects and combine these findings in a mathematically meaningful process which demonstrates the strategic significance of associated projects. MCDM methods can fulfil these requirements; for example, their scoring techniques are used for large portfolios while pair-wise comparison methods are more suitable for smaller projects. However, finding the most suitable method(s) for PPM is a challenging task that requires a constructive review and comparison of MCDM methods to identify the most suitable one(s) for PPM decision making for determining which projects in a portfolio add most value to the organisational objectives. Moreover, the success of PPM is directly related to the level of understanding of PPM issues, with its key research challenges described below.

2.1.2. PPM Decision Making Challenges

Harris (1998) states:

"Decision-making is the study of identifying and choosing alternatives based on the values and preferences of the decision maker. Making a decision implies that there are alternative choices to be considered, and in such a case we want not only to identify as many of these alternatives as possible but to choose the one that (1) has the highest probability of success or effectiveness and (2) best fits with our goals, desires, lifestyle, values, and so on."

Paryani (2007) defines “decision making” as a technique for choosing among different options designed to achieve an objective. Therefore, the three factors underpinning “decision making” are (Derelöv, 2009):

a) there must be various options in a decision scenario;
b) these options need to produce different outcomes or approaches; and
c) there must be expected results, that is, for every choice, certain outcomes need to be more suitable than others.

There are various methodologies for portfolio management. The best-suited models indicate regular selections of the available project proposals and re-evaluation of existing projects during the implementation stage. They enable compliance with the strategic targets of an organisation without exceeding its available resources or violating business constraints, and responses to the minimal requests of the organisation in accordance with its different requirements (Archer & Ghasemzadeh, 1999), such as its potential revenue, acceptance and quantity of assets.

Recently, as PPM has received interest as a means of aligning projects with strategy as well as ensuring sufficient resourcing for projects, this has prompted businesses in different sectors to improve their PPM capabilities (Crawford, 2006; Maylor et al., 2006). PPM procedures assist organisations to control their projects using a variety of tools or methods developed to produce and evaluate project information as well as drive decision making in order to manage well-balanced portfolios in parallel with key objectives (Cooper et al., 2001b; Levine, 2005). Most publications indicate that the effective management of project portfolios transcends the techniques employed and realise that its business framework, individuals and tradition are all essential elements of an organisation's total capability to handle its project portfolio (Killen & Hunt, 2010). Studies frequently imply that PPM must be developed over time (Cooper et al., 2001b; Martinsuo & Lehtonen, 2007) and its different procedures and tools customised and specified for optimum outcomes (Loch, 2000). The remarkable increase in best-practice research and growth in techniques emphasises the existing links between PPM and improvements in final results (Kahn, Barczak, & Moss, 2006; O'Connor, 2004; Pennypacker, 2005; Project Management Institute, 2008). Furthermore, the strong focus on PPM processes and techniques demonstrates the existing link between the growth and outcomes of PPM and also the capability to improve these outcomes (Archer & Ghasemzadeh, 1999; Cooper et al., 2001b; De Reyck et al., 2005; Jeffery & Leliveld, 2004; Kahn et al., 2006; Killen, Hunt, & Kleinschmidt, 2008; O'Connor, 2004; Pennypacker, 2005; Phaal, Farrukh, & Probert, 2006; Project Management Institute, 2006, 2008). Some researchers suggest that there is a need for a mutual link between the project and strategic levels of an organisation rather than a one-way relationship from the strategic down to the project level as PPM procedures obtain information from both (Bridges, 1999; Cooke-Davies & Dinsmore, 2006; Dietrich et al., 2003; Meskendahl, 2010; Nelson, Gill, & Spring, 1999; Turner, 1993). PPM functions have been proven to enable top-down strategic objectives to be mixed with bottom-up strategy processes in a number of different scientific experiments (Burgelman, 1991; Miloševic & Srivannaboon, 2006; Noda & Bower, 1996).

Portfolio decisions ensure resource adequacy and agility, and also implement better adjustments at the portfolio than project level (Floricel & Ibanescu, 2008; Petit, 2012). Nonetheless, PPM decisions depend on the limited intellectual abilities of humans to assess a range of different data in restricted timeframes. PPM techniques and procedures are created to support such decision making by offering a pure perspective of a project portfolio, ensuring that information is accessible and providing appropriate strategies and resources to simplify examinations of project details (Cooper et al., 2001b; De Reyck et al., 2005; Kester et al., 2011). Classical metrics and strategies emphasise that efficiency and performance are driven by cost, schedule, quality and scope (Kerzner, 2006) but do not examine, monitor or track portfolios/projects to analyse their strategic benefits.

The challenges of executing and delivering PPM are related to the uncertainties created by turbulences in the relevant industry, sudden technological variations and uncommon resources being shared among the many areas of an organisation (Eisenhardt & Brown, 1997; Elsenhardt & Martin, 2000). To be able to confirm the possible implementation of a portfolio, PPM needs to visualise the options for, and potential outcomes of, project decisions across it, with the quality of decision making a key element of a successful project portfolio (Matheson & Menke, 1994). An organisation's achievements rely on proper PPM strategies, techniques and tools that enhance the quality associated with its portfolio-level decisions. Project interconnections and relationships among activities that increase the complexity of PPM decision making need to be considered along with financial, strategic, risk, resource and other elements. As portfolios of complex and interdependent projects are common, there is certainly a clear need for advanced methods that can recognise and handle their associations. Research on portfolio management has identified that, if decisions depend on several criteria, such as product, market and financial, over-emphasising a single measure is linked to poorer performance (Cooper, Edgett, & Kleinschmidt, 1999; Ronkainen, 1985).

While several studies describe various PPM issues, such as obtaining executive-level support and commitment (Kendall & Rollins, 2003), gaining a perception of a portfolio across projects (McDonough III & Spital, 2003; Wheelwright & Clark, 1992b), and having proper information (Martino, 1995; Wideman, 2004) and sufficient time to perform PPM (Lawson, Longhurst, & Ivey, 2006; Vähäniitty, 2006), a major concern is ascertaining the key challenges of PPM.

Earlier studies imply that PPM must be used properly in each circumstance as it cannot be regarded as a fixed structure and each situation may have a unique function (Blomquist & Müller, 2006). Wheelwright and Clark (1992b) and Cooper et al. (1998) claim that, to apply an organisational strategy, an organisation must assess and select the resources for several types of projects. Also, it needs to choose options and projects using an adaptable decision-making practice (Bessant, Von Stamm, & Moeslein, 2011; Blichfeldt & Eskerod, 2008; Wheelwright, 1992; Wheelwright & Clark, 1992b); for example, assessing and selecting a brand new technological project is much more comprehensive, ambiguous and uncertain than improving a current one (Wheelwright & Clark, 1992b).

The issues regarding project, program and portfolio management highlighted in a number of studies (Artto, 2001a, 2001b; Rintala, Poskela, Artto, & Korpi-Filppula, 2004; Staw & Ross, 1987) demonstrate the following common challenges involved in selecting a project portfolio.

Cooper et al. (2001c) describe a number of issues and concerns regarding achieving successful PPM, with the key ones being resource management, project prioritisation, decision making without reliable data and there being too many small projects in a portfolio. Prioritisation is challenging because selection techniques are incapable of comparing different projects, some of which are tangible and others intangible (Archer & Ghasemzadeh, 1996). Also, as some projects are unique, they cannot be compared with others although grouping them with the others makes comparisons easier; for example, some projects could refer to work procedure improvements and others to the delivery of IT devices (Blichfeldt & Eskerod, 2008). There are uncertainties related to project variables (e.g., cost and risk) (Radulescu & Radulescu, 2001). A simple analysis of formerly well-known products entails a lower level of risk than that of projects attempting to develop a completely new technology (Verbano & Nosella, 2010). DMs may experience conflicting understandings of a project's concept and organisational requirements (Brun et al., 2008; Brun, Steinar Saetre, & Gjelsvik, 2009) or even be unable to fully identify an entirely new product concept (Engwall & Jerbrant, 2003). Another key organisational issue is the lack of connection between strategic and project selection levels (Elonen & Artto, 2003).

There are different types of portfolios such as financial, construction, environmental and agricultural portfolios. Although these types are distinct in theory, they tend to overlap in practice. Consequently, a district program may include several different types of portfolios, serving several different purposes. No matter which kind of portfolio there is in place, the aim of this study is to focus on PPM in general and identify the key challenges of PPM. For example, interdependencies between projects in a portfolio is one of the challenges and regardless of whether we are managing a construction or agricultural portfolio, we still need to consider the interdependencies between the projects for both portfolios. This will also apply to the New Product Development (NPD) portfolios whereby a business's list of active new products (and R&D) are constantly up-dated and revised. DMs may also experience conflicting understandings of a project's concept and organisational requirements or even be unable to fully identify an entirely new product concept. This issue is the most critical challenge in the decision-making process, known as 'uncertainty'.

DMs need to incorporate different types of decision-making tools that integrate various methods and judgements, such as formal and informal (Blichfeldt & Eskerod, 2008; Olausson & Berggren, 2010), as well as well-ordered and not well-organised (Steffens, Martinsuo, & Artto, 2007). However, PPM studies have not yet properly highlighted the difficulties DMs might have to deal with when integrating various methods (Geraldi, 2008) those of organisations incorporating different methods for identifying options and projects (Bessant et al., 2011).

Most organisations encounter difficulties when selecting specific projects (De Reyck et al., 2005; Meskendahl, 2010) using an adaptable decision-making practice (Bessant et al., 2011; Blichfeldt & Eskerod, 2008). While several PPM studies indicate the significance of selecting a specific group of projects, they do not properly examine the issues faced during the selection process (Bessant et al., 2011). PPM studies have not presented a comprehensive idea of exactly how processes for selection and project prioritisation are actually stated in PPM. Therefore, further investigation is required to determine exactly the types of methods employed for the examination and selection of projects (Geraldi, 2008).

The challenges of assessing and selecting options and projects are discussed below through an examination of PPM studies as well as observations based on decision-making principles.

2.1.2.1. Sensitivity Analysis/Uncertainty Treatment

The level of a project's complexity depends on its degree of uncertainty regarding the direction in which to go and the way to achieve its goals (Marmgren & Ragnarsson, 2001). Organisations deal with several uncertainties, including insufficient data, inaccurate cost information, the completion period and availability of resources and benefits (Cooper et al., 2001b). A sensitivity analysis is an essential aspect of quantitative decision models (Dantzig, 1998; Insua, 1990) and an effective process because it demonstrates the advantages and disadvantages of a/the particular examination (Commission, 1992) while efficient uncertainty management is the most critical challenge in the decision-making process (Felli & Hazen, 1998; Steffens et al., 2007). A comprehensive decision assessment demands an in depth sensitivity examination (Belton & Hodgkin, 1999) which can be very challenging (Larichev, 2000). Despite the degree of agreement on the impacts of uncertainty, there is less regarding common terms for uncertainties (Norton, Brown, & Mysiak, 2003; Refsgaard, van der Sluijs, Højberg, & Vanrolleghem, 2007; Walker et al., 2003; Warmink, Janssen, Booij, & Krol, 2010; Zhang & Achari, 2010), with the word 'risk' representing incidents rather than sources. Experts have recommended introducing the wider term 'uncertainty management' rather than risk management that concentrates mainly on threats and incidents (Cleden, 2012). French (1995) describes some sources of uncertainty that might occur (e.g., judgemental assessments, contrasting definitions and unreliable numerical calculations). Wenyi (2008) recommends introducing the component of sensitivity examination into models designed for the selection of project portfolios.

The selection process consists of numerical inputs which might not be fully accurate (French et al., 1998). Every step in the MCDM procedure consists of some kind of uncertainty, such as selecting the technique (Bouyssou, 1990) and factors, examining the factors' values and choosing weights (Janssen, Nijkamp, & Rietveld, 1990). Consequently, a DM usually has to first estimate the effect of change on the relevant portfolio and then calculate the essential information with considerably higher degrees of accuracy and reliability. For these reasons, a sensitivity analysis of MCDM challenges must be conducted. Insua (1990) emphasises the need for this as difficult decisions can be extremely sensitive to certain changes in the issues; for example, assessing and selecting an entirely new system which is being created is an extremely unknown/uncertain situation (Wheelwright & Clark, 1992b). Furthermore, Steffens et al. (2007) consider that informal decisions regarding complicated system processes are associated with handling uncertainty and, as outlined by Olausson and Berggren (2010), both formal and informal methods are essential when dealing with them. Formal ones confirm that judgements are prepared as according to all the targets and detailed information about supply in order to analyse past selections and decisions while informal ones, determined by communication as well as learning, are essential for observing uncertainty. Also, DMs usually work in groups which make both formal and informal choices (Christiansen & Varnes, 2007; Gutiérrez, Janhager, Ritzén, & Sandström, 2008) at different levels in an organisation (Kester, Hultink, & Lauche, 2008). Selection techniques have to consider uncertainty through a scoring phase and have the capability to deal with uncertain, imprecise and missing information. The successful development and supervision of, and insights into, uncertainty according to the suggested criteria is regarded as a challenging task for MCDM (Felli & Hazen, 1998). Formal and strict methods are likely to be insufficient for dealing with uncertainty since they require a concept or project description to be specified (Brun et al., 2008; Brun et al., 2009; Engwall & Jerbrant, 2003; Westling, 2002).

2.1.2.2. Dependencies

Dealing with a portfolio of projects with uncertainty is a difficult task exacerbated by the existence of interdependencies (Perminova, Gustafsson, & Wikström, 2008) which is among the reasons for a PPM failure (Elonen & Artto, 2003). PPM procedures are used to determine dependencies among the projects in a portfolio so that decisions can be made knowing the potential impacts of these projects on each other (Shenhar et al., 2001). Although the interdependencies in portfolios with several projects need to be known to facilitate good judgements (Blau, Pekny, Varma, & Bunch, 2004), communications among the various procedures/methods available are extremely complicated (Dawidson, 2006). Choices or unforeseen situations occurring in a single task impact on other functions (e.g., re-prioritisations of programs or evaluations of strategies). Most scientific studies of PPM manage each project as an individual process while recognising the value of considering projects' interdependencies

(Collyer & Warren, 2009; Dahlgren & Söderlund, 2010; Söderlund, 2004). To indicate the additional characteristic of PPM compared with individual project management, Cooper and Edgett (2003) employ the analogy that a project procedure addresses the 'fingers' while PPM focuses on the 'fist'.

Also, Ausura (2002) highlights that it is inadequate to consider only new programs and all of them in every phase of a system production sequence need to be regarded as parts of the overall portfolio. Program choices generated at the portfolio level have the capability to contemplate the relationships among programs and connections between their portfolio and organisational goals. Normally, projects/programs in portfolios are naturally interdependent; for example, in the event that program B depends on program A, program A needs to be subsequently chosen in the event that program B is included in a portfolio while program A might be contained in the portfolio even if program B is not. Joint programs (several programs, projects and initiatives, of which only one can possibly be chosen) indicate an additional type of interdependence which has to be considered as well.

2.1.2.3. Decision Traceability

To deal with PPM complexities, such as uncertainty or dependencies among projects, it is essential to keep track of data and ensure that critical data is not eliminated or unnecessary data incorporated. This process has to be traceable (backwards and forwards throughout the decision cycle and from the strategic to operational levels) (Danilovic & Browning, 2007).

2.1.2.4. Simplicity

Although there are more than 100 different methods which can be used to calculate, examine and select decision options, most are seldom employed because: they are complicated and involve an excessive amount of input information; provide insufficient management of risk and uncertainty; are incapable of identifying interrelationships and related requirements; might simply be too difficult to understand or apply; and might not be considered from the perspective of a structured method and practice (Cooper, 2001; Cooper, Edgett, & Kleinschmidt, 1997a). Although several earlier decision-making techniques tried to improve formulaic options via mathematical models and optimisation methods, generally, they are not often applied because of their complex structures (Coldrick, Longhurst, Ivey, & Hannis, 2005). Costa (1988) states that, although there are various MCDM techniques which might be useful (in theory), they are subject to failure due to their lack of simplicity, with their complexities being the main reason for DMs preferring simple weight-rating methods. Despite the fact that there is no shortage of decision-making methods with individual positive aspects, there is certainly a lack of an overall framework for rationally arranging them in an adaptable procedure which could sustain the practice of portfolio decision making, partly because of the complexities involved in using some of them. DMs are unlikely to apply a technique/method/tool that is not both effective and simple to operate (Moore & Benbasat, 1991). To attempt to overcome these issues, suitable techniques need to provide the best features of some current techniques with fewer complexities. Therefore, simple decision-support tools/techniques are key elements for multiple decision making (Bender & Simonovic, 2000).

2.1.2.5. Quantitative and Qualitative Measures

The strategic arrangement of projects in a portfolio, which is critical, requires both quantitative and qualitative techniques (Kester et al., 2009). It is also in line with analysing specifications that assist the selection of project options and decisions (Bergman & Mark, 2002). Although quantitative information is very important for making effective decisions, its source and reliability are more significant, and it is usually regarded as being more valuable than qualitative information (McLaren & Simonovic, 1999).

A project's related risk level is a qualitative factor, its estimated profit a quantitative one, and its involvement in organisational strategy both qualitative and quantitative ones (Ohr & McFarthing, 2013). Although quantitative data, such as costs and time, is readily available for most projects, qualitative analysis is more often used for complex ones. In current PPM, most portfolio decisions are subjective based on assessments of various project options.

2.1.2.6. Number of Projects

The number of programs/projects planned for a given portfolio can be quite significant (Cooper et al., 1997a) and confusion regarding portfolio decisions arises as the number of projects to be taken into consideration increases (Levine, 2005). Cooper and Edgett (2003) justify the significance of excellent decision making and the need to acquire top-quality information for that purpose. Selecting and delivering a number of projects beyond an organisations' capacity are among the main reasons for projects' failures to achieve organisational objectives (Almendra & Christiaans, 2009; Yelin, 2005). As the possibility of reaching sound organisational decisions can be diminished if many programs/projects must be considered, verification processes must be conducted before the commencement of portfolio selection to justify the inclusion of specific programs/projects in this process.

2.1.2.7. Trade-offs/Conflict

MCDM enhances a DM's ability to examine trade-offs between options and assess their influences on different stakeholders (Mysiak, Giupponi, & Rosato, 2005). There are several, usually inconsistent, targets linked to the selection of programs/projects for inclusion in a portfolio; for instance, are financial targets more important than political ones, and if so, to exactly what degree? In a MCDM's closing stage, the ideal option is that which offers an appropriate cross-section of trade-offs among variables (Simonovic, Burn, & Lence, 1997).

There are two main issues linked to MCDM which cause these problems to become difficult to resolve. Firstly, some targets are qualitative (e.g., political ones) and, secondly, different targets usually conflict with each other.

Hwang and Yoon (1981) propose two techniques for solving such problems: non-compensatory and compensatory methods.

2.1.2.7.1. Non-compensatory Methods

These techniques tend to not allow trade-offs between elements, that is, a negative value in one cannot be mitigated by a positive value in any other because, as every one has to be considered alone, evaluations are conducted on an attribute-by-attribute base. As non-compensatory methods can remove dominant solutions/options, they could introduce several alternatives which are only suitable if the elements are similar and, also, may not be effective for making decisions. Therefore, they are omitted from this study.

2.1.2.7.2. Compensatory Methods

These methods allow trade-offs between elements (e.g., scoring) whereby a minor decrease in one element is appropriate when supported by improvements in others.

2.1.2.8. Group Decision Making

As DMs usually work in groups, which make formal and informal choices at different levels (Gutiérrez et al., 2008), their decision-making processes are a great deal more complicated than that of an individual or, arguably, even inefficient (Proctor, 2001). The members of a decision group may vary from an organisation's senior executives with similar targets to its mid-level managers with entirely opposite ones (Davey & Olson, 1998). Group decision making provides connections among DMs and also between them while this support process enables portfolio decisions to be made that more closely satisfy all the targets and goals of the organisation. A key factor behind the complexities of group decision making is the lack of a strategy in which all DMs are able to present their opinions (Georgopoulou, Lalas, & Papagiannakis, 1997), but there are few methods which can adequately overcome this difficulty (Leyva-Lopez & Fernandez-Gonzalez, 2003). It is necessary that DMs ensure that their perspectives are considered in a decision-making process (Miettinen & Salminen, 1999). Souder (1975) seeks to achieve consensus on portfolios by discovering mixtures of integrated comparisons, group discussions and participant connections in decision making.

2.1.2.9. Hierarchical Structure (Mutual Links between Projects and Strategic Levels)

A PPM procedure starts from, and reports to, the strategic level and manages a link between that and the operational level (Poskela, Dietrich, Berg, Artto, & Lehtonen, 2005). As previously stated, PPM decision-making methods can be very complicated, difficult to use and normally require large amounts of input information (Cooper et al., 2001c). To minimise these types of issues, a portfolio is structured hierarchically, with each phase beginning from a top-down (i.e., strategic level) or bottom-up (i.e., project/operational level) perspective. Moreover, PPM is generally set up at several levels within an organisation, including departmental, divisional, branch or unit ones, while some techniques, e.g., top-down and bottom-up ones, can line operations up at only an organisation's strategic level (Cooper & Edgett, 2008). The capability of PPM to use top-down strategic objectives with bottom-up strategic processes are examined in various investigations (e.g., Crawford, 2001), with many studies (e.g., Meskendahl, 2010) suggesting the need for a mutual connection between the operational and strategic levels of an organisation. Cooper, Edgett, and Kleinschmidt (2004) analyse the success of their own recommended PPM goals but provide limited guidance on the importance of the connection between portfolio- and organisation-level outcomes. Killen et al. (2008) believe that the association of new system achievements with portfolio performance is a key factor for organisational growth. An example of a hierarchical portfolio structure is presented in Figure 3.

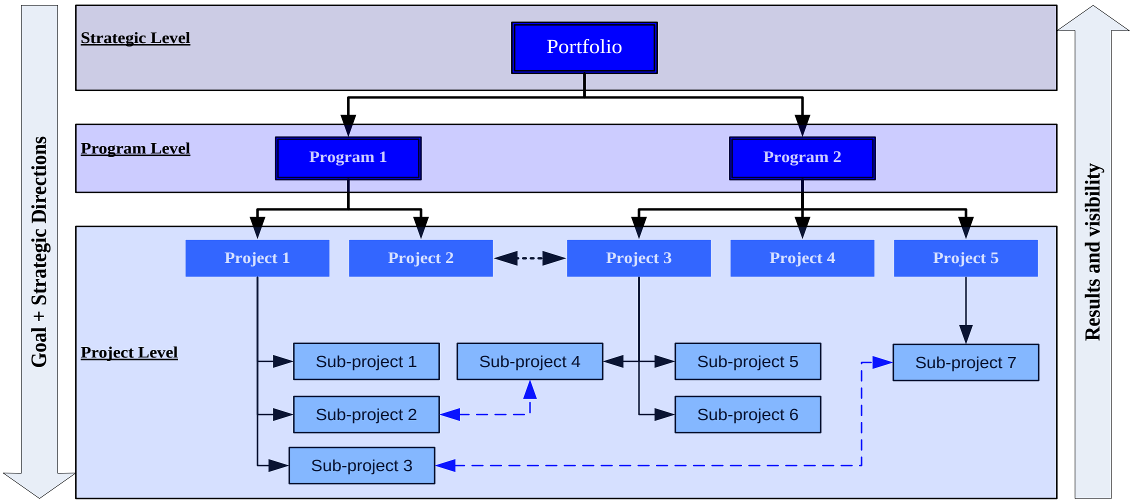

Figure 3. EXAMPLE OF HIERARCHICAL PORTFOLIO STRUCTURE

2.1.2.10. Other Criteria

Other challenges and requirements in accordance with operational assumptions (e.g., workforce management, financial availability, honesty, and politics and policy variations) are not considered in this assessment because they rely more on managing capabilities than on the techniques themselves. Nevertheless, this does not imply that these factors are less important during a PPM MCDM assessment process but that they are more in line with the operational stage following the selection of the preferred MCDM method(s).

A summary of the key PPM challenges in this study are presented in Table 1.

Table 1. SUMMARY OF KEY PPM CHALLENGES

Challenging factors	Description
Sensitivity Analysis/Uncertainty Treatment	A decision assessment involves different inputs which may not be entirely specific (e.g., insufficient data, inaccurate cost information, an undetermined completion period, and little knowledge of the resources and benefits).

Dependencies	For effective decision making, the interdependencies in portfolios with several projects need to be known. Every program depends on the others and may be linked by many different dependencies. Often, as projects in portfolios are very interdependent in nature, all of them must be considered in every step of a decision-making process.
Decision Traceability	To deal with PPM complexities (e.g., uncertainty and dependencies), it is essential to keep track of data and ensure that critical data is not eliminated and/or unnecessary data incorporated.
Simplicity	While most decision-making methods are very difficult to understand and/or apply, DMs are unlikely to use one that is not effective and simple. Also, as there is an overall lack of a framework for arranging these methods, choosing simple ones is one of the key elements for multiple decision making.
Quantitative and Qualitative Techniques	The strategic arrangement of projects in a portfolio, which is extremely critical, requires both quantitative and qualitative techniques.
Number of Projects	As the number of possible projects in a portfolio can be enormous, the method used to solve decision challenges cannot be restricted to dealing with a certain number of items or options which is the case in some techniques.
Trade-offs/Conflict	There are several, usually inconsistent, targets linked to the selection of programs, with prioritising them a challenging task. As non-compensatory methods fail to permit trade-offs between elements, only compensatory ones are selected for detailed analysis in this study.
Group Decision Making	Large and difficult decisions, especially at executive senior management levels, often require several DMs operating in groups.

Mutual link between Projects and Strategic Levels (Hierarchical Structure)	PPM is generally set up at several levels, with its decision-making methods very complicated and usually requiring large amounts of input information. To minimise these types of issues, a portfolio needs to be structured in a hierarchical way so that each phase can begin from a top-down (strategic level) or bottom-up (project/operational level) perspective and examine the maturity of all levels in a PPM process (e.g., project, program and portfolio management/strategic ones).

2.2. Classification of PPM Decision-making Techniques

An appropriately harmonic combination of projects must be selected to increase the benefit of a portfolio and its organisational strategy (PMI, 2006). Given that each project performs a unique function and presents an individual input to PPM, organisations have to determine, choose, prioritise and allocate options to different kinds of projects (Geraldi, 2008).

Techniques for eliminating and resolving multi-criteria issues are continually being developed while the number of MCDM-related articles is gradually increasing (Wallenius et al., 2008). As there is no single MCDM method or tool that can support strategic PPM decision making, different ones are used to suit different PPM situations (Killen et al., 2008; Verbano & Nosella, 2010).

Despite the fact that earlier investigations examined and evaluated decision making, the work of Neumann and Morgenstern (1947) and Savage Leonard (1954) can be regarded as the beginning of multi-criteria studies. Belton and Stewart (2002) introduce an in-depth examination of MCDM techniques and several articles (e.g., Sun, 2005) examine existing PPM decision-making techniques. However, there are basically two main issues related to conducting assessments: the number of MCDM techniques is rapidly increasing (Bouyssou, Marchant, Pirlot, Tsoukiàs, & Vincke, 2006); and researchers almost never provide good reasons for selecting or categorising these techniques.

Little practical research has been applied to analysing the classification of MCDM techniques in PPM and it is very unlikely that any scientific experiments have examined them on a scale similar to that of this study. With the intention of considering the wide variety of decision-making techniques as well as their complexities, a classification model is developed in this study, in which all methods identified in ANNEX A can be examined and classified.

2.2.1. Proposed Classification Framework

On the basis of an extensive literature review of various decision-making methods (e.g., Hwang and Yoon, 1981; Hobbs, 1986; Hwang & Yoon, 1981; MacCrimmon, 1973; Ozernoy, 1992), this study proposes a mixture of all those taxonomies in three categories which also incorporate those which may not have been presented in other publications: MCDM also called Multi-criteria Decision Analysis (MCDA), Artificial Intelligence (AI) and others (Figure 4).

This research concentrates primarily on the application of decision-making methods for PPM. As, in the literature, PPM issues are related to MCDM methods, several of which are used in problem-solving procedures (e.g., Gürbüz, Alptekin, & Alptekin, 2012; Jozi, Shoshtary, & Zadeh, 2015). Therefore, non-PPM issues or methods not included in the MCDM category are not considered for further investigation in this study. Figure 4 presents a framework for classifying decision-making methods.

All AI techniques are omitted from this study since they are normally employed to determine approximate answers and options for difficult optimisation conditions; for example, a genetic algorithm (GA) method is incapable of ensuring a truly ideal solution to a complex optimisation problem (Xu & Ding, 2011). As other methods, such as the Chance Constrained and GA (CCGA) (Azadeh & Alem, 2010) and Numerical Taxonomy (NT) (Sokal & Sneath, 1963), are designed for a specific industry or situation, they may not be suitable for many real-life challenges, including general PPM decision making; for example, CCGA is a genetic model and NT a classification method in biological systematics which involves grouping numerical types of taxonomic units according to their characteristics.

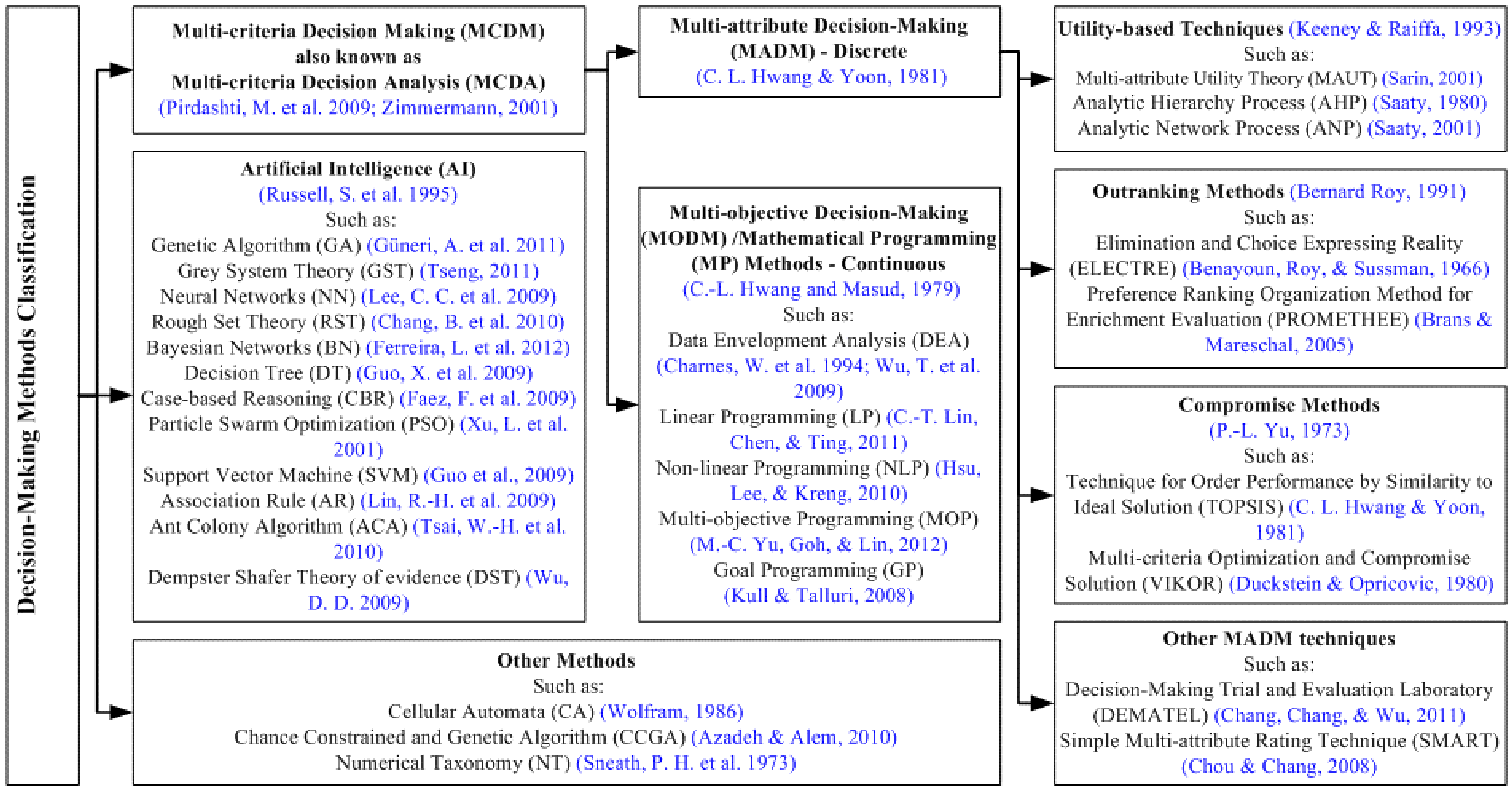

Figure 4. CLASSIFICATION OF DECISION-MAKING TECHNIQUES

2.2.2. Multi-criteria Decision Making (MCDM)

To develop ongoing communication and come up with viable choices for making a decision, a DM in an organisation no longer considers only one criterion but multiple ones. However, decision challenges, such as ranking, selection and sorting, are sometimes complicated since they often consist of various criteria.

MCDM is a structure for analysing decision issues with complex multiple targets (Nijkamp, Rietveld, & Voogd, 2013; Zeleney, 1984) and can handle long-term options, unknown aspects, risks and complicated values. The practice of MCDM generally defines targets, selects the requirements for determining them, specifies options, modifies the measurement values, assigns weights to the requirements, and uses a mathematical algorithm to score options and choose them (Hajkowicz & Prato, 1998; Howard, 1991; Keeney & Keeney, 2009; Massam, 1988). MCDM also incorporates several methods that enable estimations of various requirements to assist DMs to select, rank and evaluate various options (Belton & Stewart, 2002), and examine decision problems specified by various difficult goals (Nijkamp et al., 2013).

MCDM methods for minimising the challenges and complexities involved in dealing with large amounts of data during decision-making operations appear to have been used for the first time in the financial industry in the 1960s (Figueira, Greco, & Ehrgott, 2005), with a significant number of MCDM assessments based on a more recent investigation by MacCrimmon (1973). The increase in the development of MCDM methods has led to a variety of studies that outline their advantages and disadvantages for handling the difficulties of decision making (Hajkowicz, Young, & MacDonald, 2000; Herath & Prato, 2006; Kiker, Bridges, Varghese, Seager, & Linkov, 2005; Lahdelma, Salminen, & Hokkanen, 2000; Mendoza & Martins, 2006). MCDM methods have been employed in different fields, such as:

a. policy examination (Haimes & Hall, 1974; Keeney, 1975; Keeney, McDaniels, & Swoveland, 1995);
b. environmental protection (Anselin, Meire, & Anselin, 1989; Bakus, Stillwell, Latter, & Wallerstein, 1982; Bell, 1975; Gehlbach, 1975; Janssen, 1992; Sargent & Brande, 1976; Smith & Theberge, 1987);
c. production systems (Wabalickis, 1988);
d. mixed production (Putrus, 1990);
e. engineering applications (Wang & Raz, 1991);
f. investment assessment (Boucher & MacStravic, 1991);

g. structural design (Cambron & Evans, 1991);
h. food security (Haettenschwiler, 1994);
i. resource management (Hayashi, 2000; Herath, 1982; Prato, Fulcher, Wu, & Ma, 1996; Romero & Rehman, 1987; Xu, Prato, & Ma, 1995);
j. water, ecosystem and wildlife management (Keeney, McDaniels, & Ridge-Cooney, 1996; Prato, 1999; Prato et al., 1996; Prato & Hajkowicz, 2001);
k. forest and wetland management planning (Ananda & Herath, 2003a, 2003b, 2005; Herath, 2004; Kangas & Kangas, 2005; Kangas, Kangas, Leskinen, & Pykäläinen, 2001; Prato, 2006; Pukkala, 2002);
l. portfolio and financial assets management (Subbu, Russo, Chalermkraivuth, & Celaya, 2007);
m. location selection (Kaboli, Aryanezhad, Shahanaghi, & Niroomand, 2007);
n. procurement and selection of best supplier (Li, Cui, Chen, & Fu, 2008);
o. forest management (Kangas, 1994; Kangas, Karsikko, Laasonen, & Pukkala, 1993; Kangas & Kuusipalo, 1993; Penttinen, 1994);
p. sustainable development (Hai-yang & Fang, 2009);
q. evaluation of performances of business units (Tan, Lee, & Goh, 2010);
r. health care system (Daichman, Greenberg, Pikovsky, & Pliskin, 2013);
s. finance (Kou, Peng, & Wang, 2014);
t. energy (Kabak & Dağdeviren, 2014); and
u. environmental risk assessment (Jozi et al., 2015).

Many MCDM methods require determination of the most suitable techniques for managing the issues associated with decision making (Brunner & Starkl, 2004). Although several researchers explain these issues in a basic manner by outlining their individual components and patterns, only a few (e.g., Goicoechea, Hansen, & Duckstein, 1982; and Milan, 1982) clarify the steps in their algorithms.

There are a few different opinions regarding the way in which MCDM techniques should be sub-divided (Hajkowicz, 2000). The requirement to compare them and the significance of their selection issues were most likely identified for the first time by MacCrimmon (1973) who recommends a classification of them. Some researchers discuss processes for classifying and selecting a suitable MCDM technique based on its input specifications (e.g., Hwang and Yoon, 1981; Hobbs, 1986; Hwang & Yoon, 1981; and Ozernoy, 1992). Also, Jelassi and Ozernoy (1989) recommend using a professional framework to select MCDM techniques, with Jacquet-Lagreze and Siskos (2001) suggesting measurable, ordinal, probabilistic and fuzzy requirements.

Bouyssou (1990), Georgopoulou et al. (1997) and Al-Kloub, Al-Shemmeri, and Pearman (1997) all agree on the requirements for selecting MCDM methods, that is, they need to be simple and easy to understand, operational, complete, non-redundant and essential. Furthermore, Kheireldin and Fahmy (2001) categorise MCDM methods as cardinal, frequency, scale-modelling and mixed information. MCDM methods are also grouped according to their allocated weights (Harboe, 1992). Hajkowicz (2000) proposes classifying MCDM methods as 'continuous' and 'discrete' techniques but excludes outranking ones. Also, Olson (1996) and Yoon and Hwang (1995) present valuable reviews of MCDM techniques.

This study classifies MCDM into Multi-objective Decision Making (MODM) (or continuous) and Multi-attribute Decision Making (MADM) (or discrete) techniques. The former can be used for an unlimited (infinite) number of options implicitly identified by their difficulties whereas the latter consider a limited (finite) number of options and criteria (Hajkowicz et al., 2000) which enables them to be sub-divided into ranking techniques (Nijkamp et al., 2013). Therefore, MODM techniques handle design/search problems and seek an optimal quantity which may change considerably in a decision challenge whereas MADM ones are effective for selection/evaluation problems (Hwang & Lin, 2012). The MODM and MADM models are compared in Table 2 (Hwang & Yoon, 1981).

Table 2. Comparison of MODM and MADM models

	MODM	**MADM**
Criteria defined:	Objectives	Attributes
Objectives defined:	Explicitly	Implicitly
Attributes defined:	Implicitly	Explicitly
Constraints defined:	Explicitly	Implicitly
Alternatives defined:	Implicitly	Explicitly
Number of alternatives:	Infinite (Large)	Finite (Small)
DM's control:	Significant	Limited
Decision-modelling paradigm:	Process-oriented	Outcome-oriented
Relevant to:	Design/Search	Selection/Evaluation

Additional information regarding MCDM techniques is available in: Goicoechea et al. (1982); Tecle (1988); Islei (1987); Vincke (1992b); and e Costa and Vincke (1990); and an in-depth outline of MCDM in Akadiri and Olomolaiye (2012); Dyer, Fishburn, Steuer, Wallenius, and Zionts (1992); and Herva and Roca (2013); Huang, Keisler, and Linkov (2011); Munda (2005); Rowley, Peters, Lundie, and Moore (2012); Stewart (1992).

2.2.2.1.Multi-attribute Decision Making (MADM)/Discrete Methods

According to Yoon and Hwang (1995), MADM techniques share the following features: they screen, prioritise, select and rank a limited (finite) number of options; have various elements per issue and a variety of units of measurement among the elements; usually require data regarding the relative advantages of each element; generally, are available based on ordinal or cardinal data; and their difficulties can be stated in a matrix structure.

MADM methods are used in many fields for solving different problem situations; for example, Azar (2000) apply several MADM techniques (e.g., SAW, WPM and TOPSIS) as ways of examining the overall performance of imaging for breast cancer diagnosis. They are also applied in Enterprise Resource Planning (ERP) decision making by Bernroider and Mitlohner (2015), and, furthermore, to rank water supply systems (Mianabadi & Afshar, 2008) and population growth rates (Soltanpanah, Farughi, & Golabi, 2010).

In many studies, MCDM refers to MADM for which a variety of methods is available. Research conducted during the past three decades shows an increasing number of new and combined MADM techniques with different classifications (e.g., Nijkamp et al., 2013), most of which belong to the categories of Multi-attribute Utility (utility-based); Outranking; and Mixed (compromise) methods. Greco, Matarazzo, and Słowiński (2004) classify these methods in the three categories of utility features, outranking relationships and models of decision principles. while Kangas, Kangas, and Pykäläinen (2001), and Guitouni and Martel (1998) categorise them as: (i) the Value and Utility Theory (known as 'American School' techniques); (ii) Outranking (a.k.a. 'European School' techniques); and (iii) Interactive approaches. Based on the theories behind them, this study groups MADM methods as follows.

2.2.2.1.1. Utility-based Techniques (UBT)

(a.k.a. Multi-attribute Utility Techniques, Compensatory Methods or Performance Aggregation-based Methods)

Neumann and Morgenstern (1947) and Savage Leonard (1954) were the first to present effective observations of how multi-criteria decisions are made. However, their experiments do not clearly assist DMs in making decisions involving complex multi-criteria tasks. In order to overcome these challenges, Keeney and Raiffa (1993) present UBTs that basically aim to allocate a utility amount to every alternative, for example the Analytic Hierarchy Process (AHP) or Analytic Network Process (ANP). What might make their recommendations useful is that their model considers uncertainty and provides options for the alternatives to communicate with each another. Using a UBT, DMs can obtain accurate responses and solutions to a variety of choices (Belton & Stewart, 2002). UBTs are also referred to as Compensatory Methods because of their inadequate performances for some criteria (Linkov et al., 2006). A UBT does not consider choices to be mutually independent and tends to be more user-friendly and straightforward than other MCDM methods. However, its use of additive utility features is only applicable when the criteria are independent.

2.2.2.1.2. Outranking Methods

(a.k.a. Partially Compensatory or Preference Aggregation-based Methods)

Outranking methods assess sets of preferences to determine whether option 'A' is at least as effective as option 'B' (Roy, 1991), that is, they rely on the philosophy that, as one option can attain a level of control over other available ones (Kangas, Kangas, & Pykäläinen, 2001), all the options need to be ranked (Rogers & Bruen, 1998). Two methods in this category are: Elimination and Choice Expressing Reality (ELECTRE); and Preference Ranking Organisation Method for Enrichment Evaluation (PROMETHEE). As Outranking methods do not assume that only one best option is available; for instance, they do not consider the relative levels of importance of under- and over-performances, they are also referred to as Partially Compensatory Methods. Usually, they are used when the factor metrics are difficult to aggregate or there are broad ranges of different units and unique dimensions for each factor (Seager & Theis, 2004). The major issue regarding the use of an Outranking method is the different definitions of what represents outranking and how its threshold variables are arranged and later adopted by a DM.

2.2.2.1.3. Compromise Methods

The Compromise model (Milan, 1982; Yu, 1973) can assist DMs to arrive at a final decision for a problem with mixed factors and offer the best possible practical option by sharing ideas. Sometimes, the selection process draws on political factors whereby a DM can define the essential elements of compromise options (Yu, 1973). Compromise methods, such as the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), are driven by an aggregating feature that provides bonding to the ideal (Chatterjee, Athawale, & Chakraborty, 2009) and a foundation for discussions concerning a DM's choice based on the factors' weights (Sayadi, Heydari, & Shahanaghi, 2009).

2.2.2.2.Multi-objective Decision Making (MODM)/Continuous Methods

It is quite normal to simultaneously deal with various targets without having a clear direction as to which refer to performances and which to issues. These difficulties of 'many multiple decision criteria', 'depending on limitations' and 'several targets' are generally known as MODM problems. It is most likely that Kuhn and Tucker (1951) were the first to identify these issues which are also called 'vector-maximum' ones. The challenges of MODM (in a mathematical programming framework) are broken into different groups. The first does not require obtaining any data from DMs throughout the process of selecting an alternative as its techniques depend on pre-assumptions about the DMs' choices (Milan, 1982; Zeleny, 2012). The second involves collecting cardinal or ordinal selected data prior to the solving process. A few of these approaches collect only cardinal priorities while others, such as Goal Programming (GP), use a combination of the capabilities of both cardinal and ordinal data. The third delivers a number of alternative options from which DMs are able to select the ideal one, for example, Data Envelopment Analysis (DEA) which offers options and results consistently connected to a DM's opinion (Wu & Blackhurst, 2009).

MODM methods are much better at describing reality and verifying a large number of options than MADM ones (Cohon, 2013).

More detailed information on MODM and MADM methods and applications can be found in Hwang and Masud (1979) and Hwang and Yoon (1981).

2.3. CHAPTER II SUMMARY

PPM has become an essential part of an organisation's capability to successfully direct its projects (Cooper, Edgett, & Kleinschmidt, 1997b). It is a decision-making practice that examines and selects options, prioritises them and directs them between activities (Cooper et al., 2001c). However, few studies have addressed using MCDM in PPM decision making.

PPM aims to present a logical structure by which to determine the projects that need to be performed by a corporation (Tidd et al.1997; Jonas, 2010; Killen & Hunt, 2010), with those associated with organisational policies required to be compared. Therefore, it is essential to identify the most suitable projects in PPM for selection and prioritisation procedures (Archibald, 2004; Englund & Graham, 1999; Wheelwright, 1992). Different projects may possess unique functions, with their types indicating various difficulties for final decisions and choosing PPM practices (Blomquist & Müller, 2006). Nevertheless, PPM studies have not yet properly highlighted the difficulties that DMs and organisations might encounter when integrating various methods (Geraldi, 2008) for identifying different options and projects (Bessant et al., 2011).

In this chapter, the PPM challenges are described and the problems associated with them are discussed in detail. Moreover, PPM MCDM techniques are broadly reviewed in light of other studies (e.g., Cooper et al., 2001c; Danilovic & Sandkull, 2005; Dawidson, 2006; Dye & Pennypacker, 1999; Verbano & Nosella, 2010).

There is a considerable degree of uncertainty related to the scoring of projects based on particular measures while decision assessments have different inputs which may not be entirely specific (French et al., 1998). According to Zimmermann (2000), a shortage of data might be the most common reason for uncertainty. Different studies that recommend procedures for modelling uncertainty are primarily concerned with examining criteria weights (CWs) (Wolters & Mareschal, 1995). This is certainly insufficient since many other areas of multi-criteria elements (i.e., CW and assessment techniques) can have an impact on the review and rating of options.

It would be an advantage for applications to put their techniques into practice, execute and control their data, and present their outcomes from both specific and multi-perspective viewpoints. This study identifies that practical functionality acts as a significant factor in the selection of a suitable technique (Miettinen, 2001). Another key element identified as important for selecting a technique for portfolio management decision making is the number of panel members responsible. A portfolio decision is normally arrived at by a committee which combines both the goal and weighted factors concerning organisational requirements defined by a program decision committee.

There are two main issues linked to MCDM which are hard to resolve. Firstly, some targets are qualitative (e.g., they have political targets) and, secondly, the targets usually conflict with each other. Hwang and Yoon (1981) propose two techniques (i.e., compensatory and non-compensatory) for solving such problems and identify that compensatory methods (e.g., scoring ones) allow trade-offs, that is, a minor decrease in one element is appropriate when it is supported by improvements in others. On the other hand, non-compensatory methods tend not to allow trade-offs, that is, a negative value in one element cannot be mitigated by positive values in any other. Therefore, as every element/aspect must be considered individually, evaluations are produced on an attribute-by-attribute basis. Although non-compensatory methods can remove dominant solutions/options, as they can suggest several alternatives which may not be effective for making decisions, they are excluded from this study.

As a result of this investigation, the key challenges of PPM include a sensitivity analysis of its interdependencies, traceability, simplicity, supporting quantitative and qualitative data, project quantity, trade-offs, group decision making and the mutual links between portfolio levels.

The major difficulty of this practice is classifying different MCDM techniques. An examination of the literature available on MCDM during the past three decades demonstrates that the complexity and diversity levels of this area of study have increased significantly, resulted in more new and mixed techniques and led to many classifications being proposed (e.g., Figueira, Greco, et al., 2005). However, this study discovers that those classifications are generally not independent of the authors' intentions in undertaking their examinations. Another issue is that some classifications are confusing or even conflicting, with identical inaccuracies related to several methods identified; for example, AHP is regarded as a qualitative method by some researchers (e.g., Alphonce, 1997) and a quantitative one by others (e.g., Moffett & Sarkar, 2006).

This study identifies that MCDM methods are the most suitable for dealing with PPM issues and classifies them in two groups, MODM and MADM techniques. Then, MADM ones are grouped in the three sets of: UBTs; Outranking; and Compromise methods. It seems that MADM techniques, in particular UBTs, are more suitable for PPM than MODM ones due to their simplicity and capability to handle uncertainty. They may also be applied when working with non-compensatory decision procedures (Ma, 2006) to deal with incomparability (O'Neill, 1997; Stewart & Losa, 2003). However, their major drawback is probably that, in many difficult circumstances, they require many specifications to indicate an appropriate condition for decision making which makes them complicated and problematic (Ma, 2006).

Several researchers identify project prioritisation as a key factor in PPM (Elonen & Artto, 2003; Fricke & Shenhar, 2000). To date, there has been no comprehensive study focusing on managing the entire process from strategic planning using PPM to organisational achievements; for example, there is no ideal approach for adopting PPM, identifying the appropriate method for organising activities or techniques for use with organisational factors (Dawidson, 2006). Businesses prefer methodologies that fit their own cultures and enable them to examine the program aspects they think are the most critical (Cooper, 2012; Hall & Nauda, 1990). Also, the most suitable methodologies for developing a portfolio for one program might not be the best for another. Therefore, finding the most suitable PPM MCDM technique(s) is a challenging task which requires further investigation.

2.4. CHAPTER II HIGHLIGHTS

In this chapter, the first six research questions identified in CHAPTER I were investigated, with its key findings highlighted below.

(a) The main challenges and failure factors of PPM were identified.

(b) It was determined that MCDM methods are the most suitable for dealing with PPM issues.

(c) A solid MCDM classification structure was proposed.

(d) MCDM methods were classified in two groups, MODM and MADM techniques.

(e) The MADM techniques, in particular, the utility-based techniques appeared to be more suitable for PPM due to their simplicity and capability to handle uncertainty.

(f) No MCDM method was ideal for managing the challenges of PPM.

(g) Further investigation is required to find the most suitable PPM MCDM technique(s).

Figure 5 presents a snapshot of the key findings of CHAPTER II and outlines the following main priority research questions investigated in the next chapter.

1. Could MCDM methods be used for PPM decision making?
2. Which MCDM methods are the most suitable for PPM decision making?
3. How can MCDM methods be selected?

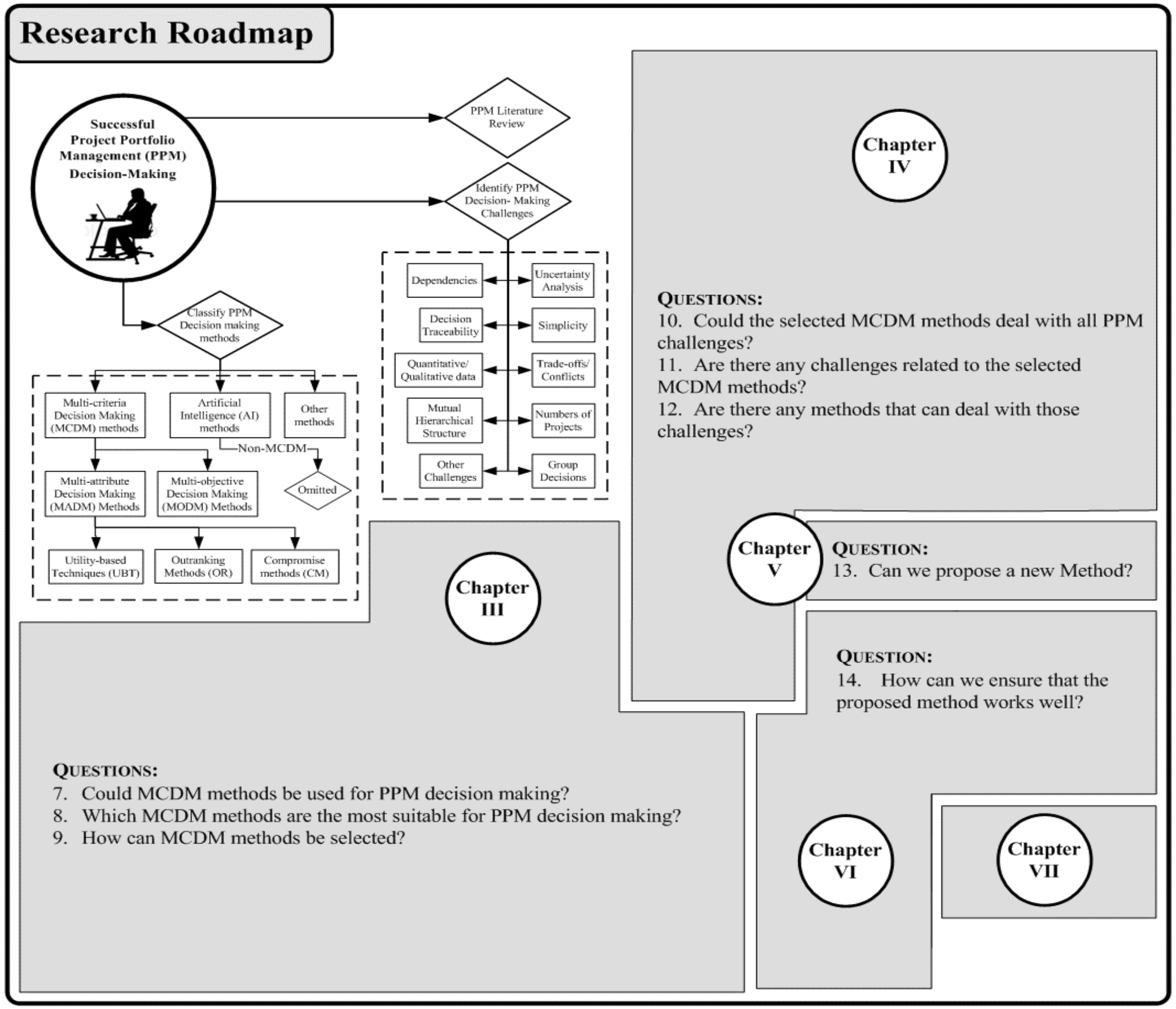

Figure 5. RESEARCH ROADMAP – CHAPTER II

CHAPTER III

3. EXECUTIVE SUMMARY

The successful delivery of organisational objectives is significantly linked to the effective collection of project portfolios. There are many different Multi-criteria Decision-making (MCDM) methods available which can be used to calculate, examine and select Project Portfolio Management (PPM) decision options. However, finding the most suitable one is a challenging task which requires a constructive review and comparison of existing PPM MCDM approaches. This study identifies the strengths and weaknesses of MCDM methods for assisting in PPM decision making. Of more than 100 methods identified, eight (AHP, ANP, DEA, DSRA, ELECTRE, PROMETHEE, TOPSIS and VIKOR) that best suit PPM are down-selected and compared. Although none is ideally suited for application to portfolio management, two standard ones (AHP and DEA) are shown to be the most suitable and are recommended for further investigation and validation.

3.1. Comparison of PPM MCDM Techniques

There are more than 100 MCDM methods and techniques available in the literature to assist decision-making. Many of them are not usually applied since they are very complicated and require large amounts of input data. They are neither capable of sufficiently managing risk and uncertainty nor understanding the interdependencies among factors. Also, their calculation processes are very complicated or do not have an organised structure (Cooper, 1988). Without undertaking a systematic review of MCDM methods in the literature, a DM has the challenge of choosing a suitable one for supporting PPM decision making. None is the most suitable in all circumstances and the selection of a particular one is restricted by uncertainty (Mysiak et al., 2005). Since different techniques usually generate different outcomes, even when applied to a similar issue and information, the most critical question is probably "which method is the most practical?" (Triantaphyllou, 2001).

Based on an extensive literature review carried out as part of this study, it is clear that, despite the fact that there are several techniques which can be applied for PPM, no single one can deal with all its previously discussed challenges. In existing PPM studies, there is little consideration of adopting a mixed structure that could also: examine various factors to identify the best option; include the complete engagement of a DM; obtain the full benefit of the features of a technique by dividing its procedure into a flexible and practical number of actions; and implementing the best method in each step. As previously described, because this is due mainly to the challenges associated with PPM, selecting a particular MCDM technique is usually based primarily on familiarity with it (Guitouni & Martel, 1998). Accordingly, instead of seeking the best technique, the decision situation is modified to ensure that the chosen one matches the DM's preferred option rather than its suitability for the problem considered. The selection of an appropriate MCDM technique could be considered a multi-criteria challenge (Abrishamchi, Ebrahimian, Tajrishi, & Mariño, 2005). As MCDM techniques possess unique positive and negative values, it is very difficult to claim that any one is more suitable. However, certain ones tend to be more appropriate if uncertainty is the main issue and others if trade-offs are a more critical factor (Von Winterfeldt & Edwards, 1993). Also, as using different techniques will most likely provide different suggestions, selecting MCDM ones for PPM needs to be fully investigated which is the primary objective of this study.

3.2. Review of suitability of MCDM Techniques for PPM

Comparing different types of MCDM techniques is a difficult task (Olson, Moshkovich, Schellenberger, & Mechitov, 1995) and usually the selection of one is based on a random choice rather than a clear reason (Bottomley, Doyle, & Green, 2000). Studies in the literature present several different criteria for these comparisons. However, although various models have been introduced, there has been little analysis of their applicability, particularly for PPM decision making. Brief outlines of a number of the research papers published in the literature which discuss such comparisons are provided below.

Belton and Stewart (2002) introduce an in-depth examination of MCDM techniques while several articles (e.g., Sun, 2005) examine existing PPM decision-making methods. Despite this, there are basically two main issues involved in conducting these assessments: the number of MCDM techniques is rapidly increasing (Bouyssou et al., 2006); and researchers almost never provide good reasons for selecting a particular one. Furthermore, researchers identify that a set of MCDM techniques needs to be employed as there is no single one that can fully support PPM decision making (Verbano & Nosella, 2010).

Eckenrode (1965) states that ranking techniques are less complicated and likely to be more beneficial than those involving suitable decisions being indicated by ratios of criteria weights. Maystre, Pictet, and Simos (1994) compare discrete and continuous distributions of options while Vincke (1992a) presents a criteria aggregation approach. MacCrimmon (1973) identifies the demand for evaluating MCDM methods as well as the significance of a decision's difficulty and recommends a classification of MCDM techniques. Hwang and Yoon (1981) present a comparison model of a few Multi-objective Decision Making (MODM) and Multi-attribute Decision Making (MADM) techniques. Duckstein, Gershon, and McAniff (1982) compare three MCDM techniques (i.e., ELECTRE, Compromise Programming (CP) and Multi-attribute Utility Theory (MAUT) with regard to several criteria: "(1) the type of information (qualitative or quantitative); (2) consistency of the outcomes between methodologies; (3) stability of the outcomes in relation to variations in the parameters' principles; (4) simplicity of computation; and (5) level of activity necessary between the decision making and with decision analyst". Hobbs, Chankong, Hamadeh, and Stakhiv (1992) reveal that knowing a technique's aspects influences a user's opinion of how they function. Munda, Nijkamp, and Rietveld (1994) and Munda, Nijkamp, and Rietveld (1995) consider different factors, such as the differences between qualitative and quantitative data as well as the level of uncertainty. Accessibility, flexibility, facilitation, learning, interaction and simplicity are presented as critical features of a Decision

Support System (DSS) in a study conducted by Simonovic and Bender (1996). Also, Weistroffer and Narula (1997) present a number of criteria for method selection, that is, a technique should: be practical and simple to operate; record and represent ideas; assist DMs to structure circumstances according to the primary steps in decision making; handle different types and numbers of decision tasks; and be possible to use while obtaining knowledge of the relevant DSS's functions. Moshkovich, Mechitov, and Olson (2002) mention that ordinal inputs are less complex and more specifically represent a DM's choices than cardinal ones. The compensation level among factors is presented by Hayashi (2000) and the regulatory, descriptive, practical and normative characteristics of decision-making introduced as the main criteria by Bouyssou et al. (2006). As Kangas and Kangas (2005) consider that selecting the most effective technique means understanding each one, simple and straightforward MCDM methods are preferable. Taylor (2006) outlines that a good comparison model needs to be practical, capable, flexible, simple, cost-effective and easy to calculate, with Souder (1973) proposing on the first five requirements and Meredith and Mantel Jr (2011) the last. The Standard for Portfolio Management (PMI, 2013) recommends different strategies for optimising a portfolio (e.g., developing a list of portfolio elements to be considered for prioritisation), such as applying scoring methods like multi-criteria analysis to set aside those projects not fulfilling threshold requirements. This guideline recommends using single-criterion prioritisation, multi-criteria weighting ranking and multi-criteria scoring techniques for weighting and ranking portfolio elements.

Despite the fact that many researchers have attempted to identify the best technique for a decision situation and different MCDM ones have been compared with each other, there is no commonly agreed structure or procedures that enable the most suitable one(s) to be chosen for a particular scenario; for example, although Denpontin (1983) establishes an extensive catalogue of various techniques, he claims that it is challenging to group them because decision-making experiments vary in their numbers, values and accuracy of data. Also, each technique may generate different outcomes once used for the same issue under the same assumptions and by the same DM (Gershon & Duckstein, 1983). Moreover, most techniques suitable for a particular decision circumstance may not produce the same outcomes in another situation (Al-Shemmeri, Al-Kloub, & Pearman, 1997) while using different MCDM techniques can easily result in completely different outcomes (Hersh, 1999; Munda et al., 1994). Also, Karni, Sanchez, and Tummala (1990) indicate that different algorithms and scaling elements produce varying results. On the other hand, a number of experts believe that different MCDM methods can provide basically the same options and outcomes for the same type of issue (DAVID, 1993; Goicoechea, Stakhiv, & Li, 1992; Karni et al., 1990; Salminen, Hokkanen, & Lahdelma, 1998).

Gershon and Duckstein (1983) compare four MADM classification techniques (ELECTRE, CP, Cooperative Game Theory (CGT) and MAUT) and suggest that the main differences between them are the ways in which they behave. Roy and Bouyssou (1985) compare methods from a Utility-based model (MAUT) with the ELECTRE method from the outranking category. Brans, Vincke, and Mareschal (1986) assess two well-known MADM outranking methods, i.e., PROMETHEE and ELECTRE, and determine that the former is more reliable than the latter. Tecle, Fogel, and Duckstein (1988) implement three MCDM methods, CP and CGT to select the most suitable option and ELECTRE to down-select options. A comparison of ELECTRE, AHP, Simple Additive Weighting (SAW) and the Weighted Linear Assignment Method (WLAM) undertaken by Karni et al. (1990) indicates that the ranking results obtained from ELECTRE, AHP and SAW in each case study do not differ greatly but the WLAM presents a different outcome. White (1990) provides a bibliography of MODM methods while Nijkamp and Vindigni (1998) and Figueira, Greco, et al. (2005) compare MODM and AI methods. Corner and Kirkwood (1991) review techniques published between 1970 and 1989 in major English-language publications. In a comparison study of six methods (i.e., AHP, SAW, ELECTRE, GP, additive utility functions and multiplicative utility functions) carried out by Hobbs et al. (1992), no method is considered more suitable than or preferred over others. In a different study, Shafike, Duckstein, and Maddock (1992) use three MCDM methods, CP, ELECTRE and MCQA, to select the most suitable option, with the results revealing that, while these approaches are based on different concepts, they achieve the same outcomes. Also, the AHP and ZAPROS methods are compared in a study conducted by DAVID (1993) which concludes that ZAPROS presents accurate outcomes and has a number of behavioural advantages. Duckstein, Treichel, and Magnouni (1994) compare CP, ELECTRE, MAUT and Utility Theory Additive (UTA) techniques and concluded that all produce the same outcomes. Hobbs and Meier (1994) examine holistic, Additive Value Function (AVF) and GP methods, and suggest that, as none can be considered the best, multiple techniques should be applied.

A comparison study of AHP, MAUT and ZAPROS methods conducted by Olson et al. (1995) who concludes that, once the option values are equal, each method produces different solutions for the same option. Moreover, Bella, Duckstein, and Szidarovszky (1996) uses ELECTRE and CP to rank options while Özelkan and Duckstein (1996) compare PROMETHEE, GAIA, Multicriterion Q-analysis (MCQA), CP and CGT, and reveal that they are not significantly different. Hobbs and Horn (1997) compare the holistic method with the AVF and conclude that no single technique is the most suitable method when used individually. A comparison of SMART and ZAPROS methods conducted by Moshkovich, Schellenberger, and Olson (1998) conclude that SMART presents key measures for options that could be employed to determine the best solutions while ZAPROS provides a limited number of options. Narasimhan and Vickery (1988) observe no differences between the AHP and Z-W while Raju and Kumar (1998) indicate that three methods (PROMETHEE, EXPROM-2 and CP) can all achieve the same results. Lerche, Brüggemann, Sørensen, Carlsen, and Nielsen (2002) compare the Hasse Diagram Technique (HDT), PROMETHEE, NAIDE and ORESTE methods and identify the HDT and PROMETHEE as the preferred ones. Based on a study carried out by Corner and Kirkwood (1991), Keefer, Kirkwood, and Corner (2004) present a review of major English-language processes published from 1990 to 2001 and observe an increase in the number of decision analysis publications. The TOPSIS and VIKOR methods are studied and compared by Opricovic and Tzeng (2004), and Tzeng, Lin, and Opricovic (2005). Salminen et al. (1998) apply ELECTRE, PROMETHEE and Simple Multi-attribute Rating Technique (SMART) methods to four real environmental problems in Finland using ELECTRE both alone and in combination with different techniques. Guitouni, Martel, Vincke, North, and Val-bblair (1998) recommend a primary investigative structure for selecting a suitable multi-criteria process which, however, is very complex and designed for skilled research workers. Cooper, Edgett, and Kleinschmidt (2001a) highlight the popularity of project selection techniques. They discover that organisations apply a combination of techniques to better select and manage their projects and, although financial techniques are widely used, they are not suitable for assessing portfolio performances, with organisations required to follow strategic methods instead to obtain better outcomes. Raju, Duckstein, and Arondel (2000) claim that DMs might evaluate techniques using extra factors, such as their considered ease-of-use, reliability, stability and quality. Since most MCDM techniques need a relative weight for each criterion, a weighting method should also be considered. Degraeve, Labro, and Roodhooft (2000) present a taxonomy of supplier preference models from a Total Cost of Ownership (TCO) view. They discover that mathematical programming techniques outperform rating ones and multiple-item approaches lead to much better outcomes than single-item ones. Kangas, Kangas, Leskinen, et al. (2001) draw a similar conclusion when comparing Multi-attribute Value Theory (MAVT), ELECTRE and PROMETHEE methods, finding that each generates different outcomes for the same issue and, moreover, the propose mixed MCDM techniques as a possible direction for future study. In planning for sustainable energy, Pohekar and Ramachandran (2004) identify that the AHP is the most widely used method and is often accompanied by outranking methods such as PROMETHEE and ELECTRE. In both government and service sectors, Zanakis et al. identify five techniques worthy of comparison: SAW, MEW, AHP, ELECTRE and TOPSIS (Zanakis, Mandakovic, Gupta, Sahay, & Hong, 1995). For municipal waste management, Cheng (2000) indicates that there are five common MADM techniques: the SAW; Weighted Product Method (WPM); Cooperative Game Theory (CGT); TOPSIS; ELECTRE with complementary analysis; PROMETHEE; and AHP. Various later studies assess a number of MCDM techniques for dealing with real-world challenges (e.g., Aamer & Sawhney, 2004; Afsordegana, Sánchezb, Agellc, & Gamboae, 2014; Aghajani, 2012; Antucheviciene, Zakarevicius, & Zavadskas, 2011; Antucheviciene, 2011; Aruldoss, Lakshmi, & Venkatesan, 2013; Caterino, Iervolino, Manfredi, & Cosenza, 2009; Cheraghi, Dadashzadeh, & Subramanian, 2011; Chitsaz & Banihabib, 2015; De Boer, Labro, & Morlacchi, 2001; Degraeve et al., 2000; Denpontin, 1983; Estrella Maldonado, Delabastita, Wijffels, Cattrysse, & Van Orshoven, 2014; Ginevičius, Krivka, & Šimkūnaite, 2010; Ginevičius & Podvezko, 2008, 2009; Ho, Xu, & Dey, 2010; Hobbs, 1986; Holt, 1998; Hwang, 1981; Kadziński & Słowiński, 2015; Li, Wu, & Lai, 2013; Opricovic & Tzeng, 2004; Ozernoy, 1987, 1992; Podvezko, 2011; Savitha & Chandrasekar, 2011a; Tahriri, Osman, Ali, & Yusuff, 2008; Weber, Current, & Benton, 1991; Zavadskas, Vilutiene, Turskis, & Tamosaitiene, 2010).

As revealed in a number of articles, the reason for selection in the majority of cases might be that those methods are used more widely in industry-related analyses; for example, the two most-used techniques in the area of sustainability-related studies are the AHP for the utility-based theory and ELECTRE and PROMETHEE for the outranking relation theory (Herva & Roca, 2013; Wang, Jing, Zhang, & Zhao, 2009). The following is a summary of examples in response to the question 'what are effective MCDM method(s) for strategic PPM decision-making?

Agarwal (2011) reviews the characteristics of MCDM methods regarding supplier selection, covering 68 research articles from 2000 to 2011, and identifies the following usage: DEA 30%, MP 17%, AHP 15%, CBR 11%, FST 10%, ANP 5%, SMART 3 %, GA 2% and ELECTRE and PROMETHEE 7 %. However, these data vary in other publications; for example:

"It is observed that Analytic Hierarchy Process (AHP) is the most popular technique followed by outranking techniques PROMETHEE and ELECTRE. Validation of results with multiple methods, development of interactive decision support systems and application of fuzzy methods to tackle uncertainties in the data is observed in the published literature." (Pohekar & Ramachandran, 2004).

*"Of the many decision-making methods available we have chosen the following five for comparison in our research: Simple Additive Weighting (SAW), Multiplicative Exponent Weighting (MEW), Analytic Hierarchy Process (AHP), ELECTRE and TOPSIS. The rationale for selection has been that most of these are among the more popular and widely used methods and each method reflects a different approach to solve multi-attribute decision-making problems. SAW's simplicity makes it very popular to practitioners (*Hobbs et al., 1992*;* Zanakis et al., 1995*).*

*MEW is a theoretically attractive contrast against SAW. However, it has not been applied often, because of its practitioner-unattractive mathematical concept, yet in spite of its scale invariant property (depends only on the ratio of ratings of alternatives). TOPSIS (*Hwang, 1981*) is an exception in that it is not widely used; we have included it because it is unique in the way it approaches the problem and is intuitively appealing and easy to understand."* (Zanakis et al., 1995).

Cheng (2000) indicates that there are five common multi-attribute decision-making techniques, SAW, WPM, CGT and TOPSIS, ELECTRE with complementary analysis as well as PROMETHEE (developed by Brans and Vincke (1985)) and AHP (introduced by Saaty (1980b)).

These four sample articles are a small representation of a much larger collection of relevant ones which illustrate that there is no definitive mechanism for selecting decision-making methods/models.

Topcu and Ulengin (2004) identify that it is almost impossible for experts to develop a suitable selection model for identifying the best MCDM technique because they are unable to validate their reasons for selecting one over another and often choose one either created by themselves or with which they have experience (Ozernoy, 1992; Ulengin, Topcu, & Sahin, 2001).

3.3. PROPOSED PPM MCDM METHODS COMPARISON MODEL

Having a PPM structure is essential for the processes of comparing MCDM methods and balancing a project portfolio. Based on studies conducted by Cooper et al. (2001c) and Crawford, Hobbs, and Turner (2006), this study suggests that project proposals should be broken down into sub-sets of projects with similar strategies and the same features which would assist DMs to compare them using the same criteria or methods.

This research reviews various studies that introduce different criteria for selecting the most suitable technique(s). However, there is an absence of a framework which organises them practically and specifically for PPM decisions. Therefore, it is essential to modify a structure or develop a suitable one for assessing the criteria for comparing appropriate decision-making methods for PPM (which consider a variety of criteria) and finally selecting the most suitable one(s). CHAPTER II identifies the difficulties associated with PPM decision making, that is, sensitivity/uncertainty, interdependencies in projects, decision traceability, simplicity, both quantitative and qualitative requirements, number of projects, trade-offs and conflict issues, group decision-making challenges and the lack of a mutual link between projects and strategic levels. To overcome them, this study analyses the literature and establishes a variety of conditions that must exist in cases in which a technique is to be successful in practice. It also considers the selection paradigm of Deason and White (1984), choice algorithm of Gershon (1981), selection model of Tecle (1988) and hierarchical process for portfolio selection of Cooper (2005) to present a model for comparing MCDM methods for PPM decision making according to their suitability in terms of their handling of PPM challenges, comprehensiveness and relatively simple delivery. For the purpose of this study, several MCDM techniques are analysed to determine which fulfils as many criteria/specifications as possible and categorised based on the set of seven comparison criteria (factors/groups) listed in Table 3 suggested as essential by several authors (e.g. Antunes, 2012; Buchholz, Rametsteiner, Volk, & Luzadis, 2009; Munda, 2005, 2008; Polatidis, Haralambopoulos, Munda, & Vreeker, 2006; Rowley et al., 2012; Sadok et al., 2009; Sala, Farioli, & Zamagni, 2013; Teghem, Delhaye, & Kunsch, 1989). Also, the comparisons in Figure 4 and Table 3 are evaluated according to the literature review as well as examinations of Cohon and Marks (1977) and Khairullah and Zionts (1979).

Based on the discussion in CHAPTER II, the criteria proposed for comparing PPM MCDM techniques and reducing their number to a smaller sub-set are described in Table 3.

Table 3. Proposed Selection Criteria for Comparison of PPM MCDM Techniques

Stage 1 - Mandatory Selection Criteria		
Criteria		**Description**
1	Sensitivity Analysis/Uncertainty Treatment	Does the method deal with unknown or missing data?
2	Dependencies	Does the method take into account the interdependencies of the criteria based on the weight of each criterion during the evaluation process? Does the method consider the interdependencies of the alternatives based on their weights during the evaluation process?
3	Decision Traceability	Is the method traceable (i.e., judgements and choices are required to be mutually traceable during the decision process from the strategic to operational level)?
4	Simplicity	Is the method user-friendly and easy to use (e.g., software available)?
Stage 2 - Beneficial Selection Criteria		

5	Criteria	Description
5.1	Quantitative and Qualitative	Does the method support both quantitative and qualitative information?
5.2	Number of projects	Is the method restricted to a specified number of factors or options?
5.3	Trade-offs/Conflict	Does the method support compensatory methods?
5.4	Group Decision Making	Does the method support group decision making?
5.5	Hierarchical Structure (mutual link between projects and strategic levels)	Does the method support a hierarchical structure and different levels of attributes? Does the method support maturity on all PPM process levels?
6	**Beneficial Sub-criteria**	**Description**
Note: these sub-criteria are part of the main beneficial ones described above, with the following showing exactly which elements are considered during the group down-selection process.		
6.1	Thresholds/Setting Parameters	Does the method manage indifference and options once two options are compared?
6.2	Allowing criteria and option weighting	Can the criteria be weighted within the requirements hierarchy and the alternatives weighted within the options hierarchy?
6.3	Supporting rank reversal	Does the method experience the rank reversal issue (i.e., the rating might be changed whenever another option is presented)?
6.4	Supporting sub-criteria	Does the method organise the considerations into a multi-level hierarchy (particularly when many factors are required)?
7	**Additional considerations during selection process**	
7.1	Type of Problem	Does this method support both ranking and classification processes/methods?
7.2	Advantages	What are this method's benefits?
7.3	Disadvantages	What are this method's limitations?
7.4	Area of Applications	In which industry or area of expertise has this method been used?
7.5	Integrated methods	Does this method integrate with others?
7.6	Learning dimension	Is this method difficult to learn?

These criteria are separated into the two categories of 'Mandatory Selection Criteria' (criteria 1 to 4), which eliminate methods from further evaluation when they are incapable of meeting requirements, and 'Beneficial Selection Criteria' (criteria 5 to 7) which do not necessarily eliminate methods from further examination. The Beneficial Sub-criteria (criteria 6) and Additional Consideration (criteria 7) are part of the main beneficial ones, with these criteria showing exactly which elements are considered during the group down-selection process in stage 2. Considering these sub-criteria simultaneously with criteria 5 during the methods assessment will increase the accuracy of the selection process by capturing a variety of conditions that could be existed in cases in which a technique is to be successful in practice. Figure 6 presents a flowchart for executing the model which includes the requirements of both groups.

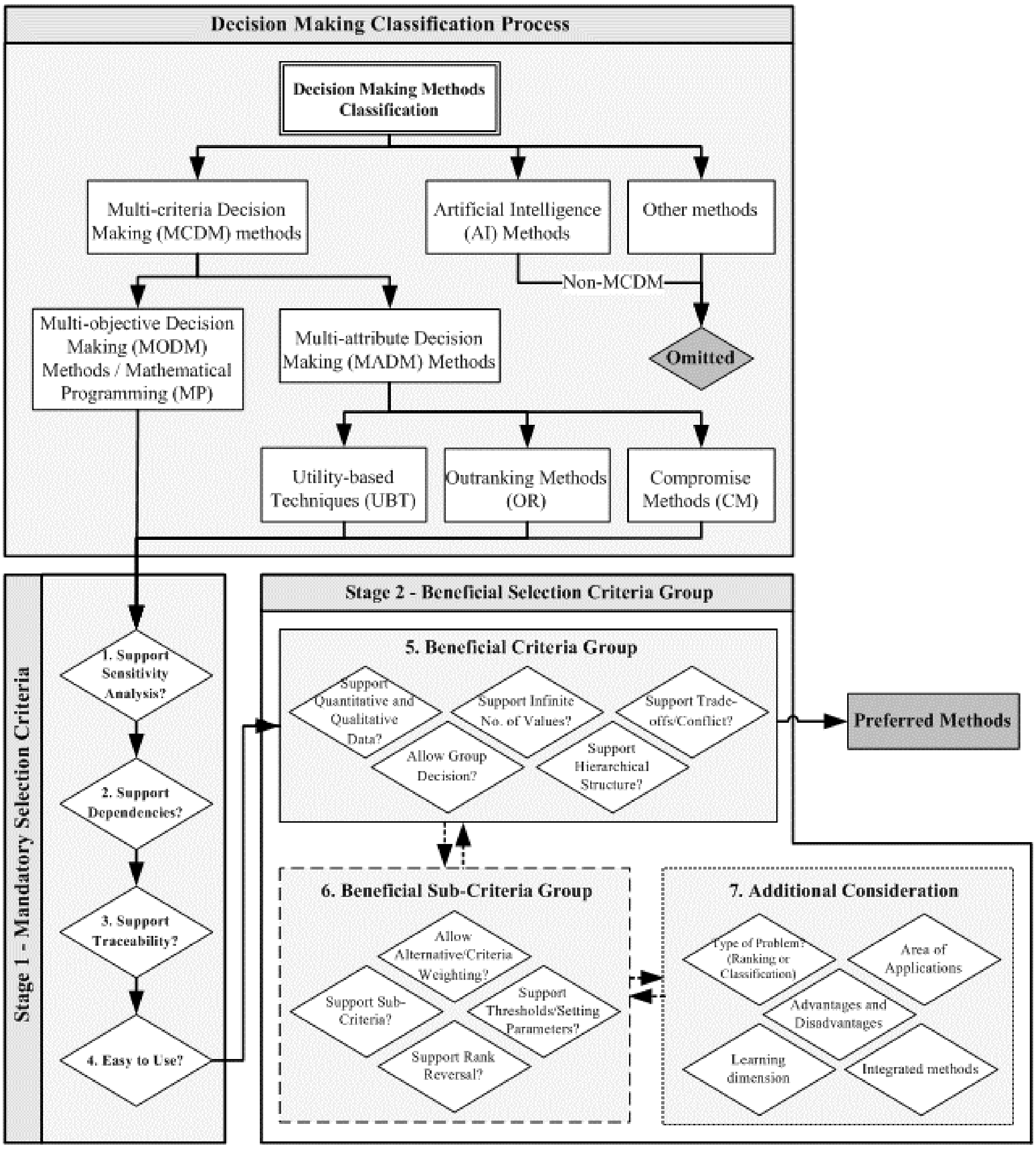

Figure 6. FLOWCHART FOR SELECTION OF PPM DECISION-MAKING TECHNIQUES

3.4. PPM MCDM Methods Comparison Results

3.4.1. Down-selection process

Many techniques from the various MCDM categories identified in CHAPTER II are examined to discover which are most suitable for PPM.

The framework proposed in this study is focused on improving and managing procedures for the selection of methods for PPM decision making. It identifies factors that are essential to DMs who have to make decisions regarding portfolio selection. All these methods are analysed through implementing the proposed selection model in Table 3 for decision-making techniques and the seven proposed comparison criteria in Figure 6.

In order to shortlist the appropriate PPM-related MCDM methods, of more than the 100 identified in the literature, a pre-selection stage (Classification of Decision-making Methods) is conducted to eliminate those designed for a specific industry/situation and unsuitable for PPM decision making or not included in the MCDM categories in Figure 6 (i.e., MADM and MODM) which are classified according to their types of data input; for example, AI techniques provide approximate answers and options for difficult optimisation conditions (e.g., GA method). Others, such as CCGA (a genetic model) are designed for a specific industry or situation and may not be suitable for many real-life challenges, including general PPM decision making. The characteristics and differences in behaviour associated with these techniques are examined and the techniques that comply with this study's essential requirements defined in Stage 2 identified for further investigation. The consecutive use of the associated requirements results in eliminating many of the MCDM methods.

Uncertainty management, which is regarded as the most critical challenge in decision making (e.g., Felli & Hazen, 1998), also requires an understanding of portfolios' interdependencies (e.g., Verma & Sinha, 2002). To deal with PPM's uncertainties and dependencies, it is essential to keep track of data (Danilovic & Browning, 2007). Moreover, DMs are unlikely to apply methods that are neither effective nor simple to operate (Moore & Benbasat, 1991). Therefore, as a first priority, any preferred method needs to be capable of dealing with 'sensitivity issues', 'support dependencies between projects', 'be traceable' and 'be simple' (as specified as mandatory selection criteria in our framework).

As the strategic arrangement of projects in a portfolio is extremely critical, both quantitative and qualitative techniques are required to estimate a project's related risk level (as a qualitative factor), profit (as a quantitative factor) and involvement in the organisational strategy (both qualitative and quantitative factors simultaneously) (e.g., Kester et al., 2009). Furthermore, the techniques that allow criteria to be defined by both objectives and attributes defined implicitly or explicitly in the best scenarios are selected, with those that have the capability to implement infinite numbers of alternatives also collected. Similarly, the mathematical approaches that cannot use qualitative values are eliminated. In addition, it is beneficial to have a process-/outcome-oriented decision-modelling paradigm as the preferred MCDM techniques need to allow DMs to choose and prioritise options and decisions in line with various requirements.

For MADM, utility-based methods have difficulties producing adequate performance values for some criteria and are incapable of considering degrees of under-performance. As arranging the threshold variables in these methods is very difficult, they are often not employed for the selection of real options (Greening & Bernow, 2004) as they consider more than one best solution. In general, a key disadvantage of MADM methods is that they are very complicated and problematic when dealing with many decision specifications in complex situations. Most of them are subjective, facilitate only quantitative values and are incapable of dealing with qualitative data. However, it seems that 'Utility-based Techniques' are suitable for PPM as most of them support uncertainty and are very easy to use.

MODM methods such as DEA are selected for further investigation as they can provide a number of options from alternatives which assist DMs to select the ideal one. They are much better for describing reality and are capable of verifying more options than MADM methods (Cohon, 2013). While, at this stage, MODM techniques for PPM are not omitted because the capability to support qualitative data and unlimited (infinite) numbers of options are critical elements of this study, many methods are not involved in this assessment, with several omitted due to issues regarding analysing 'sensitivity' and 'dependency', and the 'capability to track a discrete set of solutions'.

As shown in Table 4, of more than 100 MCDM methods presented in ANNEX A, over 40 found to be irrelevant or unsuitable for this study's direction are eliminated while only 46 of the others can adequately manage 'uncertainty'. Many methods are identified as being very complicated and requiring large amounts of input information, with the number of those for consideration significantly decreasing once the 'dependency' factor is included. Therefore, only 28 are assessed as being capable of supporting interdependencies among projects or not needing to support them while only 11 of the remaining 28 support the 'traceability' function, with three of the remainder very complicated or not following an organised structure. Details of the down-selection process for MCDM methods are provided in Table 4.

Table 4. Down-selection of MCDM methods

Only MCDM Methods (MADM and MODM)		*78 Methods*
MADM Methods		*44 Methods*
	UBT Methods	*24 Methods*
	OR Methods	*16 Methods*
	CM Methods	*4 Methods*
MODM Methods		*34 Methods*
	MP Methods	*34 Methods*
Criteria 1: *Only those supporting sensitivity analysis*		*46 Methods*
Criteria 2: *Only those either supporting or not requiring dependencies*		*28 Methods*
Criteria 3: *Only those supporting decision traceability*		*11 Methods*
Criteria 4: *Only simple or moderate methods*		*8 Methods*

A total of eight MCDM methods (AHP, ANP, DEA, DRSA, ELECTRE, VIKOR, PROMETHEE and TOPSIS) are selected for a final investigation to identify a preferred one. They are more appropriate for decision making for PPM due to their capabilities for dealing with any kind of judgement considerations, their simple outcomes, low complexity for managing criteria and the decisions they contain. Furthermore, all have been employed to address various real-life challenges (Herva & Roca, 2013), are simple in concept and computation and are applicable to multi-level hierarchies. The challenge now is to identify which of these techniques is considered the most suitable for applying to solve the challenges on which this study is focused.

The following sub-sections present short outlines of the aspects of each MCDM technique analysed as well as brief discussions of their advantages and disadvantages, concentrating on the unique functions essential for the evaluation stage. Detailed specifications of the positive and negative examination points of the techniques in terms of the comparison criteria are presented in ANNEX B and ANNEX C, respectively.

3.4.1.1. Analytic Hierarchy Process (AHP)

The AHP, which was developed in the 1980s (Saaty, 1980b), is one of the most common MCDM methods well suited to modelling quantitative considerations that employs hierarchical structures to represent a decision problem. It is designed in such a way that the overall goal is at the top, requirements at the centre and alternative decisions at the bottom levels. This approach presents an organised structure for arranging preferences at each level of a hierarchy using pair-wise analysis (Fouladgar, Yazdani-Chamzini, Zavadskas, & Haji Moini, 2012). The feature vector obtained is then compared by determining the matrix elements to find the relative value of the same unit on different levels and then rank the value of each option (Saaty, 1980b, 2005).

The AHP is very popular in the literature investigated for this study, with the majority of authors comparing it with other MCDM techniques (Lai, 1995). It has proven to be significant for application performance issues, business policy and strategy, resource management, and political planning and strategy. Also, several studies apply it for industrial development, project delivery, DSSs, risk and uncertainty assessments, measurements of project complexity, determinations of water resources (decision making in an urban water supply) (Benítez, Delgado-Galván, Izquierdo, & Pérez-García, 2012) and development of ERP systems.

3.4.1.2. Analytic Network Process (ANP)

Technically, ANP is regarded as the general form of AHP (Saaty, 2006) but in relation to positive aspects, it is more focused on a network framework. ANP enables project interdependency and it is able to prioritise groups or even clusters of components; "which will help a complicated networked decision-making with different intangible criteria" (Tsai, Leu, Liu, Lin, & Shaw, 2010). A hierarchy is not essential in the ANP technique, whereas clusters of components exchange levels and every single group includes nodes or elements. In ANP nodes are likely to be arranged in groups. ANP replicates the way humans make choices in which the importance of requirements can transform with the available options.

The downside of employing the ANP technique could be a restricted number of criteria and alternatives. As a result of feedback loops and interconnections it might be hard to develop ANP in a general tool such as an Excel spreadsheet. ANP's efficiency scores might be changed whenever another option is presented. However, its biggest weakness is that it undermines the outcomes of weighing the clusters (Wang, 2012). AHP utilises a basic weighted total for aggregation, while ANP needs the super matrix to be squared frequently. Therefore, ANP is not recommended when no dependency is available. Given that the ANP draws on setting up choices between requirements and options employing pair-wise evaluations, it only facilitates quantitative values—it cannot deal with qualitative data.

Designed in 1996, the method continues to be employed for activities in assessment investigation (Jinyuan, Kaihu, Lin, Rui, & Xiaoli, 2012), performance evaluation (Chen & Lee, 2007), information system (Liang & Li, 2008), university-industry and supply chain virtual enterprises partner selection processes (Ning & Xue-wei, 2006; Xiao-bo & Ting-ting, 2009), R&D projects (Jung & Seo, 2010), environmental risk assessment (ERA) (Chen, Li, Ren, Xu, & Hong, 2011), inter-enterprise performance (Verdecho, Alfaro-Saiz, & Rodriguez-Rodriguez, 2012), ERP (Gürbüz et al., 2012), organisational performance (Boj, Rodriguez-Rodriguez, & Alfaro-Saiz, 2014) and measuring the complexity of mega construction projects (He, Luo, Hu, & Chan, 2015) as well as for project preference and supply-chain management.

3.4.1.3. Data Envelopment Analysis (DEA)

Suggested by Charnes, Cooper, and Rhodes (1978), DEA is a mathematical programming technique that presents related performance assessments for decision-making units (DMUs) with several inputs and outputs (Adler, Friedman, & Sinuany-Stern, 2002). To enable its application to a broad number of activities, a DMU refers to anything examined in the model which it considers to be *n* DMUs. DEA employs a linear programming approach to determine appropriate selections of options/choices (Thanassoulis, Kortelainen, & Allen, 2012) which it compares, with the best obtaining a score of one and the others less than one.

A significant benefit of DEA is that, it is a non-parametric method with no requirement to apply past assumptions or connect inputs and outputs (Seiford & Thrall, 1990). Consequently, it eliminates subjective elements, minimises errors and makes the estimation process easier (Qiang Chen, Lu, Lu, & Zhang, 2010). However, an issue handled by DEA could be dealt with equally well using multi-criteria examinations (Belton & Vickers, 1993). Although it might not be obvious compared with other techniques, DEA can establish connections between inputs and outputs based on which it calculates the performances of DMUs. Therefore, in order to present every DMU in the most effective way, it optimises the weightings of all variables with those of the inputs and outputs not allocated by DMs (Giannoulis & Ishizaka, 2010). Instead, it sets target values and identifies all benchmarks to assist DMs in estimating DMUs' efficiencies.

A major disadvantage of DEA is the fact that it will "not handle imprecise information and considers that all input and output information are accurately identified but this theory might not necessarily be true" (Wang, Greatbanks, & Yang, 2005). Its outcomes vary according to the outputs and, moreover, it cannot deal with variables with negative or zero values.

DEA is applied to compare project efficiencies (Hadad, Keren, & Laslo, 2013), Group Decision Support Systems (GDSSs) (Barkhi & Kao, 2010), safety performances (El-Mashaleh, Rababeh, & Hyari, 2010), project evaluation and selection strategies (Ghapanchi, Tavana, Khakbaz, & Low, 2012), R&D portfolio assessments (Vandaele & Decouttere, 2013), risk analyses (Shi, Zhou, Xiao, Chen, & Zuo, 2014) and ERPs (Sudhaman & Thangavel, 2015). Ramanathan (2003) provides excellent introductory material for DEA beginners, with a more detailed explanation provided in Cooper, Seiford, and Tone (2006).

3.4.1.4. Dominance-based Rough Set Approach (DRSA)

The DRSA is (Greco, 1997) capable of managing classification, selection and scoring difficulties. It draws on a data desk, the rows in which are referred to as options and the columns broken down into conditions, specifically, the requirements for examining the options and decision elements, to provide a general analysis of options which can easily be defined as a concept or professional decision (Slowinski, Greco, & Matarazzo, 2009). DRSA estimates the data according to the selection aspects by looking at the information in the requirements as well using "if... then..." decision specifications (Greco, Matarazzo, & Słowinński, 2005). These types of guidelines are straightforward primary links between condition and decision requirements (Roy & Słowiński, 2013).

Quantitative, qualitative, incomplete and inconsistent data can be accommodated by the DRSA. It requires a pair of examples from which to extract specifications but is limited by previous experiences and suffers from rank reversal problems.

3.4.1.5. ELimination Et Choix Traduisant la REalite—Elimination and Choice Expressing the Reality (ELECTRE)

The ELECTRE method was first presented in 1968 (Roy, 1968) to handle outranking connections by conducting a pair-wise analysis between options of each factor independently. It has a number of variants, such as ELECTRE I, II, III, IV and TRI (Balaji, Gurumurthy, & Kodali, 2009), each of which was developed to resolve various decision issues, such as selecting, scoring and explaining their concepts (Certa, Enea, & Lupo, 2013; Fernandez, Navarro, Duarte, & Ibarra, 2013; Figueira, Mousseau, & Roy, 2005; Figueira, Greco, Roy, & Słowiński, 2013; Roy, 1991). As ELECTRE focuses on a pair-wise analysis of options (Figueira, Mousseau, et al., 2005), it generally aims to determine whether option A is at least as effective as option B (Roy, 1996).

The key benefit of an ELECTRE technique is its capability to avoid compensation between requirements and any specific normalisation practice that distorts the initial information. It can prioritise options and remove those with less efficiency which is very useful when there are decision issues that have several requirements with many options.

However, an ELECTRE technique has the disadvantage that it requires a number of technical variables which means that it is often not simple to fully understand. It has not been proven to be a comprehensive solution for dealing with the variables and, as well as its results, its procedure might be difficult to clarify. Because of the way it integrates choices, factors with lower priorities or performance values are not presented. Its outranking technique has advantages as well as problems with options that are not perfectly recognised or outcomes that need to be checked (Konidari & Mavrakis, 2007). Also, it would not normally result in a single solution being differentiated from others as it identifies a sub-set of options to be chosen from the primary group of alternatives. Therefore, an ELECTRE technique is generally regarded as appropriate for decision issues identified by very few requirements and a number of options for helping to differentiate among a sub-group of more suitable alternatives. Developing and analysing quite a large number of retrofit options is costly. In such a situation, the DM is simply interested in determining which option is better for putting into practice rather than helping to reduce the primary group of options into a smaller set. Therefore, an ELECTRE technique might not be suitable for selecting the best option as it only generates the major ones.

3.4.1.6. Preference-ranking Organisation Method for Enrichment Evaluations (PROMETHEE)

The PROMETHEE created by Brans and Vincke in the 1980s (Brans & Vincke, 1985) is categorised under MADM techniques/outranking methods. It is an outranking model that proposes the most suitable option for a DM from existing alternatives. Basically, its approach consists of three steps: (1) defining a preferred option in line with the objectives; (2) defining a multi-criteria decision index and preference flows; and (3) achieving a complete or partial ranking of options in accordance with the specified decision framework.

The PROMETHEE is simple to employ and assumes that the requirements are proportionate. Given its framework, it can be performed directly on the factors used in the decision matrix without the need for any specific normalisation. It classifies options that are difficult to analyse due to its trading off assessment specifications as non-comparable options. It eliminates the need to carry out more pair-wise assessments while relative options are added or removed (Seo, Jeong, & Song, 2005).

This method cannot clearly allocate weights and does not provide an exact process for assigning values. Its efficiency scores are estimated from both negative and positive values and presented as different types of options. A traditional network representation of the PROMETHEE does not provide any visual details regarding variations in values. Finding out exactly how a rating is dependent on minor variations in the weighting of the requirements is another challenge of using this method which deals with only quantitative data and suffers from the rank reversal problem. It has been used in many fields, such as the automotive sector (Ignatius, Behzadian, Malekan, & Lalitha, 2012), web service selection (Karim, Ding, & Chi, 2011), exploration strategies for rescue robots (Taillandier & Stinckwich, 2011), evaluations of suppliers (Wang, Chen, & Chen, 2008) and DSS (Doumpos & Zopounidis, 2010).

3.4.1.7. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The TOPSIS, which was developed by Hwang and Yoon (1981), is used to rank alternatives with limited numbers of factors. It uses the basic prospect of minimising the negative ideal option and maximising the positive one (Hwang & Yoon, 1981; Yoon, 1980).

The TOPSIS facilitates quantitative values and is user-friendly, with its number of stages remaining the same regardless of the number of elements (İç, 2012). Its functionality and capability to retain the same number of stages irrespective of an issue’s dimension enables it to be applied rapidly and stand by itself as a decision-making application. It allows just one alternative to be decided as the ideal one and can handle any types of factors and requirements. The TOPSIS approach requires a minimal variety of inputs from DMs and its outcome is straightforward, with its only subjective variables the weights connected to the requirements. A variety of its applications is available in Behzadian, Otaghsara, Yazdani, and Ignatius (2012).

As the Euclidean Distance function in TOPSIS does not consider the relationship among elements, it is complicated to weight elements or maintain decision stability, particularly with added elements. Another disadvantage of this technique is that it does not assist in determining uncertain or missing information and, like the majority of MCDM techniques, can experience the rank reversal issue.

The TOPSIS approach is applied in different domains. such as design, systems engineering, logistics and environmental management (Amiri, 2010; Bottani & Rizzi, 2006; Chen, Lin, & Huang, 2006; Tong, Wang, & Chen, 2005; Wu, Lin, & Lee, 2010).

3.4.1.8. VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)

VIKOR was developed by Duckstein and Opricovic (1980). It scores the options (A_i (i=1, 2, …, n)) based on the amounts of three values (S_i, R_i and Q_i) required to be estimated for all choices.

It is able to simultaneously assess many alternatives, even using many unrelated criteria, and score them all in a numerical order from worst to best. Moreover, it does not require a consistency test, and is simple to use but only capable of dealing with quantitative data.

According to Huang, Yan, and Ji (2008): the '*VIKOR algorithm can order directly without considering that the best solution is closer to the ideal point or more farther to the worst ideal point'*. Although this is why some DMs may prefer VIKOR over other methods, such as TOPSIS, there is no tool available that is designed to execute it. Also, it finds it difficult to cope with incomplete and uncertain data, and also experiences the rank reversal issue. It is applied in different areas, such as networks (Bashiri, Geranmayeh, & Sherafati, 2012), MCDM problems in intuitionistic environments (Ying-yu & De-jian, 2011) and supplier selections (Jianxun, Zhiguang, & Feng, 2007).

3.4.2. Tools available for MCDM Methods

Dealing with a complex portfolio of projects with uncertainty is much more difficult than handling complexity in classical project management (Aritua, Smith, & Bower, 2009), especially controlling project interconnectivities (Collyer & Warren, 2009; Perminova et al., 2008), which could be one of a PPM's shortcomings (Elonen & Artto, 2003).

Different systems, applications and methods are frequently presented and analysed in PPM research (Dawidson, 2006; Dickinson, Thornton, & Graves, 2001; Kester et al., 2009). Nevertheless, assessing the impact of a different application or technique is complicated since the nature of every organisation is unique and it might have different aspects that affect project efficiency. Despite several studies of organisational environments, a reliable one from which the results can be generalised is not yet available.

Although several studies indicate that strategic PPM decisions are considered in group sessions through applying graphical applications, these tools must be specially developed or modified according to an individual organisation's needs and desire for highly valuable decisions (Christensen, 1997; Cooper et al., 2001b; De Maio, Verganti, & Corso, 1994; Dickinson et al., 2001; Killen et al., 2008; Mikkola, 2001; Phaal et al., 2006; Rungi, 2007); for example, portfolio maps present projects and their options on two axes and are supported by extra information such as variations and risk (Cooper et al., 2001b; Mikkola, 2001; Phaal et al., 2006). Although these mapping tools offering a portfolio-level perspective, they generally look at projects independently. On the other hand, project interconnectivities might result in unexpected responses in their procedures (Aritua et al., 2009; Collyer & Warren, 2009; Perminova et al., 2008) that indicate the importance of projects' dependencies for making effective decisions (Blau et al., 2004; Verma & Sinha, 2002). Using classical PPM tools is no longer acceptable because the complexity of a project portfolio is dramatically increasing and most projects are no longer considered independently or, if so, their independencies must be fully understood for successful decisions (Blau et al., 2004; Verma & Sinha, 2002). Although various organisations collect data related to projects' interconnectivities, their capabilities for using or applying this information or identifying multi-stage dependencies are limited (Danilovic & Browning, 2007; Dickinson et al., 2001). To meet these challenges, particularly as the complexities of decision-making systems increase, experts are participating in developing different ones (Aritua et al., 2009).

Only a few MCDM software tools are available in the market, most of which are commercial, with those for the eight MCDM techniques under consideration: the AHP (e.g., Expert Choice, Mind Decider, HIPRE 3+, MAkeItRational, Transparent Choice, Decision Analysis Module for Excel (DAME), ChoiceResults, 123AHP (Online), Decisions Lens and Super Decisions); ANP (e.g., ANP SOLVER, WEB ANP SOLVER, Decisions Lens and Super Decisions); DEA (e.g., Efficiency Measurement System, Win4DEAP and DEAFrontier); DSRA (e.g., 4eMka2 and jMAF); ELECTRE (e.g., ELECTRE III/IV and ELECTRE TRI); PROMETHEE (e.g., Visual PROMETHEE Academic and PROMETHEE); TOPSIS (e.g., Triptych); VIKOR (not applicable); and multi-software (e.g., SANA (ELECTRE I & 3, TOPSIS and PROMETHEE II), Decision Deck and DECERNS (AHP, PROMETHEE and TOPSIS)). Recently, Oxford University presented an application with a decision support system called OUTDO that examines the way variations in external variables influence complex or unknown selection procedures (Hunt, Bañares-Alcántara, & Hanbury, 2013). The software packages available for the MCDM methods under consideration is presented in ANNEX E.

3.5. Comparing Shortlisted/Down-selected Methods

The results from comparisons of the top eight MCDM methods against each criterion are discussed below with related references.

In PPM, the decision-making process often involves various options (alternatives) which require both ranking and classification processes and/or methods. However, if there are no alternatives available, only the classification process needs to be considered. Moreover, in the event that a portfolio consists of new as well as active components, both processes can be considered according to the individual elements. The DEA, DSRA and ELECTRE methods use classification processes and the others are based on ranking ones.

Uncertainty can be accounted for when the requirements are weighted together with examinations of the options' performances. Also, there is an important difference between managing unknown data in the input and output steps, and conducting a sensitivity examination (Buchholz et al., 2009), the examination highlights that all the methods perform well in this case and can deal with uncertainty. The PROMETHEE and ELECTRE techniques can manage uncertainty perfectly (Polatidis et al., 2006; Rowley et al., 2012) while the DEA, DSRA, ELECTRE and PROMETHEE are capable of managing unknown data better than the AHP, ANP and TOPSIS through their possibility distributions and threshold management. The DRSA deals with unknown data through allocating possibility ranks to the principles of which the requirements are capable (Greco, Matarazzo, & Slowinski, 2001a) or rating intervals instead of exact values in imprecise datasets (Dembczyński, Greco, & Słowiński, 2009). The interdependencies between the criteria and alternatives can be considered since all methods except the DRSA support them.

Although all eight methods are traceable, the publications on MCDM techniques fail to explain this fact and, in particular, that their frameworks do not restrict the amounts or natures of the factors which can be considered input criteria (Belton & Stewart, 2002; Figueira, Greco, et al., 2005). Therefore, it is simply emphasised that every phase of an objective item is accounted for. As the AHP is backed up by several tools and its structure is simple, it is very easy to use and understandable (Linkov & Moberg, 2011). However, as a result of the large numbers of variables, assessment processes based on similarity and dissimilarity indices and de-selection processes, and outcomes reflected according to kernel graphs, ELECTRE techniques rank low (Munda, 2008; Polatidis et al., 2006). Although PROMETHEE is subject to the verification of time-intensive thresholds, it is less difficult to learn or apply compare to ELECTRE (Munda, 2008), is not difficult to use as a tool and has a variety of interfaces . The DRSA ranks perfectly in such cases since it is presents various capabilities for organising the judgements and applying as well as explaining the outcomes (Roy & Słowiński, 2013; Slowinski et al., 2009). There is a lack of proper applications and tools for many techniques (e.g., VIKOR) while, as DECERNS, super decisions and ELECTRE, together with DRSA programs, fail to simultaneously analyse opinions in accordance with diverse inputs, it is necessary to re-run the program to get individual outcomes (Antunes, 2012).

While all methods except the DEA and DRSA are capable of dealing with quantitative data, the DSRA does not require the modification of information (Greco, Matarazzo, & Slowinski, 2001b). On the other hand, the most important steps in decision-making techniques are probably precise evaluations of the relevant information. This issue is particularly critical for techniques that have to elicit qualitative data from the DM, which can be achieved by DEA and DRSA, while the others support quantitative values.

It is not recommended that the AHP and ANP methods be applied individually given that PPM sometimes involves more than ten options and factors. On the other hand, the DEA can support an infinite number of values. Likewise, some applications, such as PROMETHEE ACADEMIC, restrict the quantity of options or criteria.

The rank reversal issue is a common problem of all the selected MCDM techniques, except the DEA, when another option is presented. Ratings are viewed as robust if the addition or removal of an option does not influence the classification or rating of any of the others, with the AHP criticised by Dyer (1990) as a flawed method because it results in arbitrary ratings. However, Saaty (1990) presents a separate aspect of this concern, declaring that this event can occur and, instead of becoming an issue, is a requirement. Experts have demonstrated that ELECTRE experiences rank reversal possibly as a result of the framework of its decision method which depends on a pair-wise analysis and is influenced by the total number of options, as is the AHP (Wang & Triantaphyllou, 2008). Generally, an ELECTRE technique does not result in the selection of only one answer/option from among the others and is one of the approaches that need to determine various criteria, most of which have no specific or realistic definitions. Moreover, its exploitation system is considered by several experts as unclear and difficult to understand (Brans & Vincke, 1985) while its graphical restriction makes its assessment a great deal more difficult. Also, it usually struggles to provide rankings of all the options and, instead, chooses a sub-set of alternatives regarded as being more suitable than others. Therefore, it might be better for decision issues with a few criteria and options for which it can identify more suitable choices (Lootsma, 1990). ELECTRE, PROMETHEE and VIKOR methods need considerable user interaction when dealing with a problem. Figueira and Roy (2009) emphasise that a turning point in the rankings is connected to variations in the input information which impact on the level of reliability of the value graphs and total scorings, suggesting the characteristics of this event are understandable and valid. PROMETHEE techniques are influenced by similar events since they also depend on pair-wise assessments. Mareschal, De Smet, and Nemery (2008) verify that rank reversal can be limited to a specific pair of circumstances, a concern recently further examined by Roland, De Smet, and Verly (2012). The robustness outcomes of the DRSA are affected by the appropriate assistance of specifications which means that the number of options that complies with the principle is in accordance with the total number of options on the data platform (Slowinski et al., 2009), factors that also apply to the PROMETHEE, ELECTRE and AHP techniques. There is a lack of published research concerning the rank reversal problem in the DRSA despite this method being likely to experience it because it relies on outranking comparisons.

Thresholds can be applied for two reasons: to help manage the difference between options if two options are examined (Mendoza & Martins, 2006); and to influence the level of compensation among the individual requirements (Buchholz et al., 2009). Several techniques, such as VIKOR, cannot set parameters values and there is no possibility of applying thresholds for the basic AHP and ANP methods (Antunes, 2012; Buchholz et al., 2009). In contrast, ELECTRE and PROMETHEE approaches deal with various thresholds given that they form frameworks on which techniques are based and both need the two categories of indifference and preference. However, PROMETHEE requires an additional category known as veto (Brans & Mareschal, 2005) and has to associate decisions and threshold values with every factor to help perceptions of the measurement scales of the factors. The DRSA enables thresholds to be determined from selection specifications (e.g., 'if' and 'then' situations) (Roy & Słowiński, 2013; Slowinski et al., 2009).

Group decisions can be only partially arrived at as, of the eight MCDM techniques considered, only the ANP and DEA methodologies are capable of grouping the criteria and alternatives. The AHP, ANP, DEA, PROMETHEE and VIKOR all allow the criteria to be organised into sub-criteria. The AHP and ANP methods support a hierarchical structure, with the former proven to be very useful if an elemental hierarchy carries over three levels (Yeh, 2002) which means that the goal needs to be placed on the top, factors which define options on the centre and options on the bottom levels. All the methods except ELECTRE and DRSA support the dependencies and weightings of criteria. Therefore, prioritising criteria is not possible when applying ELECTRE or DRSA while the ANP also undermines the outcomes of weighting clusters. The AHP, ANP and

DEA are the only methods that support the weighting of alternatives. The ANP has a scalability problem and, because of its specific drawbacks, the AHP has experienced higher useability, particularly when mixed with other MCDM techniques. Of all the methods, the AHP, ANP and DEA are the most integrated ones. Figure 7 illustrates the results obtained from a comparison of the top eight MCDM methods.

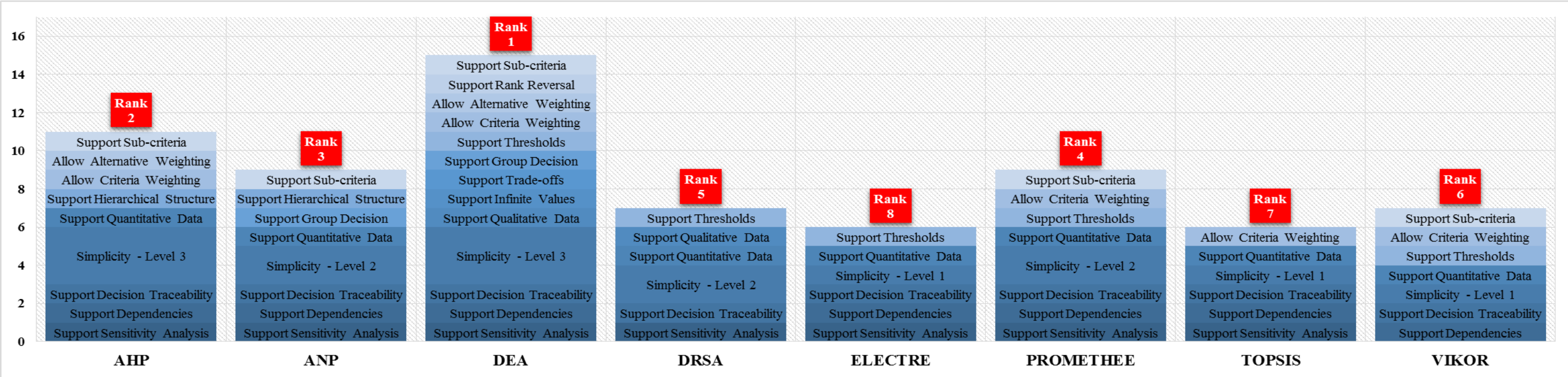

Figure 7. Outcomes of Comparison of top eight PPM MCDM methods

3.6. CHAPTER III SUMMARY

What makes this study unique is the fact that it is probably the first of its kind to analyse PPM MCDM methods on this scale by comparing more than 100 MCDM techniques as well as proposing a solid framework for comparing and ranking them based on their advantages and disadvantages. The following conclusions can be drawn as a result of this investigation:

In order to analyse applications of MCDM techniques, as an initial objective, a literature review was conducted (covering more than 100 techniques in over 1400 articles) that addressed: (1) strategic PPM problems; and (2) decision-making methods and problems. From it, the most suitable MCDM methods for a portfolio decision-making process were selected, with the top eight down-selected and compared in more detail in order to determine their suitability for PPM decision making.

In summary, this investigation demonstrated that specific MCDM techniques are better suited to, and designed for, particular circumstances/scenarios while other applications need to completely ignore them. Also, it was study determined that there is no single standard MCDM method that can both support a PPM's strategic decision making and deal with all its challenges. Moreover, not all portfolio decision-making specifications can be accomplished using current techniques. A few, such as those working with both quantitative and qualitative values might be achieved in the case of a customised application. This review indicated that using particular techniques significantly increases a planning procedure's performance and it would be better to apply more than one MCDM technique or even a hybrid method. There is some evidence that it might be beneficial to choose and implement multiple MCDM methods (Bell, Hobbs, Elliott, Ellis, & Robinson, 2001; Kangas, Kangas, Leskinen, et al., 2001; Salminen et al., 1998), with those more useful for PPM problems a combination of MADM and MODM techniques.

The capabilities of the AHP and DEA methods to deal with any type of judgement specifications or factors with both quantitative and qualitative data, the simplicity of their outcomes and their relatively low levels of complexity when managing preferences leads to the conclusion that they are the most effective approaches (of the numerous methods examined during this study) for the targeted process. They can provide better solutions related to PPM decisions and, in particular, offer the prospect of re-evaluation. Some techniques take significant amounts of a DM's time and usually are not capable of ranking options. The ANP, DRSA, ELECTRE, PROMETHEE, TOPSIS and VIKOR methods were omitted given that, despite the fact that they may take even less time than the AHP or DEA, their solution procedures would still be complicated for a large group of targets while their procedures for a sensitivity examination would be challenging. The evaluation results showed that the AHP and DEA are slightly easier to use than the other methods but, to apply the former for the purpose of PPM decision making would require modifications to it or possibly its integration with other methods that can support both infinite and qualitative data. Although it is possible that a hybrid method could be customised for this specific problem, there are still many questions and limitations which need further investigation, such as the requirements for obtaining feedback about the quality of a prediction or reliability/accuracy of a solution.

In accordance with the outcomes discussed in this chapter, details of attempts to improve them which involve applying the selected methods, both individually and in an integrated decision support system format, and examining them in real decision-making scenarios are provided in the next chapter.

3.7. CHAPTER III HIGHLIGHTS

In this chapter, three questions presented in CHAPTER I (i.e., questions 7, 8 and 9) were examined. The key findings are highlighted below.

a) A MCDM comparison model based on key PPM failure factors was proposed.
b) Over 100 methods were assessed to identify the most suitable PPM MCDM one(s).
c) There was no single MCDM method that could deal with all the PPM challenges alone.
d) A combination of the MADM and MODM techniques is required for better PPM outcomes.
e) AHP and DEA are the most effective means of making better PPM decisions.

Also, Figure 8 presents a snapshot of the key findings in CHAPTER III and outlines the main priority research questions required to be investigated in the next chapter which are as follows.

10. Could the selected MCDM methods deal with all PPM challenges?
11. Are there any challenges related to the selected MCDM methods?
12. Are there any methods that can deal with those challenges?

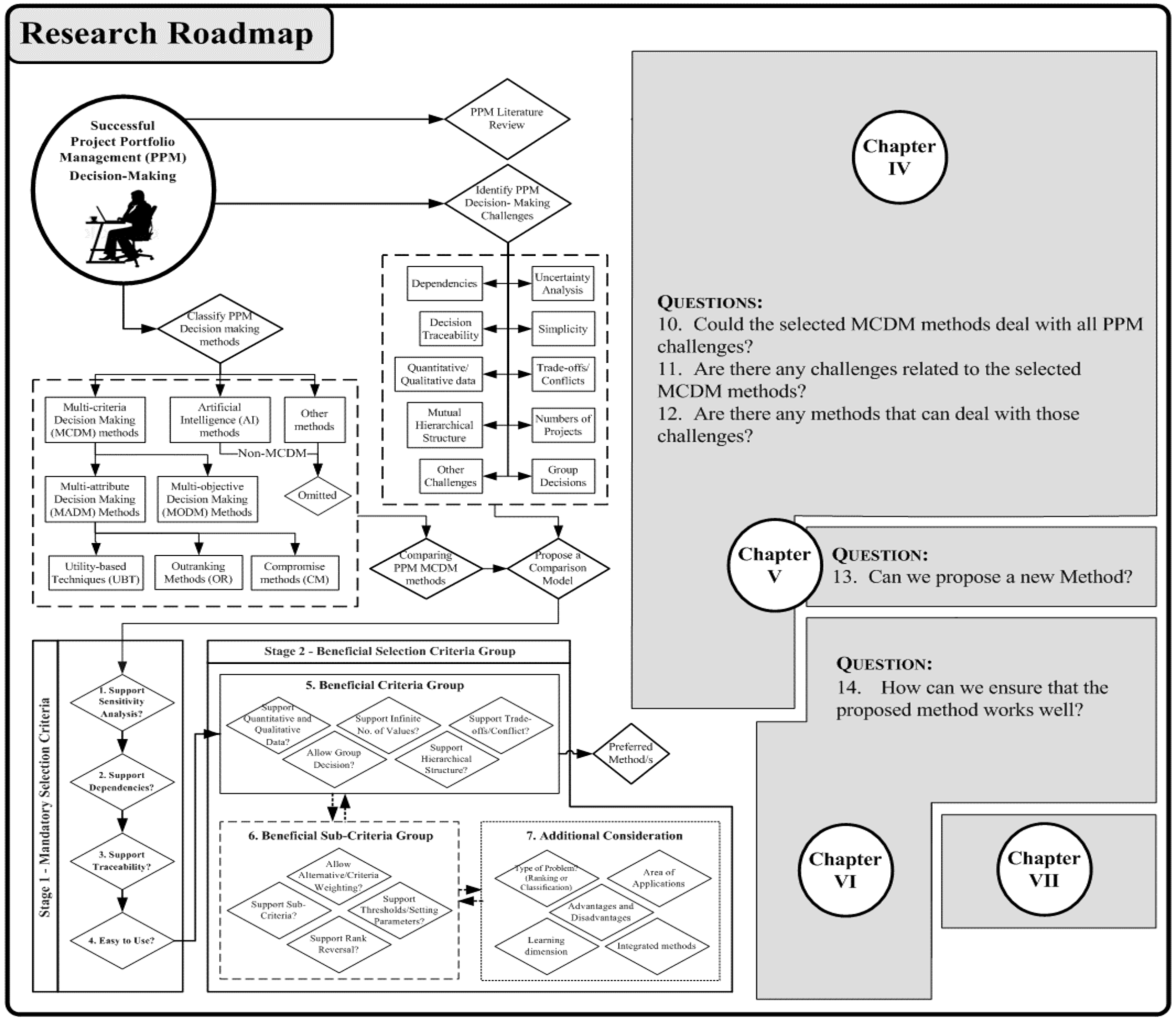

Figure 8. RESEARCH ROADMAP – CHAPTER III

CHAPTER IV

4. EXECUTIVE SUMMARY

This study proposes a novel method for portfolio selection/decision making that combines the Portfolio Theory (PT), Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA) cross-efficiency technique. It takes into account the profits, risks and proficiency of a portfolio and is shown to be useful for selecting one with positive and negative data and subsequently measuring its efficiency using AHP, with a consistency test conducted to verify the objectivity of the results. To test the applicability of the proposed model, it is used to determine the efficiency levels of ten of the largest companies in Australia for the years 2014 and 2015. Two criteria, namely, the expected return and variance, are used to identify the preference status of each company. The results indicate that the proposed model is feasible and adoptable for the contemporary industrial scenario as it simultaneously analyses profits, risks and proficiency.

4.1. PORTFOLIO THEORY (PT)

As DMs may discover completely different assets on which to decide, each with unique risks and returns on investment (Classroom, 2006), it may be difficult for them to select a portfolio that fulfils their requirements. The Portfolio Theory (PT) is a decision structure for portfolios influenced by aiming to maximise the estimated profits and minimise the asset risks (Fabozzi, Gupta, & Markowitz, 2002).

In general, the risk element of PT is determined by several mathematical steps and can be minimised through a diversification designed to choose an effective weighted selection of assets that jointly present lower risks than with any specific asset or category of assets. Diversification is the primary reason behind PT and relates specifically to the typical logic of "never placing all your eggs in a single basket". (Fabozzi et al., 2002; McClure, 2010; Veneeva, 2006). Markowitz (1952) verified that a DM can minimise a portfolio's priorities to manage its estimated return and risk (Sciences, 1990). These essential PT terms are discussed further in the following sub-sections.

4.1.1. Portfolio's Expected Return

The expected return is the weighted average of each asset's estimated returns (Sharpe, 1970). These assets affect the returns of the portfolio, subject to the weight of each asset.

There are various ways of calculating the estimated return of an investment. One would be to calculate the possibilities of various return results and compare them with historical information. To create a portfolio, it is essential to assess the profit of each asset and then the return of the entire portfolio can be estimated (Sharpe, 1970). Also, the expected return is often known as the mean or average return or historical average of an asset's return over a period of time (Benninga, 2010). Developing formulas for a portfolio of assets basically require determining the weighted average of the estimated profits for each asset (Ross, R, & Jaffe, 2002). Eq. (1) demonstrates the expected return of a portfolio and Eq. (2) its actual return.

$$E(R_p) = \sum_{i=1}^{N} x_i E(R_i) \tag{1}$$

where:

$E(R_p) = the\ expected\ return\ of\ the\ portfolio$

$x_i = the\ weighting\ of\ component\ asset\ i$

$E(R_i) = the\ expected\ return\ of\ asset\ i$

$$R_p = \sum_{i=1}^{N} x_i R_i \tag{2}$$

where:

$R_p = actual\ return\ of\ the\ portfolio$

$R_i = actual\ return\ of\ asset\ i$

If a portfolio consists of two assets with return amounts of R_1 and R_2 and weights of w_1 and w_2, the portfolio return will be the weighted average of the two assets' profits as:

$$R_p = w_1 R_1 + w_2 R_2 \tag{3}$$

where:

$R_p = Portfolio\ return$

$w_1 = Weight\ of\ Asset\ 1$

$w_2 = Weight\ of\ Asset\ 2$

$R_1 = Return\ of\ Asset\ 1$

$R_2 = Return\ of\ Asset\ 2$

4.1.2. Portfolio's Return Risk

A portfolio's return risk is the possibility that an asset's actual return will differ from its expected one (Markowitz, 1952). It consists of the potential loss of a few or even all the primary investments and that of a specific portfolio's return can be identified by different techniques. Although the standard deviation and variance are the two best-known procedures, the former is not only the weighted average of the two assets.

4.1.2.1. Return Variance

The return variance is the average squared variation between the actual and average return, that is, a "*measure of the squared deviations of a stock's return from its expected return*" (Bradford & Miller, 2009; Ross et al., 2002).

A higher variance indicates higher risks. Whenever several assets are retained as a group in a portfolio, as those reducing in profit are usually compensated by others increasing in profit, the risk is reduced. Therefore, the variance of a portfolio reduces as the quantity of assets increases (Frantz & Payne, 2009). Consequently, with portfolios consisting of many assets, DMs can more effectively minimise their risk which is expressed as:

$$\sigma^2 = \sum_{i=1}^{n} P_i \, [R_i - E(R_p)]^2 \qquad (4)$$

where:

$E(R_p) = expected\ return\ of\ the\ portfolio$

$P_i = the\ probability\ that\ the\ rate\ R\ occurs$

$R = the\ return\ level$

$i = counts\ the\ number\ of\ assets$

4.1.2.2. Standard Deviation of Return

A portfolio's standard deviation is the variation in its assets which can be a measure of the expected inconsistency of its returns. It needs to be less than the weighted average of the standard deviations of each asset, with a greater one resulting in a higher risk and return (Sharpe, 1970).

The standard deviation can be calculated as:

$$\sigma = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \rho_{ij} \sigma_i \sigma_j} \qquad (5)$$

$$where\ \sigma \text{ is also } = \sqrt{w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\sigma_1\sigma_2\rho_{1,2}}\ \ or\ \sqrt{w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2Cov_{1,2}}$$

$$or\ simply\ \ \sigma = \sqrt{\sigma^2} \qquad (6)$$

where:

$x =$ proportions invested in each asset

$\rho =$ correlation coefficients between i and j or asset 1 and asset 2

$\sigma =$ standard deviation of each asset

$w =$ weight of each asset in the portfolio

In order to define the standard deviation of returns, firstly, the covariance and correlation of the assets need to be identified. The covariance reveals the co-movements of the profits of the assets and, providing that the assets are completely linked, it can reduce the overall risk.

4.1.2.3. Covariance of Return

A portfolio's variability is estimated through its variance and standard deviation. However, when a link between the returns in a portfolio is required, it is critical to determine both its covariance and correlation. As they can determine the connectivity between two random factors (Ross et al., 2002), there is a need to identify the level of risk in the entire portfolio.

As outlined by Markowitz (1959), the risk of a portfolio is not the variance of each of its assets but the covariance of the entire portfolio. The more the assets move in the same direction, the higher the possibility that economic changes will push them all down simultaneously. As the assets in a portfolio are less risky once the covariance between them is low, it is ideal to obtain portfolios with minimal covariances. The covariance is the result of the correlation coefficient and standard deviation of the return (of a pair of assets), as demonstrated in Eq. (7). Also, that between returns can be considered the weighted average of the assets.

$$Cov_{jk} = \rho_{jk}\sigma_j\sigma_k \qquad (7)$$

where:

ρ_{ij} = Correlation coefficients

$\sigma_i\sigma_j$ = Standard deviation of each asset

If the returns are correlated, their covariance will be positive but, if they are negatively correlated or not completely connected, it will be adverse or become zero (Ross et al., 2002).

4.1.2.4. Correlation Coefficient of Returns

The correlation coefficient measures the level of connectivity between factors and is the last measure for estimating risk as:

$$\rho_{AB} = \frac{cov_{AB}}{\sigma_A\sigma_B} \qquad (8)$$

Correlation is the covariance of assets A and B divided by their standard deviation and is an absolute amount of the co-movement between a pair of assets limited by –1 and +1. A positive correlation of +1 ensures that the assets' returns proceed constantly in a similar direction and are positively correlated. A correlation of zero indicates that the assets have no connection to one another and are uncorrelated. A negative correlation of –1 implies that the returns proceed constantly in opposite directions and are negatively correlated (Ross et al., 2002). The higher the quantity of uncorrelated assets, the lower the risk, with inadequate correlations (between +1 and -1) typically revealing the elimination of risk. A portfolio with low correlation coefficient rates presents a lower level of risk than those with high ones (Hight, 2010).

4.1.3. Diversification

The principle of PT is to optimise the connection between risk and return by developing portfolios of assets based on their profits and risks as well as their covariance or, perhaps, correlations with different assets. The risk elimination approach consists of using the assets of different financial units, companies and organisations as well as other investment decision groups (Investopedia, 2009). Diversification is carried out by choosing individual shares, asset categories or materials. As every expected return consists of different results, this could be risky, with this association between return and risk optimised via diversification.

Diversification maximises returns and minimises risk by selecting individual assets each of which can respond uniquely to a similar event. Its impact, which represents the connection between correlation and a portfolio (Roger, 2008), is an inadequate outcome of the correlation between assets and is a useful risk elimination approach which does not compromise returns (Hight, 2010). A portfolio that fulfils such factors is considered efficient, with no other portfolio capable of obtaining a larger return with the same degree of risk (Markowitz, 1959). A portfolio is insufficient when it obtains a larger expected return without having a larger risk as well as decreasing risk while offering a similar degree of expected return (Markowitz, 1991).

4.1.4. Sharpe Ratio (*SR*)

The *SR* is used to examine returns based on different factors and indicates if the returns come from good assets or are the result of additional risk (Gregoriou, Karavas, Lhabitant, & Rouah, 2011). The larger the ratio, the greater the modified efficiency of its risk which is measured as:

$$SR = \frac{E(R_p) - R_f}{\sigma} \qquad (9)$$

where:

$SR = \text{Sharpe Ratio}$

$E(R_p) = \text{Expected Return of the Portfolio}$

$R_f = \text{Risk} - \text{free Rate}$

$\sigma = \text{Volatility of the Portfolio}$

4.2. PREFERRED PPM MCDM TECHNIQUES

This study compared more than 100 MCDM techniques in CHAPTER III and identified the DEA and AHP as the most effective approaches for providing better solutions to PPM decisions. However, each has its own shortcomings.

The following sub-sections present details of aspects of the DEA and AHP techniques, with discussions of their advantages, and present their mathematical logic, processes and numerical examples.

4.2.1. Overview of AHP

The academic perspective of the AHP method is introduced through a literature review and the works previously completed on this methodology reviewed in CHAPTER III. In this sub-section, its shortcomings and issues involved in using it to overcome MCDM problems is described in detail with a practical case study of its processes and directions for future investigation are presented.

According to Whyte (1969), “the human mind uses hierarchies as the prevailing method for classifying what we observe”. The AHP method is such an approach that presents a solution to forming key decisions into hierarchies of targets and evaluating those that support difficult choices, such as the selection of project portfolios for an organisation. It seems to be one of the most popular and appropriate of the MCDM techniques for solving portfolio decision problems because of its simplicity and applicability to multi-level hierarchies.

The AHP, which was developed in 1980 (Saaty, 1980b), is one of the most common MCDM methods and is well suited to modelling quantitative considerations and has been shown to have extensive purposes in many different fields, such as preference, assessment, design and improvement in decision making (Vaidya & Kumar, 2006). It presents the relative priorities of particular indicators (Arora, Arora, & Palvia, 2014; Dedeke, 2013; Singh, Murty, Gupta, & Dikshit, 2007).

The AHP employs a hierarchical (or network) system to indicate a decision problem (Saaty, 1980b). It is designed in such a way that the main goal is on the top level, the requirements in the centre and alternative decisions on the bottom. It presents an organised structure for arranging preferences at each level in the hierarchy using a pair-wise analysis (Fouladgar et al., 2012). The feature vector obtained is then compared by determining the matrix elements to find the relative value of the same unit on different levels and then rank the value of each option (Saaty, 1980a; Saaty, 2005). The hierarchical equation was first introduced by (Miller III, 1966) and is practiced in (Miller, 1969; Miller, 1970). Its 1-9 ratios are based on the studies by Stevens and Fechner (Fechner, 1860; Stevens, 1957) in which the values of the objects on each level are presented by Miller (1956).

The AHP method has been widely applied for performance evaluation and used by various researchers to solve different decision-making problems, with the growth in AHP-related publications enormous (Calantone, Benedetto, & Schmidt, 1999; Hadad & Hanani, 2011; Hegde & Tadikamalla, 1990; Liberatore, 1987; Vaidya & Kumar, 2006; Wallenius et al., 2008; Wang, Wang, & Hu, 2005; Yang & Lee, 1997; Zahedi, 1986). It has been employed in areas such as designing, preferencing, optimisation, resource delegation and problem solutions (Ahmad, Berg, & Simons, 2006).

Several publications examine the application of the AHP with finance considerations (Steuer & Na, 2003) while more than 100 papers look at a combined AHP (Vaidya & Kumar, 2006). Apart from being implemented in the finance sector (Steuer & Na, 2003), the AHP has also been applied in government, education, manufacturing, engineering, management, etc. (Vaidya & Kumar, 2006). Chan and Kumar (2007) applied it for global supplier selection, and Celik et al. modelled shipping registry selection by presenting a feasible decision support mechanism using it (Celik, Er, & Ozok, 2009). It has also been implemented in other fields, such as:

a. organisational performance evaluation (Tseng & Lee, 2009);
b. site selection (Önüt, Efendigil, & Kara, 2010);
c. software analysis (Cebeci, 2009; Chang, Wu, & Lin, 2009);
d. weapon selection (Dağdeviren, Yavuz, & Kılınç, 2009);
e. road planning (Niaraki & Kim, 2009);

f. warehouse selection (Ho & Emrouznejad, 2009);
g. construction method selection (Pan, 2009);
h. software design (Hsu, Kao, & Wu, 2009);
i. technology evaluation (Lai & Tsai, 2009);
j. staff recruitment (Celik, Kandakoglu, & Er, 2009; Khosla, Goonesekera, & Chu, 2009);
k. evaluation of website performance (Liu & Chen, 2009);
l. firms' competence evaluation (Amiri, Zandieh, Soltani, & Vahdani, 2009);
m. manufacturing systems (İç & Yurdakul, 2009; Li & Huang, 2009; Yang, Chuang, & Huang, 2009);
n. underground mining method selection (Naghadehi, Mikaeil, & Ataei, 2009) and its sustainability evaluation (Su, Yu, & Zhang, 2010);
o. strategy selection (Chen & Wang, 2010; Li & Li, 2009; Mansar, Reijers, & Ounnar, 2009; Wu, Lin, & Lin, 2009);
p. banks (Haghighi, Divandari, & Keimasi, 2010; Seçme, Bayrakdaroğlu, & Kahraman, 2009);
q. supplier selection (Chamodrakas, Batis, & Martakos, 2010; Labib, 2011; Wang, Che, & Wu, 2010; Wang & Yang, 2009);
r. project selection (Amiri, 2010);
s. operator's evaluation (Şen & Çınar, 2010);
t. energy selection (Kahraman & Kaya, 2010);
u. drugs selection (Vidal, Sahin, Martelli, Berhoune, & Bonan, 2010);
v. selection of recycling technology (Hsu, Lee, & Kreng, 2010);
w. customer requirement rating (Li, Tang, & Luo, 2010; Lin, Chen, & Tzeng, 2010); and
x. university evaluation (Lee, 2010).

Chou, Sun, and Yen (2012) employed the AHP to assess the weighting for each criterion in the management of human resources for science and technology. Ishizaka and Nguyen (2013) used it to measure the most important factors for selecting a student current bank account and Cay and Uyan (2013) to evaluate reallocation criteria in land consolidation studies. A safety risk assessment framework based on the theory of the cost of safety (COS) model and AHP has been presented (Aminbakhsh, Gunduz, & Sonmez, 2013); an AHP model was built to solve the MCDM problem of selecting the most suitable mobile network operator (Hassan, Ahmad, & Aminuddin, 2013); Nikou and Mezei (2013) used the AHP to identify the most relevant mobile services for consumers and the factors driving their adoption; an index for a disaster-resilient coastal community at the local level was presented by Orencio and Fujii (2013); Yasser, Jahangir, and Mohmmad (2013) developed a MCDM approach to locate the dam site and construct a multipurpose earth dam in Harsin City at the western part of Iran; identifying barriers to the implementation of a green supply chain management (Green SCM) based on procurement effectiveness discussed by Govindan, Kaliyan, Kannan, and Haq (2014); and the selection of renewable energy sources for sustainable development of electricity generation system in Malaysia using AHP presented by Ahmad and Tahar (2014). Yuen (2014) used AHP to compare the Primitive Cognitive Network Process in healthcare and medical decision making; Deng, Hu, Deng, and Mahadevan (2014) used an AHP methodology extended by D numbers for supplier selection; de Luca (2014) investigated whether and how multiple-criteria decision analysis, based on the AHP approach, may support the participatory process of the public in the whole transportation planning process; Zhü (2014) discussed the validity of the AHP in complex and uncertain environments and Zietsman and Vanderschuren (2014) discussed the application of an AHP analysis for the assessment of a potential multi-airport development; Zhu and Xu (2014) discussed hesitant judgements in AHP; a structure-based software reliability allocation using fuzzy AHP presented by Chatterjee, Singh, and Roy (2015); Papadopoulos et al. (2015) develop a general method based on the analytic hierarchy process (AHP) methodology to rank the substances to be studied in a Total Diet Studies (TDS); Bahmani, Javalgi, and Blumburg (2015) used AHP for a Consumer Choice Problem and Yaghoubi and Motevalli (2015) used AHP for selecting nanoparticles in the medical industry. AHP method is conducted for selecting an optimal transportation model in the Navy logistics between Taiwan Island and Kinmen Island (Han, Sung, Dye, Chou, & Wei, 2015); AHP also used by Anima (2015) to select a maintenance policy for the Regional Maritime University workshop. Zhang, Zhao, Gao, and Hao (2015) proposed an evaluation method that can comprehensively expressed the technological performance of unmanned ground vehicles based on AHP; Han presented an AHP-Based Fuzzy Comprehensive Evaluation for Urbanization of Mountainous Area in Xianning (Han, 2015); Smart Grid Strategy Assessment Using the Fuzzy AHP presented by Janjić, Stanković, and Velimirović ; livestock husbandry cluster is proposed by Jote, Beshah, and Kitaw (2015) to mitigate the problems of Ethiopian leather sector at animal husbandry stage using Fuzzy AHP approach; and Jain and Rao (2015) developed a decision-making tool/template using AHP for DMs in a focused area of medical research.

Apart from the abovementioned studies and investigations, many other articles have described the achievements of the AHP approach (Forman & Gass, 2001; Golden, Wasil, & Harker, 1989; Liberatore & Nydick, 2008; Saaty & Forman, 1992; Shim, 1989; Sipahi & Timor, 2010; Vaidya & Kumar, 2006; Vargas, 1990; Zahedi, 1986).

4.2.1.1. Mathematical Logic and Process of AHP

The AHP incorporates DMs' inputs and defines a process for decision making, with its procedure consisting of the following steps (Saaty, 1980b).

1- Decomposing (structuring or constructing) a decision problem into factors in accordance with their characteristics and the development of a hierarchical model with different levels which breaks down a situation into related clusters.
2- Making comparative judgements (measuring or priority analysis) by comparing the relative importance of each factor in a cluster to each of the others 'with regard to the parent of the cluster' (Forman & Selly, 2001) to obtain their preferences.

Table 5. Comparative Judgements

	Intensity Scale	
Less important than	Extremely less important	1/9
		1/8
	Very strongly less important	1/7
		1/6
	Strongly less important	1/5
		1/4
	Moderately less important	1/3
		1/2
	Equal Importance	1
More important than		2
	Moderately more important	3
		4
	Strongly more important	5
		6
	Very strongly more important	7
		8
	Extremely more important	9

3- Combining (synthesising or verifying consistency) is an advantage of the AHP which incorporates the results from the measuring step into a group of mathematical results by applying accurate mathematical techniques for calculating eigenvectors (Forman & Gass, 2001). In this step, the AHP method receives the priority weights of factors by calculating the eigenvector of matrix A ($w = (w_1, w_2, \ldots, w_s)^T$) which is related to the largest eigenvalue (λ_{max}) as:

$$Aw = \lambda_{max} w \qquad (10)$$

where A is an $n \times n$ pair-wise comparison matrix with n the number of factors considered for examination. Likewise, matrix B for the priority weights of the sub-factors is:

$$e_h = (e_{h1}, e_{h2}, \ldots, e_{hs'})^T$$

B is an $m \times m$ pair-wise comparison matrix with m the number of options evaluated as.

$$Be_h = \lambda_{max} e_h \qquad (11)$$

Saaty (1980b) described a statistical equation for examining the consistency index (CI) of a respondent as:

$$CI = \mu = \frac{\lambda_{max} - n}{n-1} \qquad (12)$$

where n is the dimension of the matrix and λ_{max} the maximal eigenvalue.

The random index (or random indices) (RI) is the average of the CI for a large number of randomly generated matrices. Its values for small problems ($n \leq 10$) are presented in Table 6 developed by Saaty (1977).

The consistency ratio (CR) is a critical function of the AHP which aims to avoid the potential for inconsistency in the criteria's weights. It is used to determine if the inconsistency in a comparison matrix is practical as:

$$CR = \frac{\lambda_{max} - N}{(N-1)RI} \qquad (13)$$

A CR of less than or slightly above 0.1 is regarded as sufficient (Saaty, 1980b) with those greater than 0.1 unreliable and require the comparison scores to be reconsidered.

Table 6. RANDOM INDEX FORM

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

4.2.1.2. Numerical Example of AHP

This study developed an AHP executive dashboard as an alternate decision-support tool for DMs to measure and track a portfolio's activities and assess its performance, inputs and outputs generated from the AHP model. The following is a numerical example using this system. The type and nature of the data used in the following example is not the focus of this study. Instead, the reaction of AHP method towards the random data is our main concern.

Five evaluation criteria (n = 5) and five alternatives to be evaluated (m = 5) are considered to describe the mechanism of the AHP. If more criteria need to be considered, this example can be expanded accordingly.

4.2.1.2.1. Step 1: Pair-wise Comparison

Firstly, the DM builds a pair-wise comparison matrix for n = 5 and m = 5 using the intensity scales presented in Table 5.

$$AW = \begin{bmatrix} 1 & 3 & 3 & 5 & 2 \\ 1/3 & 1 & 1 & 1 & 1 \\ 1/3 & 1 & 1 & 1 & 2 \\ 1/5 & 1 & 1 & 1 & 1 \\ 1/2 & 1 & 1/2 & 1 & 1 \end{bmatrix}$$

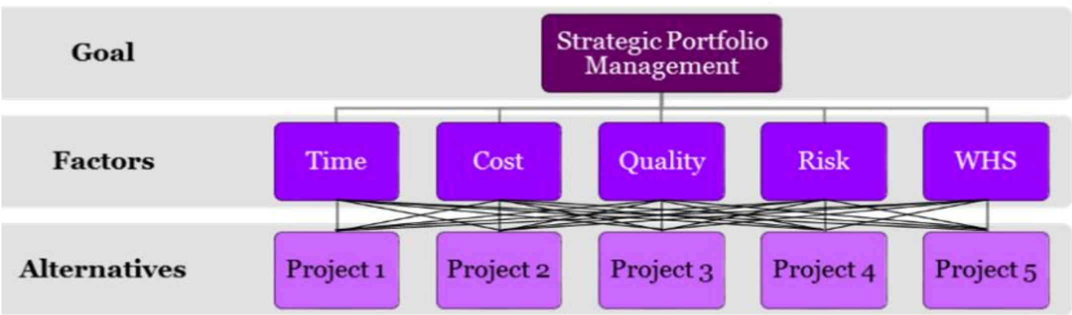

Figure 9. AHP MODEL

Table 7. PAIR-WISE COMPARISON MATRIX (FACTORS)

Factor	Time	Cost	Quality	Risk	WHS
Time	1	3	3	5	2
Cost	1/3	1	1	1	1
Quality	1/3	1	1	1	2
Risk	1/5	1	1	1	1
WHS	1/2	1	1/2	1	1
Total	**2.367**	**7.000**	**6.500**	**9.000**	**7.000**

4.2.1.2.2. Normalisation

From the comparison matrix, the priority or weight of each parameter is calculated (Table 8) by summing the values in each column, each of which is then divided by the total value of the column; for example, considering the 'Time' factor, the 'Time' value (1) divided by the total value of the 'Time' column (2.367) gives a value of 0.423, in the case of the 'Cost' factor, 3 / 7= 0.429 and so on.

Table 8. PARAMETER WEIGHTS - A

Factor	Time	Cost	Quality	Risk	WHS
Time	**0.423**	0.429	0.462	0.556	0.286
Cost	0.141	**0.143**	0.154	0.111	0.143
Quality	0.141	0.143	**0.154**	0.111	0.286
Risk	0.085	0.143	0.154	**0.111**	0.143
WHS	0.211	0.143	0.077	0.111	**0.143**
Total	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

Table 9. PARAMETER WEIGHTS - B

Factor	Total (Factors)	Weight Vector	%
Time	2.154	0.431	**43.08%**
Cost	0.692	0.138	**13.83%**
Quality	0.834	0.167	**16.69%**
Risk	0.635	0.127	**12.70%**
WHS	0.685	0.137	**13.70%**

The ‘Total (Factors)’ is the total and the ‘Weight Vector’ the average of all the factors in each raw score. The total of each column in Table 8 must be equal to one (1) or the calculation is incorrect. As indicated in Table 9, the highest weight vector is 0.431 which is related to the ‘Time’ factor of projects.

4.2.1.2.3. Consistency Analysis

The *CI* is calculated by multiplying each pair-wise comparison column by its associated weight. Then, the total value of each row is divided by the same weight and, by averaging them, the λ_{max} value is identified in Table 10 with the *RI* selected from Table 6 (*n*=5, so, *RI*=1.12).

Table 10. C*ONSISTENCY* M*EASURE* (F*ACTORS*)

Consistency Measure	
Time	5.236
Cost	5.154
Quality	5.093
Risk	5.159
WHS	5.118
λ_{max}	**5.152**

$\lambda_{max} = 5.152$

$$CR = \frac{\lambda_{max} - N}{(N-1)RI} = \frac{5.152 - 5}{(5-1)1.12} = 0.034$$

CR= 3%

Consistency= OK

Priority vectors are also applied to each sub-factor (project) which, on their own, are composite amounts of other factors; for instance, in Figure 9, as all the five factors are composite parameters (Time, Cost, Quality, Risk and WHS), priority vectors have to be created for them. An example of the ‘Time’ factor is shown in Table 11:

Time Factor

Table 11. PAIR-WISE COMPARISON MATRIX FOR 'TIME' FACTOR

Time	Project 1	Project 2	Project 3	Project 4	Project 5
Project 1	1	3	1	2	1
Project 2	1/3	1	1	1	1
Project 3	1	1	1	1	1
Project 4	1/2	1	1	1	1
Project 5	1	1	1	1	1
Total	**3.833**	**7.000**	**5.000**	**6.000**	**5.000**

Table 12. PARAMETER WEIGHTS (TIME FACTOR) - A

Time	Project 1	Project 2	Project 3	Project 4	Project 5
Project 1	0.261	0.429	0.200	0.333	0.200
Project 2	0.087	0.143	0.200	0.167	0.200
Project 3	0.261	0.143	0.200	0.167	0.200
Project 4	0.130	0.143	0.200	0.167	0.200
Project 5	0.261	0.143	0.200	0.167	0.200
Total	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

Table 13. PARAMETER WEIGHTS (TIME FACTOR) - B

Time	Total (Factors)	Weight Vector	%
Project 1	1.423	0.285	28.46%
Project 2	0.796	0.159	15.93%
Project 3	0.970	0.194	19.41%
Project 4	0.840	0.168	16.80%
Project 5	0.970	0.194	19.41%

$$Be_{Time} = \begin{bmatrix} 1 & 3 & 1 & 2 & 1 \\ 1/3 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1/2 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Table 14. CONSISTENCY MEASURE (SUB-FACTORS)

Consistency Measure	
Project 1	5.224
Project 2	5.087
Project 3	5.153
Project 4	5.106
Project 5	5.153
$\lambda_{\max}$	**5.144**

λ_{max} = *5.144*

$$CR = \frac{\lambda_{max} - N}{(N-1)RI} = \frac{5.144 - 5}{(5-1)1.12} = 0.032$$

CR= 3%

Consistency= OK

Cost Factor

*Table 15. PAIR-WISE COMPARISON MATRIX FOR '**COST**' FACTOR*

Cost	**Project 1**	**Project 2**	**Project 3**	**Project 4**	**Project 5**
Project 1	1	1	3	3	3
Project 2	1	1	1	3	2
Project 3	1/3	1	1	3	1
Project 4	1/3	1/3	1/3	1	2
Project 5	1/3	1/2	1	1/2	1
Total	**3.000**	**3.833**	**6.333**	**10.500**	**9.000**

Table 16. PARAMETER WEIGHTS (COST FACTOR) - A

Cost	**Project 1**	**Project 2**	**Project 3**	**Project 4**	**Project 5**
Project 1	0.333	0.261	0.474	0.286	0.333
Project 2	0.333	0.261	0.158	0.286	0.222
Project 3	0.111	0.261	0.158	0.286	0.111

Project 4	0.111	0.087	0.053	0.095	0.222
Project 5	0.111	0.130	0.158	0.048	0.111
Total	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

Table 17. PARAMETER WEIGHTS (COST FACTOR) - B

Cost	**Total (Factors)**	**Weight Vector**	**%**
Project 1	1.687	0.337	33.74%
Project 2	1.260	0.252	25.20%
Project 3	0.927	0.185	18.53%
Project 4	0.568	0.114	11.36%
Project 5	0.558	0.112	11.16%

Table 18. CONSISTENCY MEASURE (SUB-FACTORS)

Consistency Measure	
Project 1	5.398
Project 2	5.313
Project 3	5.408
Project 4	5.237
Project 5	5.305
λ_{max}	**5.332**

λ_{max} *= 5.332*

$$CR = \frac{\lambda_{max} - N}{(N-1)RI} = \frac{5.332 - 5}{(5-1)1.12} = 0.074$$

CR= 7%

Consistency= OK

Quality Factor

*Table 19. PAIR-WISE COMPARISON MATRIX FOR '**QUALITY**' FACTOR*

Quality	**Project 1**	**Project 2**	**Project 3**	**Project 4**	**Project 5**
Project 1	1	2	1	2	3
Project 2	1/2	1	2	1	1

Project 3	1	1/2	1	3	2
Project 4	1/2	1	1/3	1	1
Project 5	1/3	1	1/2	1	1
Total	**3.333**	**5.500**	**4.833**	**8.000**	**8.000**

Table 20. PARAMETER WEIGHTS (QUALITY FACTOR) - A

Quality	**Project 1**	**Project 2**	**Project 3**	**Project 4**	**Project 5**
Project 1	0.300	0.364	0.207	0.250	0.375
Project 2	0.150	0.182	0.414	0.125	0.125
Project 3	0.300	0.091	0.207	0.375	0.250
Project 4	0.150	0.182	0.069	0.125	0.125
Project 5	0.100	0.182	0.103	0.125	0.125
Total	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

Table 21. PARAMETER WEIGHTS (QUALITY FACTOR) - B

Quality	**Total (Factors)**	**Weight Vector**	**%**
Project 1	1.496	0.299	29.91%
Project 2	0.996	0.199	19.91%
Project 3	1.223	0.245	24.46%
Project 4	0.651	0.130	13.02%
Project 5	0.635	0.127	12.71%

Table 22. CONSISTENCY MEASURE (SUB-FACTORS)

Consistency Measure	
Project 1	5.294
Project 2	5.499
Project 3	5.266
Project 4	5.281
Project 5	5.339
λ_{max}	**5.336**

λ_{max} = *5.336*

$$CR = \frac{\lambda_{max} - N}{(N-1)RI} = \frac{5.336 - 5}{(5-1)1.12} = 0.074$$

CR= 7%

Consistency= OK

Risk Factor

Table 23. Pair-wise Comparison Matrix For 'Risk' Factor

Risk	Project 1	Project 2	Project 3	Project 4	Project 5
Project 1	1	1	1	3	1
Project 2	1	1	3	2	1
Project 3	1	1/3	1	2	1
Project 4	1/3	1/2	1/2	1	1
Project 5	1	1	1	1	1
Total	**4.333**	**3.833**	**6.500**	**9.000**	**5.000**

Table 24. Parameter Weights (Risk Factor) - A

Risk	Project 1	Project 2	Project 3	Project 4	Project 5
Project 1	0.231	0.261	0.154	0.333	0.200
Project 2	0.231	0.261	0.462	0.222	0.200
Project 3	0.231	0.087	0.154	0.222	0.200
Project 4	0.077	0.130	0.077	0.111	0.200
Project 5	0.231	0.261	0.154	0.111	0.200
Total	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

Table 25. Parameter Weights (Risk Factor) - B

Risk	Total (Factors)	Weight Vector	%
Project 1	1.179	0.236	23.58%
Project 2	1.375	0.275	27.51%
Project 3	0.894	0.179	17.88%
Project 4	0.595	0.119	11.91%
Project 5	0.957	0.191	19.13%

Table 26. Consistency Measure (Sub-Factors)

Consistency Measure	
Project 1	5.252
Project 2	5.368
Project 3	5.234
Project 4	5.172
Project 5	5.227
λ_{max}	**5.251**

λ_{max} = *5.251*

$$CR = \frac{\lambda_{max} - N}{(N-1)RI} = \frac{5.251 - 5}{(5-1)1.12} = 0.056$$

CR= 5%

Consistency= OK

WHS Factor

*Table 27. Pair-wise Comparison Matrix For '**WHS**' Factor*

WHS	Project 1	Project 2	Project 3	Project 4	Project 5
Project 1	1	1	1	1	1
Project 2	1	1	1	2	1
Project 3	1	1	1	1	1
Project 4	1	1/2	1	1	3
Project 5	1	1	1	1/3	1
Total	**5.000**	**4.500**	**5.000**	**5.333**	**7.000**

Table 28. Parameter Weights (WHS Factor) - A

WHS	Project 1	Project 2	Project 3	Project 4	Project 5
Project 1	0.200	0.222	0.200	0.188	0.143
Project 2	0.200	0.222	0.200	0.375	0.143
Project 3	0.200	0.222	0.200	0.188	0.143
Project 4	0.200	0.111	0.200	0.188	0.429
Project 5	0.200	0.222	0.200	0.063	0.143
Total	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

Table 29. PARAMETER WEIGHTS *(WHS* FACTOR*) - B*

WHS	**Total (Factors)**	**Weight Vector**	**%**
Project 1	0.953	0.191	19.05%
Project 2	1.140	0.228	22.80%
Project 3	0.953	0.191	19.05%
Project 4	1.127	0.225	22.54%
Project 5	0.828	0.166	16.55%

Table 30. CONSISTENCY MEASURE *(*SUB-FACTORS*)*

Consistency Measure	
Project 1	5.249
Project 2	5.374
Project 3	5.249
Project 4	5.399
Project 5	5.134
$\lambda_{\max}$	**5.281**

λ_{max} = *5.281*

$$CR = \frac{\lambda_{max} - N}{(N-1)RI} = \frac{5.281 - 5}{(5-1)1.12} = 0.062$$

CR= 6%

Consistency= OK

4.2.1.2.4. Portfolio Summary

Five projects were scored on the five factors described in Figure 9. Assigning an accurate weight to each element is a key factor that impacts on the outcome of this experiment. Table 31 summarises the weights and scores of the portfolio.

Table 31. PORTFOLIO SUMMARY

Summary	Time		Cost		Quality		Risk		WHS	
	Weight (w_{Time})	Score (Be_{Time})	Weight (w_{Cost})	Score (Be_{Cost})	Weight ($w_{Quality}$)	Score ($Be_{Quality}$)	Weight (w_{Risk})	Score (Be_{Risk})	Weight (w_{WHS})	Score (Be_{WHS})
Project 1	0.431	0.285	0.138	0.337	0.167	0.299	0.127	0.236	0.137	0.191
Project 2	0.431	0.159	0.138	0.252	0.167	0.199	0.127	0.275	0.137	0.228
Project 3	0.431	0.194	0.138	0.185	0.167	0.245	0.127	0.179	0.137	0.191
Project 4	0.431	0.168	0.138	0.114	0.167	0.130	0.127	0.119	0.137	0.225
Project 5	0.431	0.194	0.138	0.112	0.167	0.127	0.127	0.191	0.137	0.166

Final Score (Be_{Total})	**Final Score (%)**
0.2752	27.52%
0.2029	20.29%
0.1989	19.89%
0.1558	15.58%
0.1672	16.72%

The score matrix B is:

$$Be_{Total} = \left(Be_{Time}, Be_{Cost}, Be_{Quality}, Be_{Risk}, Be_{WHS}\right)$$
$$= \begin{bmatrix} 0.285 & 0.337 & 0.299 & 0.236 & 0.191 \\ 0.159 & 0.252 & 0.199 & 0.275 & 0.228 \\ 0.194 & 0.185 & 0.245 & 0.179 & 0.191 \\ 0.168 & 0.114 & 0.130 & 0.119 & 0.225 \\ 0.194 & 0.112 & 0.127 & 0.191 & 0.166 \end{bmatrix}$$

As mentioned in Step 1 (pair-wise comparison) and shown in Table 31, the priority weights of the factors are identified as:

$$w = (0.431, 0.138, 0.167, 0.127, 0.137)^T$$

Therefore, the final score vector is:

$$v = w.e_{Total} = (0.2752, 0.2029, 0.1989, 0.1558, 0.1672)^T$$

As a result, 'Project 1', which has a total score of 27.52% (as shown in Table 32 and Figure 10), is the project that maximises the success rate of our portfolio's strategic targets.

Table 32. PROJECTS' RANKINGS

Projects	%	Rank
Project 1	27.52%	**1**
Project 2	20.29%	**2**
Project 3	19.89%	**3**
Project 4	15.58%	**5**
Project 5	16.72%	**4**

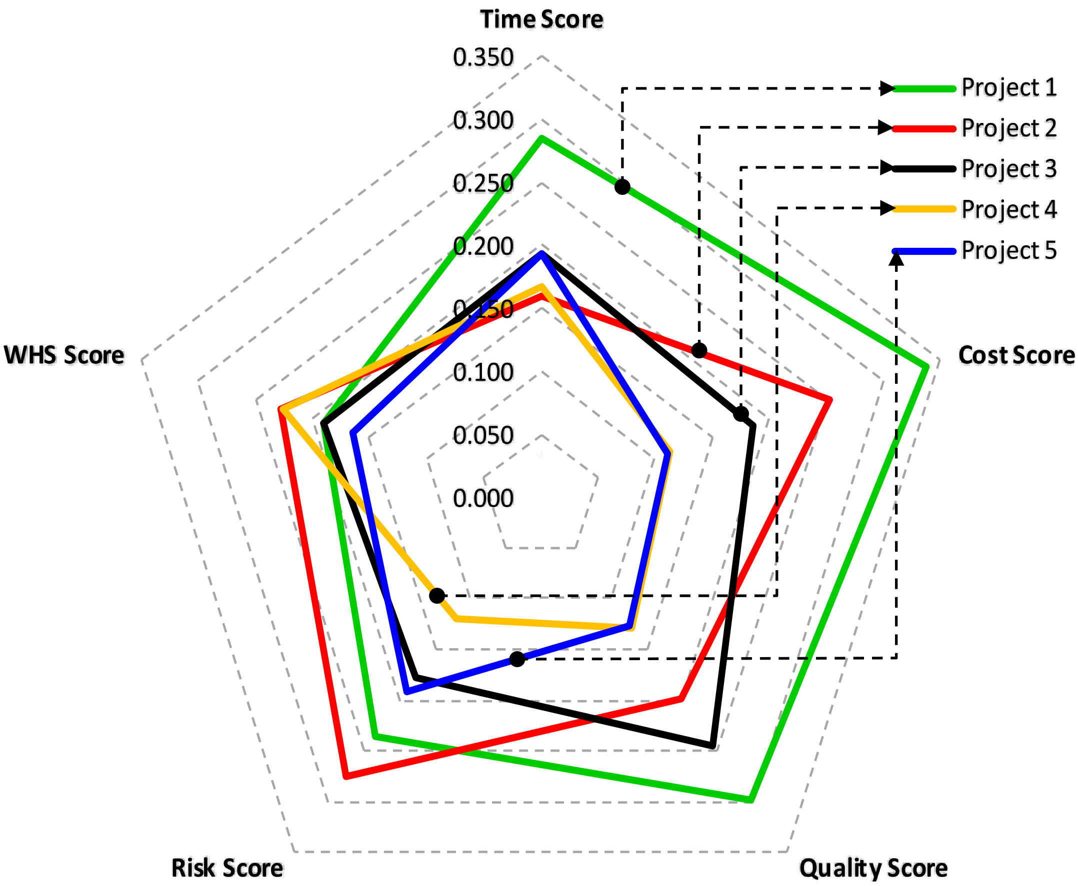

Figure 10. DIAGRAM OF PROJECTS' RANKINGS

4.2.1.3. Objectives of AHP

The main function of the AHP method is using pair-wise comparisons to help DMs weigh the coefficients and simply examine the ideal choices (Loken, 2007). It is scalable which enables it to simply modify dimensions to support almost any decision-making issue because of its hierarchical format. Given that the AHP is one of the first techniques employed for a multi-criteria decision examination, several tools make full use of it. Another of its advantages is that it allows inconsistencies in decisions and enables them to be assessed (Kamenetzky, 1982). If consistency fails, the eigenvector continues to create a number of priorities each of which is an acceptable approximation with a 10% error (Forman & Gass, 2001). Also, using a *CI*, unreasonable results can be eliminated which enable weights to be identified (Chang, 2005). Other advantages of the AHP are its convenience, flexibility and capability to verify inconsistencies and analyse a problem in which there is a hierarchy of sub-problems by applying different factors and changing its qualitative index into a quantitative one. Therefore, significant and complicated problems with contentious requirements and factors can be considerably simplified. Where quantitative data are restricted, experts' decisions regarding defining the weights of the factors and scores of the options could be very valuable. The AHP is a reliable method for supporting decision procedures that helps DMs assess the criteria's weights and choose the best alternative (Shang, 1993).

The AHP's consistency verification allows DMs to avoid unreliable decisions based on personal judgements. It presents a precise and effective strategy for determining the aspects' weights and also considers the characteristics of human decision making. Therefore, the inputs from customers and other professionals regarding the related advantages of individual factors are used in the development of a comparison matrix which eventually produces the factors' weights. The end result of AHP is weights in the ratio basis that is much more usable and accurate than the ordinal scales generated by some other methodologies. It is actually less difficult to evaluate two variables/factors simultaneously and determine their relative benefits (as in the AHP) than evaluate several criteria and sub-criteria together to precisely determine their weight values. The AHP is very simple to apply and includes a consistency-checking function designed to omit any potential inconsistencies discovered in the factors' weights.

The AHP is widely applied because of its functionality, simplicity and great flexibility while, more importantly, it can be incorporated with methods such as mathematical programming to evaluate both qualitative and quantitative aspects (Yang & Lee, 1997). Also, it offers much higher levels of individual acceptability and assurance than other decision methods (Zakarian & Kusiak, 1999). Apart from being used as a stand-alone application, the AHP has been combined with several other methods and techniques for many practical functions, such as by Ozdemir and Gasimov (2004) who investigated a problem using a binary non-linear programming approach.

4.2.2. DEA Overview

DEA has grown to become an effective application for evaluating the performances of DMUs (Ruggiero, 2004) and continues to improve substantially since being created by Charnes et al.

(1978). It is a data-oriented method for analysing the relative efficiencies of DMUs using various inputs to generate multiple outputs (Cooper, Seiford, & Zhu, 2004b).

It initially depended on only what is generally referred to as the efficient frontier estimation which was first suggested by Farrell (1957). Research interest in this topic began with an article written by Charnes et al. (1978) who extended the work of Farrell (1957) to calculate DMUs' performances for several inputs and outputs. DEA was primarily created as the Charnes-Cooper-Rhodes (CCR) model (also called the constant returns to scale (CRS)) by Charnes et al. (1978). Then the Banker-Charnes-Cooper (BCC) model (also known as the variable return to scale (VRS)) was created by Banker, Charnes, and Cooper (1984) to estimate the performances of related financial development models and develop a performance frontier based on the Pareto optimum.

Using DEA in the development of a *CI* can be classified in two steps. The first uses a regular DEA technique in which an aggregate of input and output indicators is identified to construct a composite efficiency factor (Chaaban, 2009; Murias, de Miguel, & Rodríguez, 2008; Murias, Martinez, & De Miguel, 2006). The next employs the benefit of the doubt (BOD) method in which all variables are dealt with as outputs without exact inputs (Cherchye, Moesen, Rogge, & Van Puyenbroeck, 2007; Cherchye et al., 2008; Zhou, Ang, & Poh, 2007).

After the preliminary work of Charnes et al. (1978), several scholars and experts have implemented and enhanced the DEA technique.

DEA has quickly developed into an interesting effective subject in which professionals from different fields have presented their specific roles (Barua et al., 2004; Chen, Hwang, & Shao, 2005; Chen, Chien, Lin, & Wang, 2004; Chien, Lo, & Lin, 2003; Easton, Murphy, & Pearson, 2002; Hwang & Chang, 2003; Korhonen & Luptacik, 2004; Paradi & Schaffnit, 2004); for example, Adolphson and his co-workers found a way of superconducting a supercollider by implementing a model without inputs or outputs (Adolphson, Cornia, & Walters, 1992). Sinuany-Stern, Mehrez, and Barboy (1994) employed the DEA classification for a linear programming analysis to rank DMUs. Several studies have discussed the advantages of applying the DEA to score a government's financial functionality (e.g., Charnes, W., Lewin, & Seiford, 1994; Farrell, 1957). Sinuany-Stern and his colleague used a canonical correlation analysis (CCA/DEA) to rate all DMUs (Sinuany-Stern & Friedman, 1998a) and Sinuany-Stern and Friedman (1998a); Sinuany-Stern and Friedman (1998b) applied a pair-wise performance matrix to sort them. Simos and Marouiis (2007) implemented a DEA to estimate the performances of DBB, DB, CM and

DBM in road projects. Moreover, Liu and colleagues presented a DEA/Assurance Region (AR) method for eliminating the cost, fixed and income types of factors at the same time (Liu, Li, Fu, & Wu, 2009); Sueyoshi and Goto (2012) discussed how to apply a DEA for environmental assessment; corporate sustainability management in a Korean electronics industry was measured by Lee and Saen (2012) using DEA; Liu, Lu, Lu, and Lin (2013) assessed the literature published between 1978 and 2010 by applying a citation-based approach using DEA; DEA was used to analyse the efficiency levels of different organisations (Samoilenko & Osei-Bryson, 2013); Yadav, Chauhan, Padhy, and Gupta (2013) presented a power sector-restricting model using DEA; and Cook, Tone, and Zhu (2014) addressed several issues related to the use of DEA. Also, Mirhedayatian, Azadi, and Saen (2014) proposed a novel network DEA model for evaluating a green supply chain management (GSCM); a new DEA model for selecting eco-efficient technologies in the presence of undesirable outputs was proposed by Shabani, Saen, and Torabipour (2014); Ebrahimnejad, Tavana, Lotfi, Shahverdi, and Yousefpour (2014) proposed a three-stage DEA model for the banking industry; Kao (2014) reviewed studies of network DEA; Bernroider and Stix (2015) discussed the applicability of basic and extended DEA models for various information system (IS) decisions; an evaluation of the potential growth of a bank branch using DEA was presented by LaPlante and Paradi (2015); Hatami-Marbini, Tavana, Gholami, and Beigi (2015) proposed a four-step bounded fuzzy DEA model for application to safety in the semiconductor industry; to assess DMUs' efficiency scores, Atici and Podinovski (2015) also used DEA; and the reactions of China's banks towards the reform program were examined by Xu, Gan, and Hu (2015) using DEA.

Studies of DEA applications are available in Seiford (1996) and Emrouznejad, Parker, and Tavares (2008). Furthermore, there are several studies which apply the DEA to compare project efficiency (for example, Eilat, Golany, & Shtub, 2008; Hadad, Keren, & Hanani, 2013; Hadad, Keren, & Laslo, 2013; Mahmood, Pettingell, & Shaskevich, 1996; Vitner, Rozenes, & Spraggett, 2006). Ramanathan (2003) presented outstanding introductory material for DEA beginners while a more detailed DEA explanation can be obtained from Cooper et al. (2006).

4.2.2.1. Mathematical Logic and Process of DEA

There are several approaches for scoring DMUs from a DEA perspective (Adler et al., 2002; Hadad & Hanani, 2011). Cooper, Seiford, and Tone (2007) presented the four standard models: the CCR; BCC; Additive; and Slack-based measure (SBM).

A CCR model considers a CRS factor whereby an increase in inputs leads to an increase in outputs. The BCC model, which adopts a VRS factor, has the same results but its levels of increases between the inputs and outputs are different. While CRS and VRS approaches are concerned with input or output, the Additive one considers both elements. The SBM model provides scalar efficiency scores that involve all the inefficiency options that can be identified from the Additive model.

CCR and BCC models of DEA are usually applied in studies. The following section presents the CCR model applied in this work which allows for an objective examination of the overall performance and determines both the sources and calculated quantities of the inefficiencies identified. Also, as prior assumptions are not essential in this model, DMUs can be examined in their most beneficial way. It is possible to think of a CCR structure as a reduction in the multiple output/input condition to that of a particular virtual output/input.

DEA is concerned with several alternative DMUs, the efficiencies of which are examined in terms of performance. Every ratio is analysed independently which tests whether the DMU could improve its efficiency by reducing its input or improving its output.

Assuming that *n* is the number of DMUs to be examined and every DMU uses *m* inputs and generates *s* outputs, DMU_j requires x_{ij} of input i to generate y_{rj} of output *r* as:

$$min\,\theta - \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right) \qquad (14)$$

subject to:

$$\sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- = \theta x_{i0} \qquad i = 1, 2, \dots, m;$$

$$\sum_{j=1}^{n} y_{ij}\lambda_j - S_r^+ = y_{r0} \qquad r = 1, 2, \dots, s;$$

$$\lambda_j, S_i^-, S_r^+ \geq 0 \qquad \forall i, j, r$$

where:

λ_j= the weights assigned by the linear program,

θ = the efficiency calculated,

S_i = the input slacks,

S_r = the input slacks and

ε = the non-Archimedean aspect identified to be less than a positive value.

For a better interpretation, the classic model above can be presented as:

$$max\ h_o(u, v) = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \qquad (15)$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \qquad j = 1, \dots, n; \text{ and } u_r, v_i \geq 0$$

where:

u, v = the weights to be optimised and

y_{ro}, x_{io} = the observed input/output values of the DMU to be evaluated.

4.2.2.2. Numerical Example of DEA

The following example uses the DEA decision-support system developed in this study to measure a portfolio's efficiency. The type and nature of the data used in the following example is not the focus of this study. Instead, the reaction of DEA method towards the random data is our main concern.

Considering a group of four programs in a portfolio, each with a single input measure (resources), measured based on a single output measure (cost). The values of their inputs and outputs are provided in Table 33, with the four programs ranked based on their operating efficiency (using their inputs to produce outputs).

Table 33. PORTFOLIO'S INPUT/OUTPUT DATA

DMUs	**Input**	**Output**
Program 1	25	93
Program 2	21	52
Program 3	23	74
Program 4	17	38
Weights	0.04	0.0108

As an example, Program 2 requires 21 people to complete a job with an estimated budget of $52 million. In the following, we describe how we compare these programs and measure their efficiencies by applying the above data.

Step 1: Constraints that maximise efficiency = 1

Table 34. WEIGHTED INPUTS/OUTPUTS AND CONSTRAINTS

DMUs	Weighted Input		Weighted Output	Constraints
Program 1	1.0000	>=	1.0000	0.0000
Program 2	0.8400	>=	0.5591	-0.2809
Program 3	0.9200	>=	0.7957	-0.1243
Program 4	0.6800	>=	0.4086	-0.2714

Using the '=SUMPRODUCT' function in Excel as the '=SUMPRODUCT(Program 2 Input, Inputs Weights)', we calculate the weighted inputs and outputs for each program; for example, those of Program 2 can be calculated as:

Weighted Input =SUMPRODUCT(21, 0.04) = 0.8400
Weighted Output =SUMPRODUCT(52, 0.0108) = 0.5591

The programs' constraints can estimated by calculating the difference between their weighted inputs and outputs, as follows for Program 2.

Weighted Output - Weighted Input = 0.5591 - 0.8400 = -0.2809

Step2: Constraints that selected units have weighted inputs = 1 (one unit at a time)

Selected Unit	Weighted Inputs		
1	1	=	1

Step3: Maximise the weighted outputs for the selected units (one unit at a time)

Selected Unit	Weighted Outputs
1	1

SOLVER Function in Excel

The input and output weights presented in Table 33 are calculated using the 'Solver' function in Excel by applying the following constraints and parameters.

1- 'Set Objective': the value of the weighted outputs presented in Step 3 is set as an objective.v
2- 'By Changing Variable Cells': the values of both the input and output weights in Table 33 are considered.
3- 'Subject to the Constraints':
   a. all the weighted inputs must be greater than or equal to the weighted outputs; and
   b. the weighted inputs in step 2 must equal 1.

Step 4: Resulting efficiency under preferred weights of the selected unit

In this step, a program's efficiency scores are estimated by multiplying the values of the weighted outputs and weighted inputs identified in Step 1; for example, the efficiency score for Program 2 can be calculated as:

Weighted Output / Weighted Inputs = 0.5591 / 0.8400 = 0.6656 * 100 = 66.56%

Table 35. PORTFOLIO'S EFFICIENCY SCORES

DMUs	Efficiency (%)	Rank
Program 1	100.00	1
Program 2	66.56	3
Program 3	86.49	2
Program 4	60.09	4

In this portfolio, Program 1 is identified as the most efficient followed by Program 3, with Program 4 the least efficient.

Also, we can simply calculate the DMUs' efficiency scores by dividing the output measures by the input ones to determine each program's ratio, as shown in Table 36.

Table 36. Programs' RATIOS

DMUs	Ratio
Program 1	3.72
Program 2	2.48
Program 3	3.22
Program 4	2.24

e.g., Program 1 = 93/25 = 3.72

As shown in Table 36, Program 1 has the highest ratio of 3.72 and Program 4 the lowest of 2.24. Because Program 1 has the highest, we need to compare all the other programs with it and calculate their relative efficiencies by dividing their ratios by 3.72.

e.g., Program 2 = 100 (2.48/3.72) = 66.56%

A snapshot of the DEA tool developed in this study is presented in Figure 11.

Portfolio Efficiency Assessment Using The Standard Data Envelopment Analysis (DEA) Method

Selected unit 1

	Inputs Used	Outputs produced	STEP 1: Constraints that max efficiency = 1			
DMUs	**Input 1**	**Output 1**	**Weighted inputs**		**Weighted outputs**	**Constraints**
1	25	93	1	>=	1	0
2	21	52	0.84	>=	0.559139785	-0.280860215
3	23	74	0.92	>=	0.795698925	-0.124301075
4	17	38	0.68	>=	0.408602151	-0.271397849
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						
						1
Weights	**0.04**	**0.010752688**				

STEP 2

Constraints that the selected units has weighted inputs = 1 (one unit at a time)

Selected unit = **1**
Weighted inputs 1 = 1

STEP 3

Maximize the weighted outputs for the selected units (one unit at a time)

Selected unit = **1**
Weighted outputs **1**

DEA Solver

STEP 4

Portfolio Efficiency Scores

Efficiency	**%**	**Rank**
1	100.00%	1
0.665642601	66.56%	3
0.864890136	86.49%	2
0.600885515	60.09%	4

Figure 11. Portfolio Efficiency Assessment Using Standard DEA

4.2.2.3. Objectives of DEA

The key benefit of DEA is that it does not require a prior assumption or the interdependency between the inputs and outputs (Seiford & Thrall, 1990). Given that DEA does not require pre-estimated variables, it provides the advantages of eliminating subjective elements, simplifying estimations and minimising errors (Qiang Chen et al., 2010).

Since a project decision includes qualitative and quantitative factors, DEA has been individualised to manage qualitative information, similar to quantity of knowledge transfer (Saen, Memariani, & Lotfi, 2005), services (Seydel, 2006) and vendor status (Saen, 2007). Moreover, it can be positively employed to contemplate stochastic functionality procedures (Talluri, Narasimhan, & Nair, 2006) and even control imprecise information (Saen, 2007; Wu, Shunk, Blackhurst, & Appalla, 2007).

4.3. DEA AND AHP METHODS CHALLENGES

4.3.1. Issues in using AHP Models

Although the AHP is a well-known technique, it possesses a number of disadvantages and several changes for its improvement have been recommended. It is a subjective method as it depends on the opinions of experts (Chang, 2005) and has issues associated with the interdependency between its criteria and alternatives. Given that it is based on setting up priorities between criteria and alternatives using pair-wise reviews, it only facilitates quantitative values as input to matrices (i.e., it does not verify qualitative values and missing data). The downside of employing the AHP might also be that it uses a restricted number of criteria. As it is crucial to perform a $n \times (n-1)/2$ analysis, it is recommended that no more than 10 criteria are used. For example, for an efficiency assessment of a portfolio with 100 projects and sub-projects, an examination of 4500 separate matrix (*100×(100–1)/2 =4500 matrix*) is required which can be a challenging task for a decision maker. One of the biggest criticisms of the AHP is that it suffers from the rank-reversal problem. As a consequence of comparing ratings, adding up the options towards the end may result in a reversal of the final ratings.

Some publications in the area of project management (Al-Harbi, 2001; Leung, Muraoka, Nakamoto, & Pooley, 1998; Vidal et al., 2010) criticise the AHP model for not following rank-reversal scenarios as its ranking of options might possibly be modified by summing different options for evaluation. The ranks could potentially be reversed when an irrelevant alternative is added to existing ones. However, several researchers state that the rank-reversal issue can be resolved without adjusting the scores of the current options (Forman, 1993; Pérez, Jimeno, & Mokotoff, 2006; Triantaphyllou, 2001). Moreover, one other criticism is that the AHP is not an axiomatic structure and its large number of pair-wise reviews of the options could make its application a lengthy task. In its approach, as one aspect is compared against the best factor, only the final selections will be evaluated.

A number of researchers presented different ways of improving the flexibility of the AHP technique. Boender, De Graan, and Lootsma (1989) and Chen, Hwang, Beckmann, and Krelle (1992) added a fuzzy method to it as did Sugihara and Tanaka (2001) by modifying the simple AHP matrix values into a fuzzy amount to manage the risk inherent in a human's decision as well as the limited data. Nevertheless, none provided a manageable parameter for varying the selection of the weightings. Generally, a pair-wise matrix is not totally consistent due to the excessive number of redundancies evident in pair-wise reviews. However, as a result of these redundancies, the method is unsupportive of judgemental issues (Millet & Harker, 1990).

Yeh (2002) stated that the AHP technique is very useful once an elemental hierarchy consists of more than three levels. This indicates that the overall aim and target of the problem is on the top, a number of factors which explain the options on the centre, and the competing solutions on the bottom levels. However, since a portfolio's decision-making process may have more than 10 alternatives and criteria, it is not recommended to use only the AHP method which does not support missing values and presents consistent decisions given that the *CI* is measured before developing pair-wise assessment matrices. Probably the most important step in decision-making techniques is to precisely evaluate the relevant information. This issue is particularly critical in approaches which should elicit qualitative data from a DM. However, as the AHP can only support values that are quantified, it is clearly inferior to other MCDM methods in terms of its issues framework and cannot be used when there are certain/several requirements and options.

4.3.2. Issues in using DEA Models

A minor mistake or small measurement error in allocating the input data can have a major effect on DEA outcomes or may not be able to estimate the efficiency of a DMU; for example, in the case of Atari, although it operated effectively, it missed out on its share (Thore, Kozmetsky, & Phillips, 1994).

The DMUs in DEA may appear to be efficient only because of the structures of their inputs and outputs rather than being actually/naturally efficient. The DEA method rejects the direct addition of extra data and is also incapable of identifying differences between DMUs in a small sample (Cooper, Seiford, et al., 2004b). In the classical DEA, the weights used to analyse an individual DMU only characterise that DMU cannot examine negative data. The standard DEA method might not necessarily offer high-quality preferences among DMUs, particularly when many of them are efficient. The DEA has a disadvantage in terms of the Pareto principle, that is, once almost every DM has selected a unique answer, it can choose several equally efficient options (Sinuany-Stern, Mehrez, & Hadad, 2000). The similarity of different techniques needs to be compared so the best can be selected (Sinuany-Stern & Friedman, 1998b).

4.4. Existing Methods for Dealing with Shortcomings of DEA and AHP

As previously mentioned, one of the main drawbacks of the classical DEA is that the weights for analysing an individual DMU are only used to characterise that DMU. However, the projects and programs in a portfolio are related to each other, with some closely interdependent. The cross-efficiency model can handle this issue by incorporating a peer evaluation mode.

Many researchers have tried to incorporate DEA in, or apply it, with MCDM techniques and some have actually claimed that DEA alone is a MCDM approach (e.g., Troutt, 1995). However, MCDM is often used prior to decision making or during project implementation whereas DEA is typically applied to assess existing strategies (Adler et al., 2002). A smart solution to integrating another MCDM method with DEA is to inject better data into it. Although this can be accomplished by restricting the weight values, choosing ideal input/output goals or perhaps developing hypothetical DMUs, these treatments may not provide complete rankings. The concept of integrating the AHP and DEA is not new, with DEA/AHP methods being widely applied as a solution to the multi-criteria decision-making issue.

4.4.1. DEA Cross-efficiency (DEA CE)

Sexton, Silkman, and Hogan (1986) proposed the cross-efficiency DEA technique that has both self and peer assessment capabilities for DMUs whereby each DMU is examined according to its own weight and those of every other DMUs to ensure that it is properly assessed.

Assume that n DMUs with m inputs and s outputs need to be examined, with $x_{ij} (i = 1, \dots, m)$ and $y_{rj} (r = 1, \dots, s)$, and the input and output values of DMU_j $(j = 1, \dots, n)$ and the efficiencies of these DMUs estimated by determining the following CRS model (Charnes et al., 1978):

$$max\ \theta_{kk} = \sum_{r=1}^{s} u_{rk} y_{rk} \qquad (16)$$

subject to:

$$\sum_{i=1}^{m} v_{ik} x_{ik} = 1$$

$$\sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} \leq 0 \qquad j = 1, \dots, n$$

$$u_{rk}, v_{ik} \geq 0, \quad r = 1, \dots, s \quad i = 1, \dots, m$$

where:

DMU_k = the DMU under evaluation

$v_{ik} (i = 1, \dots, m)$ = input weights

$u_{rk} (r = 1, \dots, s)$ = output weights

Allowing $u_{rk}^* (r = 1, \dots, s)$ and $v_{ik}^* (i = 1, \dots, m)$ to be the optimal solution to the above equation, $\theta_{kk}^* = \sum_{r=1}^{s} u_{rk}^* y_{rk}$ is known as the CRS efficiency of DMU_k and is the ideal efficiency applicable for the self-assessment of DMU_k. If $\theta_{kk}^* = 1, DMU_k$ is CRS-efficient, otherwise non-CRS-efficient.

$\theta_{jk} = \sum_{r=1}^{s} u_{rk}^* y_{rj} / \sum_{i=1}^{m} v_{ik}^* x_{ij}$ is known as the cross-efficiency of DMU_k to DMU_j by peer assessment, where $j = 1, \dots, n; j \neq k$. As Eq. (16) is solved n times for each individual DMU, it is possible to obtain a single CRS-efficiency value as well as (n-1) cross-efficiency values for every DMU. The n efficiency values form the cross-efficiency matrix shown in Table 37. The averaged n efficiency value represents the total efficiency and is often referred to as the average cross-efficiency value. According to the total efficiency value, the n DMUs will be fully rated.

Table 37. Cross-efficiency Matrix

DMUs	1	2	…	n	Average Cross-efficiency

1	θ_{11}	θ_{12}	$\cdots$	θ_{1n}	$(\frac{1}{n})\sum_{k=1}^{n}\theta_{1k}$
2	θ_{21}	θ_{22}	$\cdots$	θ_{2n}	$(\frac{1}{n})\sum_{k=1}^{n}\theta_{2k}$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
n	θ_{n1}	θ_{n2}		θ_{nn}	$(\frac{1}{n})\sum_{k=1}^{n}\theta_{nk}$

where:

$\theta_{kk}(k = 1, \dots, n)$ = the CRS-efficiency values of n DMUs

$\theta_{kk} = \theta^{*}_{kk}$.

There are two main benefits of using a DEA CE assessment: it offers ideal placements of DMUs, and minimises impracticable weight limits (Anderson, Hollingsworth, & Inman, 2002).

4.4.2. Integrated DEA/AHP Model

4.4.2.1. DEA/AHP Overview

As mentioned in CHAPTER III, this study found that several papers combined AHP with other MODM methods, such as mixed-integer linear programming (MILP) (Crary, Nozick, & Whitaker, 2002; Korpela, Kyläheiko, Lehmusvaara, & Tuominen, 2001, 2002; Korpela & Lehmusvaara, 1999; Korpela, Lehmusvaara, & Tuominen, 2001; Malladi & Min, 2005; Stannard, Zahir, & Rosenbloom, 2006; Tyagi & Das, 1997), integer linear programming (ILP) (Akgunduz, Zetu, Banerjee, & Liang, 2002; Braglia, Gabbrielli, & Miconi, 2001; Çebi & Bayraktar, 2003; Kearns, 2004; Malczewski, Moreno-Sanchez, Bojorquez-Tapia, & Ongay-Delhumeau, 1997; Ozdemir & Gasimov, 2004) and goal programming (GP) (Badri, 1999; Bertolini & Bevilacqua, 2006; Guo & He, 1999; Kim, Lee, & Lee, 1999; Kwak & Lee, 1998; Kwak & Lee, 2002; Kwak, Lee, & Kim, 2005; Lee & Kwak, 1999; Radasch & Kwak, 1998; Radcliffe & Schniederjans, 2003; Schniederjans & Garvin, 1997; Wang, Huang, & Dismukes, 2004; Wang, Wang, et al., 2005; Yurdakul, 2004; Zhou, Cheng, & Hua, 2000).

In a review by Ho (2008) on integrated AHP methods and their applications, five tools identified as being coupled with AHP were Mathematical Programming (MP), Quality Function Deployment (QFD), Meta-heuristics, SWOT (Strength, Weaknesses, Opportunities and Threats) analyses and DEA. Each of these tools was chosen due to its reputation, recognition, broad functionality and success in making decisions. The combination of AHP and DEA has attracted the most attention during the past few years rather than those of AHP with LP, ILP and MILP methods. Moreover, integrating the AHP method with DEA has been considered the most popular and practical decision-making tool by many researchers (e.g., Ertay, Ruan, & Tuzkaya, 2006; Saen et al., 2005; Takamura & Tone, 2003; Yang & Kuo, 2003).

As previously emphasised, DEA and AHP have some disadvantages (Kang & Lee, 2010; Saen et al., 2005). The most typical of AHP is that it is necessary for specialists to conduct many pair-wise comparisons while DEA can generate too many, even unlimited, ideal and equally efficient options or solutions (Shang & Sueyoshi, 1995). A DEA technique used on its own struggles to provide a full picture of organisational efficiency and does not consider a DM's subjective choices regarding each specification of concern, score the selected options or even DMUs. On the other hand, the AHP is able to overcome this drawback by including a DM's opinion when setting variables (weights) and prioritise DMUs with multiple inputs and outputs using pair-wise comparisons. Even a small measurement error in DEA can considerably influence the outcomes whereas the AHP is designed to construct complex multi characteristic challenges for dealing with such issues (Saaty, 1980b).

As the AHP approach can only evaluate a small number of decision options, when there are many, its pair-wise comparison process is undoubtedly infeasible. Therefore, an integrated AHP/DEA model which uses the benefits of the AHP's subjectivity and DEA's objectivity and simultaneously eliminates their disadvantages is required. It influences the desirable weights and rating elements of all DMs and determines the best performance rating of each option, efficiency scores which are later employed to rank the alternatives and define the decision weights of a group. In the combined AHP/DEA method, either quantitative or qualitative elements are considered.

Many studies have integrated DEA with AHP. Sinuany-Stern et al. (2000) presented an AHP/DEA method for rating DMUs employing a two-stage model. The weights of basic indices were calculated using both AHP and DEA techniques by Cai and Wu (2001). A mixture of AHP and DEA methodologies was applied to examine the overall quality of management activities (Yoo, 2003). The relocations of some Tokyo state organisations were studied by Takamura and Tone (2003) using a combination of DEA and AHP. Ertay et al. (2006); and Saen et al. (2005); Takamura and Tone (2003); Yang and Kuo (2003) presented an integration of DEA and AHP to identify efficiency scores by simultaneously considering quantitative and qualitative data.

Ramanathan (2006) proposed a new integrated DEA/AHP model called DEAHP. Guo, Liu, and Qiu (2006) applied an AHP/DEA method for assessing a supply chain function. Ertay et al. (2006) used AHP and DEA to design the layout of a facility. In addition to these applications, the phenomenon of integrating DEA and AHP has been used in similar studies, such as those by Guo et al. (2006); Lozano and Villa (2009); and Ramanathan (2006). Korpela, Lehmusvaara, and Nisonen (2007) used DEA to integrate input and output variables and identify the performances of warehouses using the AHP. In the area of supply chain management, probably the most significant study was conducted by Sevkli, Lenny Koh, Zaim, Demirbag, and Tatoglu (2007) who applied proper quantitative strategies. In 2007, Chen and his colleagues assessed the functions of semi–conductor industries and gave weights to the four-fold indices of the Balance Score Card (BSC) using DEA and AHP models (Chen & Chen, 2007). Azadeh et al. assessed and optimised the performance of a railway system's improvement program by integrating AHP and DEA models (Azadeh, Ghaderi, & Izadbakhsh, 2008). Sueyoshi, Shang, and Chiang (2009) applied AHP and DEA models together as a decision-making one for prioritisation. Qiang Chen et al. (2010) analysed project delivery systems in the Chinese construction industry using the AHP and DEA. Kang and Lee created an assessment method using the AHP and DEA to determine vendor capabilities (Kang & Lee, 2010). Jalalvand, Teimoury, Makui, Aryanezhad, and Jolai (2011) introduced an approach for examining the supply chains of organisations using different DEA models. Zhang and Fu proposed an index system for evaluating the performances of emergency logistics using the AHP and DEA (Zhang & Fu, 2012). The performances of Turkeys' 13 banks were assessed by Ar and Kurtaran (2013) using the DEA and AHP, and an integrated AHP/DEA was used to rank DMUs in a fuzzy environment (Alem, Jolai, & Nazari-Shirkouhi, 2013). AHP and DEA approaches were integrated to assess electricity generation firms in Organization for Economic Co-operation and Development (OECD) countries (Kasap & Kiriş, 2013), and they were integrated to identify the best retailer for online trading by Aji and Hariga (2013). Also, an integrated AHP/DEA model was applied to examine proper energy systems against high oil fees by Lee, Mogi, and Hui (2013) and one was used to evaluate the lean tools and techniques for ranking efficacy by Anvari, Zulkifli, Sorooshian, and Boyerhassani (2014). Pakkar (2015) proposed a theoretical framework for assessing the performances of DMUs by integrating DEA and AHP methodologies. Yadav and Sharma (2015) also used DEA and AHP to select the best dealer in a car company as did Kumar, Shankar, and Debnath (2015) for analysing customer preferences and measuring relative efficiencies in telecom sector. Pakkar used them for the multiplicative aggregation of financial ratios, and Mahapatra, Mukherjee, and Bhar (2015) for evaluating the performance of an organisation.

Badri and Abdulla (2004) stated that "*good decisions are most often based on consistent judgements*". The consistency factor of AHP works as a feedback system which assists DMs in an examination or reconsideration of decisions made. However, as DMs need to consider restrictions such as cost and risks, the DEA might assist the AHP to provide additional data to support them. Therefore, it would be beneficial to use DEA and AHP together for the former's objectivity and latter's subjectivity as well as indicating DMs' opinions.

4.4.2.2. Mathematical Logic and Process of Integrated DEA/AHP

Sinuany-Stern, Mehrez, and Hadad (2000) presented an integrated model in which, initially, a pair-wise assessment of DMUs was performed using an improved DEA method (Eq. (17)). Subsequently, these DMUs were examined by a cross-efficiency approach (Eq. (18)) and then the results applied for the development of a pair-wise assessment matrix for generating the source data required for AHP analyses. The selling point of the DEA/AHP rating model is the fact that each method has its own unique advantages and the AHP pair-wise reviews are the result of a functional pair-wise DEA. This DEA/AHP approach overcomes the DEA's rating inefficiency and minimises the AHP's subjective examination. A comparison matrix is established by applying standard DEA methods and then using the AHP to grade the DMUs.

The DEA is used on DMUs to develop the pair-wise assessment matrix. If there are *n* DMUs and each one has *m* inputs and *s* outputs, where X_{ij} is input *i* of unit *j* and Y_{rj} output *r* of unit *j*, the DEA technique is employed to estimate the performance of each pair of DMUs irrespective of the other DMUs, with E_{AA} and E_{BA} are the efficiencies of DMU_A and DMU_B respectively.

$$E_{AA} = \underset{u_r, v_i}{Max} \sum_{r=1}^{s} u_r Y_{rA} \tag{17}$$

$$s.t. \sum_{i=1}^{m} v_i X_{iA} = 1$$

$$\sum_{r=1}^{s} u_r Y_{rA} \leq 1$$

$$\sum_{r=1}^{s} u_r Y_{rB} - \sum_{i=1}^{m} v_i X_{iB} \leq 0 \qquad u_r \geq 0, r = 1 \ldots s, v_i \geq 0, i = 1 \ldots m$$

$$E_{BA} = \underset{u_r, v_i}{Max} \sum_{r=1}^{s} u_r Y_{rB} \tag{18}$$

$$s.t. \sum_{i=1}^{m} v_i X_{iB} = 1$$

$$\sum_{r=1}^{s} u_r Y_{rB} \leq 1$$

$$\sum_{r=1}^{s} u_r Y_{rA} - E_{AA} \sum_{i=1}^{m} v_i X_{iA} = 0 \qquad u_r \geq \varepsilon, \qquad v_i \geq \varepsilon$$

E_{BB} and E_{AB} are also determined by the same equations (Eq. (17) and (18)) following the efficiency rankings of DMU$_A$ and DMU$_B$.

$$a_{AB} = \frac{E_{AA}+E_{AB}}{E_{BB}+E_{BA}} \tag{19}$$

Eventually, a pair-wise assessment matrix from the outcomes of Eq. (19) needs to be developed for each set of DMUs' j and k, with the j row and k column factor (a_{jk}) in the AHP judging matrices:

$$a_{jk} = \frac{E_{jj}+E_{jk}}{E_{kk}+E_{kj}} \tag{20}$$

$$a_{jj} = 1, \quad a_{kj} = \frac{1}{a_{jk}}$$

The comparison matrix is:

$$\begin{vmatrix} 1 & \frac{E_{AA}+E_{AB}}{E_{BB}+E_{BA}} & \cdots & \frac{E_{AA}+E_{An}}{E_{nn}+E_{nA}} \\ \frac{E_{BB}+E_{BA}}{E_{AA}+E_{AB}} & 1 & \cdots & \frac{E_{BB}+E_{Bn}}{E_{nn}+E_{nB}} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{E_{nn}+E_{nA}}{E_{AA}+E_{An}} & \frac{E_{nn}+E_{nB}}{E_{BB}+E_{Bn}} & \cdots & 1 \end{vmatrix}$$

4.4.3. Models for dealing with negative data

While having to deal with negative data in a portfolio, e.g., profit values, is common, as the standard DEA or integrated DEA/AHP methods are not capable of achieving this, some other methods have been developed.

4.4.3.1. Range Directional Measure (RDM)

Portela, Thanassoulis, and Simpson (2004) presented the Range Directional Measure (RDM) method for determining the performances of DMUs with positive and non-positive variables in accordance with a directional distance function without the need to modify the information. The outcomes of their method were very similar to those of radial DEA which is an advantage of the RDM method compare to the additive approach.

Assuming that *n* DMUs classified by *j* are those to be examined and each one has *m* inputs and *s* outputs, DMU_j requires x_{ij} of input *i* to generate y_{rj} of output r.

Assuming that *n* DMUs are classified as $j \in (1, \dots, n)$ and each has *m* inputs $\left(x_{ij}; i = 1, \dots, m\right)$ and *s* outputs $(y_{rj}; r = 1, .., s)$:

$$Max\ \beta \tag{21}$$

subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{io} - \beta g_{xi} \qquad i = 1, \dots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \le y_{ro} - \beta g_{yr} \qquad r = 1, \dots, s$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$g_{yr} \ge 0, \quad g_{xi} \ge 0, \quad \lambda_j \ge 0, \quad j = 1, \dots, n \quad i = 1, \dots, m \quad r = 1, \dots, s.$$

where:

$g_{xi}\ and\ g_{yr}$ = random range of units' possible improvement.

Portela et al. (2004) modified Eq. (21) by presenting the IP factor as:

$$\begin{cases} IP's\ input\ ith = \left(min_{1 \le j \le n}\{x_{ij}\}\right) & i = 1, \dots, m \\ IP's\ output\ ith = \left(max_{1 \le j \le n}\{y_{rj}\}\right) & r = 1, \dots, s \end{cases}$$

$\left(g_{xi}, g_{yr}\right)$ can be chosen regarding the under − evaluation of DMU_0 as:

$$\begin{cases} g_{io} = x_{io} - \left(min_{1\le j\le n}\{x_{ij}\}\right) & i = 1, \dots, m \\ g_{ro} = max_{1\le j\le n}\{y_{rj}\} - y_{ro} & r = 1, \dots, s \end{cases}$$

The following section presents the RDM model modified by the DEA VRS method which can deal with negative data.

When DMUs perform badly:

$\boldsymbol{RDM^{+}}$

$$Max\ \beta \qquad (22)$$

subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{io} - \beta R_{xi} \qquad i = 1, \dots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \le y_{ro} - \beta R_{yr} \qquad r = 1, \dots, s$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \ge 0, \qquad j = 1, \dots, n$$

When DMUs perform well:

$\boldsymbol{RDM^{-}}$

$$Max\ \beta_o \qquad (23)$$

subject to:

$$\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro} + \beta_o \frac{1}{R_{ro}} \qquad r = 1, \dots, s$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{io} - \beta_o \frac{1}{R_{io}} \qquad i = 1, \dots, m$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \ge 0$$

where:

$g_o = (g_{io}, g_{ro})$ = vector direction (once positive values are presented).

Portela et al. (2004) presented the *I* factor to deal with negative data as follow:

$$\begin{cases} Input\ variable\ x_i\ RDM^{-}: R_{io} = x_{io} - min_j\{x_{ij}; j = 1, \dots, n\}, & i = 1, \dots, m \\ Output\ variable\ v_r\ RDM^{+}: R_{ro} = max_j\{y_{rj}; j = 1, \dots, n\} - y_{ro}, & r = 1, \dots, s \end{cases}$$

where:

$I = \left(max_j\{y_{rj}; r = 1, \dots, s\}, min_j\{x_{ij}; 1, \dots, m\}\right) (g_{xi}, g_{yr}) = (R_{io}, R_{ro})$

4.4.3.2. Modified Slack-based Measure (MSBM)

The MSBM, which can deal with both negative outputs/inputs, was developed by Sharp, Meng, and Liu (2007). It can handle the Slack-based Measure (SBM) model's transformation challenge suggested in the study by Tone (2001) based on the directional distance functionality of Portela et al. (2004).

The SBM model presented by Tone (2001) with *m* positive inputs and *s* positive outputs is:

$$Min\ \rho = \frac{1 - \frac{1}{m}\sum_i \frac{S_i^-}{x_{io}}}{1 + \frac{1}{s}\sum_r \frac{S_r^+}{y_{ro}}} \qquad (24)$$

subject to:

$$\sum_j x_{ij}\lambda_j = x_{io} - S_i^-; \quad i = 1, \dots, m,$$

$$\sum_j y_{rj}\lambda_j = y_{ro} - S_r^+; \quad r = 1, \dots, s,$$

$$\sum_j \lambda_j = 1;$$

$$S_i^- \geq 0;\ S_r^+ \geq 0;\ \lambda_j \geq 0;\ \forall i, r\ and\ j.$$

The standard SBM model can produce negative efficiency outcomes and Sharp et al. (2007) modified it as:

$$Min\ \rho = \frac{1-\sum_i \frac{w_i S_i^-}{R_{io}}}{1+\sum_r \frac{w_r S_r^+}{R_{ro}}} \qquad (25)$$

subject to:

$$\sum_j x_{ij}\lambda_j = x_{io} - S_i^-; \quad i = 1, \dots, m,$$

$$\sum_j y_{rj}\lambda_j = y_{ro} - S_r^+; \quad r = 1, \dots, s,$$

$$\sum_j \lambda_j = 1\,; \sum_i w_i = 1\,; \sum_r \upsilon_r = 1,$$

$$S_i^- \geq 0;\ S_r^+ \geq 0;\ \lambda_j \geq 0;\ w_i \geq 0;\ \upsilon_r \geq 0;\ \forall i, r\ and\ j.$$

where:

υ_r and w_i = weights allocated by DMs.

4.4.3.3. Semi-oriented Radial Measure (SORM)

Emrouznejad, Anouze, and Thanassoulis (2010) proposed the SORM for managing factors that obtain both positive and negative DMUs. This model considers that every input/output is a total of two factors, one using negative and the other positive data as:

$$Max\ \ h \qquad (26)$$

subject to:

$$\sum_{j=1}^{n} x_{ij}\lambda_j \leq x_{io}; \quad i = 1, \dots, m$$

$$\sum_{j=1}^{n} y_{rj}^{p}\lambda_j \geq h y_{ro}^{p},$$

$$\sum_{j=1}^{n} y_{rj}^{1}\lambda_j \geq h y_{ro}^{1},$$

$$\sum_{j=1}^{n} y_{rj}^{2}\lambda_j \geq h y_{ro}^{2},$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$h\ free, \lambda_j \geq 0;\ \ j = 1, \dots, n;\ r = \ 1, \dots, s$$

where:

x_j, y_j^p, y_j^N = activity vector of unit *j*

P = associated with outputs (for all *j* and *r*, $y_{rj} \geq 0$)

4.4.3.4. Variant of Radial Measure (VRM)

Cheng, Zervopoulos, and Qian (2013) recommended the VRM in which the initial data of the ranked DMUs are changed to definite values to evaluate the level of enhancement required to achieve an efficient frontier, with the input- and output-oriented radial models presented as:

Input-oriented:

$$min\,\theta \tag{27}$$

subject to:

$$X\lambda \leq \theta x_0$$

$$Y\lambda \geq y_0$$

$$[\sum_j \lambda_j = 1]$$

$$\lambda \geq 0$$

where:

DMU0 efficiency = θ

Output-oriented:

$$max\,\emptyset \tag{28}$$

subject to:

$$X\lambda \leq x_0$$

$$Y\lambda \geq \emptyset y_0$$

$$[\sum_j \lambda_j = 1]$$

$\lambda \geq 0$

where:

DMU0 efficiency = $1/\emptyset$

As stated by Banker et al. (1984), the $\Sigma\lambda$=1 limitation factor is retained in the VRS model but omitted from the CCR one. The above models are modified by replacing θ with 1-β and φ with 1+β as follows.

Input-oriented VRM under VRS model:

$$max\ \beta \tag{29}$$

subject to:

$X\lambda - \beta|x_0| \leq x_0$

$Y\lambda \geq y_0$

$\sum_j \lambda_j = 1$

$\lambda \geq 0$

where:

β = measurement of inefficiency

DMU0 efficiency = $1 - \beta$

Output-oriented VRM under VRS model:

$$max\ \beta \tag{30}$$

subject to:

$X\lambda \leq x_0$

$Y\lambda + \beta|y_0| \geq y_0$

$\sum_j \lambda_j = 1$

$\lambda \geq 0$

where:

DMU0 efficiency = $1/(1 + \beta)$

4.5. CHAPTER IV SUMMARY

To perform PPM effectively, an organisation should revise its strategies and prioritise its targets in its business plan to achieve effective portfolio decisions. It should map its candidate projects to its objective(s) and prioritise them against all other projects.

The PT (Markowitz, 1952) is viewed as the premise of many existing assessment models used to choose portfolios in a broad range of applications. Many researchers have extended it by adding many different ideas and limitations as well as targets, such as the cardinality limit or operational expenses, to help it become even more practical (e.g., Arditti, 1975; Ho & Cheung, 1991; Kane, 1982). The principal method used to identify a portfolio's functionality is the DEA which was presented by Charnes et al. (1978) and used for only commercial banks taking into account risk and return procedures. Also, its diversification was evaluated and a way of dealing with it demonstrated (Lamb & Tee, 2012). However, no researchers have incorporated PT with DEA and AHP nor have studies addressed the normalisation of weighting scores.

In the standard DEA model, as each DMU is evaluated using only its own weight, it should not consider other sets of weights possibly chosen by its competing peers. While this mechanism is valid in the context of efficiency evaluation itself, it is not appropriate when we use DEA for portfolio selection. As, in this situation, each DMU is exposed to the risk of a change in weight, this needs to be considered more seriously which, in turn, justifies incorporating a peer evaluation mode into the standard DEA model, with cross-efficiency evaluation a potential contender.

Standard DEA models presume that the values of each of the inputs or outputs of DMUs are only positive; in other words, they cannot examine non-positive data. Although some DEA software does permit applying negative inputs and outputs in a few DEA models, typically, the weights of the negative outputs and inputs are absolute zeroes. To eliminate this issue, a number of models have been designed with the intention of enhancing the distinguishing factor of DEA.

The idea behind the CCR (a.k.a. CRS) DEA model (Banker et al., 1984) is the fact that, as every part of an efficient DMU can also be efficient, it is merely justifiable for positive information. With negative inputs/outputs, the VRS additive method of Banker et al. (1984) (a.k.a. BCC) is applied mainly as a translation-invariant model according to Ali and Seiford (1990). Despite this, the application of radial methods of performance in the VRS DEA method is challenging and impossible without transforming the data. The output performance ranking relies on the degree of interdependency of the non-positive output vector. Also, the output radial efficiency ranking is difficult to analyse and translate when there are negative inputs/outputs. However, the additive model fails to produce a performance estimate which can really be interpreted or easily rank a DMU's efficiency.

Unlike the return, the variance as a variable in the PT model can adopt non-negative values which is not convenient for conventional DEA methods that presume positive values for both inputs and outputs. Therefore, these models cannot function if DMUs consist of both positive and negative inputs and outputs. Many different techniques for managing non-positive information have been suggested. To determine the performances of DMUs with negative variables, Portela et al. (2004) presented the RDM, Tone (2001) the SBM, Sharp et al. (2007) a modified SBM based on the directional distance functionality of Portela et al. (2004) called the MSBM, Emrouznejad et al. (2010) the SORM and Cheng et al. (2013) the VRM models.

Although the abovementioned methods might be employed as a way of dealing with negative data, they have shortcomings. Specifically, the additive model cannot present an efficiency estimate while the RDM technique is generally limited once the DMUs under consideration are considered to have the highest rates for outputs or the lowest for inputs and its efficiency rankings do not include all types of inefficiency. Portela et al. (2004) demonstrated that their method is equally unit- and translation-invariant with 1–ß regarded as a measure of performance. However, they mention that ß fails to encapsulate all types of inefficiency given that its ideal values for certain inputs/outputs might obtain non-zero slacks. The MSBM and SORM models can achieve aggregated targets but have problems if all their inputs or outputs are not positive. The mixed-sign factor in the VRM model is the total summary of two artificial factors ($v = v^1 + v^2$) one of which uses negative and the other positive data. If a variable has a positive mixed-sign factor, the VRM will deal with a monotonic problem (that is, one with values that never increase or decrease). Moreover, these models may sometimes not present total efficiency rankings for DMUs.

Therefore, the standard input-/output-oriented radial models produce inaccurate and problematic results because of their disadvantages when determining the significance of negative information in the optimisation procedure.

Both the DEA and AHP methods have disadvantages. The latter requires many pair-wise comparisons to identify units' efficiency scores and cannot individually support strategic decision-making for a complex PPM. The standard DEA has a disadvantage in the Pareto concept, that is, when almost all DMs or MCDM techniques would choose a solution, a DEA may view several DMUs as equally efficient (Sinuany-Stern et al., 2000). Basically, it could generate too many, or even an unlimited number of, ideal options or solutions (Shang & Sueyoshi, 1995). Whenever the quantity of inputs/outputs increases, so do the number of DMUs which can obtain a performance ranking of one as they are specially examined in relation to other DMUs. The DEA/AHP approach overcomes the DEA's rating inefficiency and minimises the AHP's subjective examination, with the former using quantitative and the latter qualitative data.

DEA and AHP methods are widely applied as solutions to the multi-criteria decision-making issue. However, In the literature, there are only a few scientific attempts to incorporate the AHP with a DEA method, such as those of (Ramanathan, 2006; Sinuany-Stern et al., 2000; Takamura & Tone, 2003; Wang, Liu, & Elhag, 2008; Yang & Kuo, 2003; Zhang & Cui, 1999), or use this methodology in large and complex organisations (Lin, Lee, & Ho, 2011). In this context, most authors concentrated on the efficiency of DMUs not their optimal allocations. Very few considered the weight of the input elements which impact on the output factors when DMUs are efficient. Despite the fact that Ramanathan (2006) verified that the DEAHP method assesses the real local weights of consistent decision matrices, he failed to develop his idea for matrices with different levels of inconsistencies. Although Sinuany-Stern et al. (2000) presented a combined DEA/AHP method for arranging DMUs, the selection method could not obtain efficient/inefficient ratings when several inputs and outputs were involved, thereby unreasonably selecting an efficient DMU from inefficient ones. The pair-wise assessment matrix established by Eq. (20) of Sinuany-Stern et al. (2000) consisted of many 'one' variables (Guo et al., 2006; Oral, Kettani, & Lang, 1991; Sinuany-Stern et al., 2000; Zhang, Li, & Liu, 2005) signifies that a pair of DMUs is regarded as equally efficient. Consequently, many similarities in a pair-wise assessment matrix can cause strict selection of DMUs since the rating weights generated from this matrix can be similar, or even identical, to those of other DMUs.

As a performance analysis using DEA involves both inputs and outputs, a decision matrix of $n \times n$ requires n DMUs and n outputs. The results are regarded as outputs since they have the features of outputs and a DMU obtaining a high score is preferable to those with lower ones. As a DEA cannot be generated by only outputs, it needs a minimum of one input.

Two executive dashboards were developed as alternate decision-support tools for DMs to measure and track a portfolio's activities and assess its performance generated from the DEA and AHP models.

This chapter concludes that the connection of the DEA and AHP methodologies requires further investigation as it cannot be used in its current form to deal with all the PPM challenges presented in this study. Therefore, future studies will apply different DEA theories with the AHP or develop an integrated DEA/AHP approach for properly scoring projects.

4.6. CHAPTER IV HIGHLIGHTS

Questions 10, 11 and 12 presented in CHAPTER I were examined in this chapter and the following are the key findings.

a) Both DEA and AHP have their own disadvantages.
b) AHP cannot individually support the strategic decision-making required for a complex PPM.
c) AHP is a subjective method that does not support missing values and facilitates only quantitative ones.
d) AHP employs a restricted number of criteria and suffers from the rank-reversal problem.
e) The standard DEA model cannot deal with negative data and requires a least one input.
f) The standard DEA model can generate too many, or an unlimited number of, best options that are equally efficient.
g) Existing models developed to deal with negative data have several shortcomings and, in some cases, cannot estimate a portfolio's efficiency scores in the presence of negative data.
h) A combination of DEA with AHP appears to be useful as one uses quantitative and the other qualitative data.
i) The DEA/AHP approach overcomes the DEA's rating inefficiency and minimises the AHP's subjective examination.
j) The pair-wise assessment matrix in the standard integrated DEA/AHP consists of many 'one' variables which signifies that some DMUs in a pair are considered equal.
k) Two executive dashboards developed to assess a portfolio's performance are generated by DEA and AHP models.

Figure 12 presents a snapshot of the key findings in CHAPTER IV and outlines a key question for investigation in the next chapter. The drawbacks and limitations of the current standard MCDM methods for dealing with the challenges of PPM are demonstrated in CHAPTER IV. In response to question 12 presented in CHAPTER I and with reference to the key findings highlighted above, CHAPTER V aims to find a means of dealing with the shortcomings of PPM MCDM methods identified in this chapter.

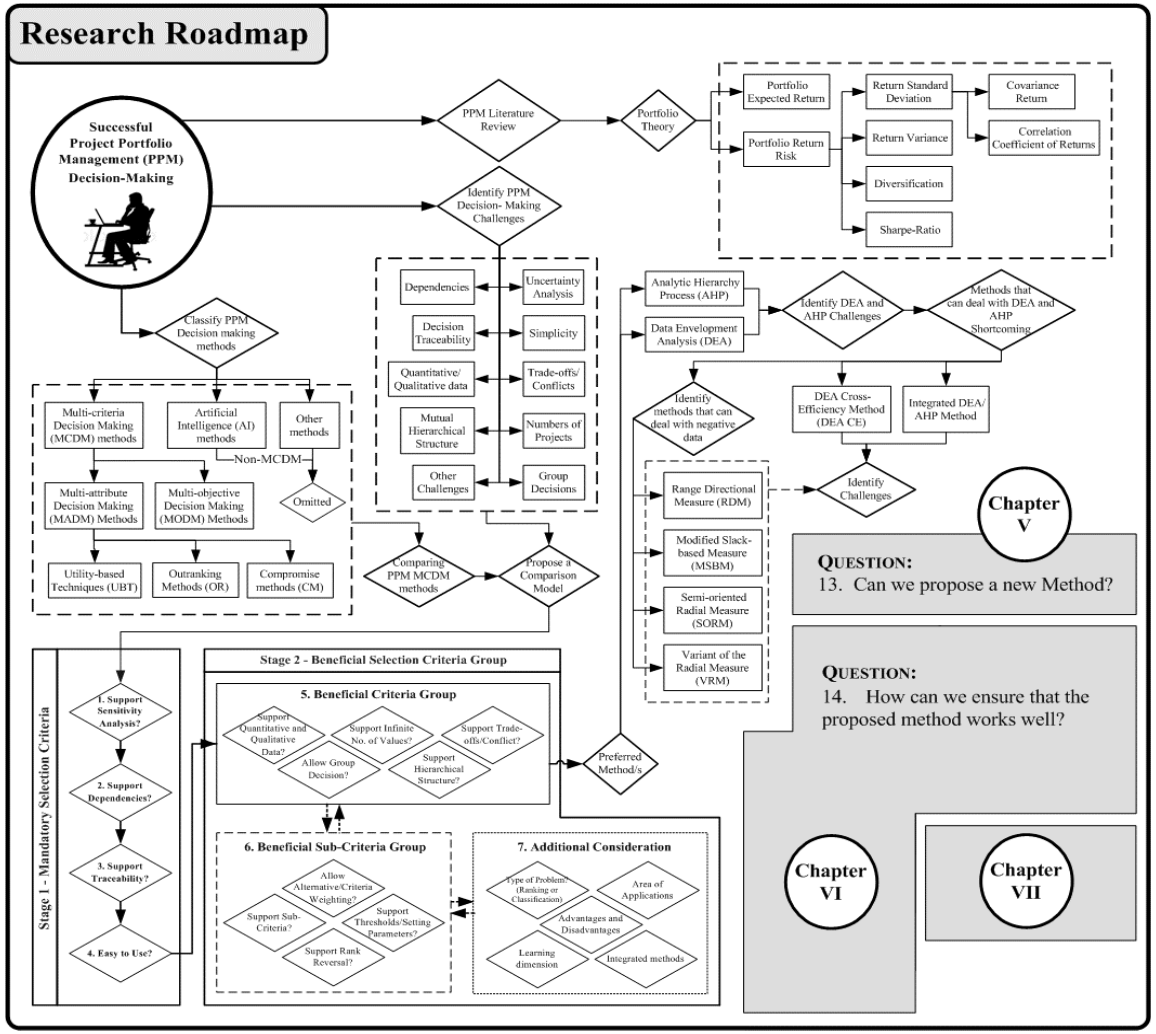

Figure 12. *RESEARCH ROADMAP – CHAPTER IV*

CHAPTER V

5. Executive Summary

In this chapter, the intention to build a reliable and operational model for examining the overall efficiency and success of a portfolio with regard to their comparative efficiencies influenced by the quality of efficiency outcome is discussed. A multi-objective model that applies the PT to identify the expected return and risk, and modifies the DEA-CE to properly score the efficiency of DMUs using AHP are proposed. Then, the portfolio's performance is combined with the PT standard theory. Finally, a comparison table is produced to assist DMs to select the best assets characterised by the values of the expected return, risk, Sharpe ratio and efficiency scores obtained from the proposed model. Then, DMs can optimise the portfolio based on the outcomes of an examination and determine whether the modifications enhance the efficiency of original portfolio. The results obtained from the proposed model can assist organisations to understand their advantages and disadvantages, and the current possibilities and options, or threats, of their portfolios.

Since the successful delivery of a portfolio depends on the quality of the decisions made while creating and managing it, organisations are searching for better decision support tools. Often, there are too many DMs in large organisations which may create diffused, and sometimes confused, decisions and lead to unstructured portfolios and poor selection and feedback mechanisms. To improve the effectiveness of portfolio decisions, a fundamental change is required to visualise their interdependencies and assist DMs in the selection of the most efficient projects/programs/investments. To capture the full extent of an organisation's portfolio, an executive management system called the Strategic Portfolio Management Tool (SPMT) is proposed as an alternative decision support system for DMs. It is an integrated model that combines the PT, AHP and DEA-CE techniques, and simultaneously considers the profit, risks and proficiency of a portfolio. The test results obtained for an investment portfolio indicate that the proposed system is practicable and adoptable, and provides enhanced situational awareness and the capacity to quickly analyse and cross-examine information through existing dashboards and reports. SPMT identifies problems early in a portfolio's lifecycle so that timely remedial actions can be undertaken if necessary.

5.1. PROPOSED MODEL

As DMs usually apply various techniques to make portfolio decisions, there is no classic portfolio selection method with easily specified steps and procedures which may be used in all projects. Standard DEA/AHP models are not able to use negative values or simultaneously obtain an efficiency ranking that can be easily employed to assess DMUs. Also, the basic application of only cross-efficiency ranking in portfolio decisions may lead to inadequately expanded portfolios in terms of their efficiency regarding several input/output aspects. The concept of the proposed model is simple: the portfolio with the lowest risk at a given expected return (on investment) can be found with a higher efficiency rank.

The proposed model is based on the PT of Markowitz (1952), integrated DEA/AHP method of Sinuany-Stern et al. (2000) and standard DEA Cross-efficiency model (DEA CE) of Sexton et al. (1986). However, it does not have the disadvantages of former techniques and improves the accuracy of an efficiency assessment. As, in the standard DEA/AHP, the outcomes of the comparison model are calculated by DEA with the DM not involved in the weighting process, the parameters are entered by the DEA to produce the answer. Using the PT, this study develops a model that enables DMs to modify the expected return and obtain the best portfolio with a minimum risk for that amount which guarantees efficient ratings once negative values are applied. The new methodology determines the cross-efficiency of the DMUs and generates a pair-wise assessment matrix in accordance with each DMU's weights and the outcomes of the assessments of two DMUs. Then, it is normalised using the AHP to produce the final efficiency ranks. Also, it provides objectives which are much easier to obtain than those of other approaches.

This study proposes the following five-stage model for prioritising DMU's efficiencies in order to select appropriate portfolios. The calculation principles of the proposed model in this chapter are presented based on the outcome of CHAPTER IV.

5.1.1. Step 1 - Developing Portfolio

As a first step, the data required to estimate a portfolio's efficiency need to be collected, based on which a portfolio of several DMUs is created. Monthly, quarterly and/or annual information is necessary to develop portfolios with different timeframes. Although DMs usually develop portfolios for a year or more, this study collects only weekly data for convenience, based on which one week's average growth is calculated as:

$$One\ week\ growth = 100\ \times \left(\left(\frac{v_2}{v_1}\right) - 1\right) \qquad (31)$$

where:

$v_2 =$ current week's amount; and

$v_1 =$ previous week's amount.

5.1.2. Step 2 - Calculating Portfolio's Parameters

A return, which consists of the money received in different periods and is the difference between buying and selling, is not usually obvious. This uncertainty in the rate of expected return is defined as the deviation of return which is called risk. An investor's aim would be to obtain the highest likely return on an asset with the least potential risk. According to this logic, the expected return is considered an output and any deviation from it an input that leads to the selection of the best asset.

This step identifies the expected return (on investment) and risk for a portfolio using Eqs. (1) and (5). The process begins by a DM having a certain amount of funds to spend. Given that a portfolio is an accumulation of assets, it is more beneficial to choose the best portfolio. Therefore, a DM needs to identify the expected return and standard deviation which implies that the DM desires to both increase the expected return and decrease the level of risk.

The fundamental problem of a portfolio can be introduced in two means: whether the DM wishes to reduce the variance related to a specified expected return (R_{min}) as:

$$min \sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \rho_{ij} \sigma_i \sigma_j \qquad (32)$$

subject to:

$$\sum_{i=1}^{n} x_i E(R_i) \geq R_{min}$$

$$\sum_{i=1}^{n} x_i = 1$$

$$x_i \geq 0 \qquad i = 1, \dots, n$$

or increase the expected return in a specified variance as:

$$max \sum_{i=1}^{n} x_i E(R_i) \tag{33}$$

subject to:

$$\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \rho_{ij} \sigma_i \sigma_j \leq \sigma_{max}$$

$$\sum_{i=1}^{n} x_i = 1$$

$$x_i \geq 0 \qquad i = 1, \ldots, n$$

This process is adequate for realising that both the return and variance should be considered when establishing an ideal project portfolio (Siew, 2016), with either the expected return or risk tending to be estimated using historic information. The expected return is determined through applying the mathematical aspect of returns and the risk through applying variances/standard deviations of the returns during past periods. According to the PT, if the expected return on investment *i* is $E(R_i)$ and the value given to this investment (x_i), the expected return on the investment in a portfolio can be identified in Eq. (1) as:

$$E(R_p) = \sum_{i=1}^{n} x_i E(R_i)$$

where:

$$\sum_{i=1}^{n} x_i = 1$$

As previously mentioned, the standard deviation or variance can signify the level of investment risk and an investment variance is determined in accordance with Eq. (4) as:

$$\sigma^2 = \sum_{i=1}^{n} P_i \, [R_i - E(R_p)]^2$$

The standard deviation demonstrates the average variation of an investment's profit from the mean of the sample with regard to the same measures using Eq. (6) as:

$$\sigma = \sqrt{\sigma^2}$$

5.1.3. Step 3 – Collecting Input and Output Data for DMUs

To rank the efficiency level of a DMU, the two criteria of the variance and expected return are considered the input and output respectively. After Steps 1 and 2, financial input/output parameters are identified.

5.1.4. Step 4 – Proposed Integrated DEA Cross-efficiency/AHP Model

5.1.4.1. **Phase 1:** pair-wise comparison matrix

A pair-wise comparison matrix is formed using the DEA method as follows.

The CRS classic model is implemented for each *n* of DMUs as (1,2,…,n) (Eq. 34): given that there are *n* DMUs all with *m* inputs and *s* outputs, the applicable performance of a specific one (DMU_k ($k \in \{1,2,\dots,n\}$)) is gained by determining:

$$\theta_{kk} = max\frac{\sum_{r=1}^{s} u_{rk}y_{rk}}{\sum_{i=1}^{m} v_{ik}x_{ik}} \qquad (34)$$

subject to:

$$\frac{\sum_{r=1}^{s} u_{rk}y_{rj}}{\sum_{i=1}^{m} v_{ik}x_{ij}} \leq 1 \quad j = 1,2,\dots,n$$

$$u_{rk}, v_{ik} \geq 0, \quad r = 1,\dots,s \quad i = 1,\dots,m$$

where:
j is the DMU factor;
j =1,2,...,*n* the output factor;
r =1,..., *s*;
i the input factor *i* =1,...,*m*;
y_{rj} the amount of the r^{th} output for the j^{th} DMU;
x_{ij} the significance of the i^{th} input for the j^{th} DMU;
u_{rk} the weight directed at the rth output; and
v_{ik} the weight provided to the i^{th} input.
Note that DMU_k is efficient providing $\theta_{kk} = 1$.

DMU_k prefers weights that maximise the output to input ratio depending on the limitations. An applicable efficiency rating of one implies that the DMU of interest is efficient and a lower rating that it is inefficient. Eq. (34) can be changed into a linear programming approach in which the best value of the target performance considers the related performance of DMU_k.

As in Eq. (16), the standard cross-efficiency can be formulated as:

$$\theta_{kk} = max \ \sum_{r=1}^{s} u_{rk} y_{rk} \tag{35}$$

subject to:

$$\sum_{i=1}^{m} v_{ik} x_{ik} = 1$$

$$\sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} \leq 0 \qquad j = 1, \dots, n$$

$$u_{rk}, v_{ik} \geq 0, \quad r = 1, \dots, s \quad i = 1, \dots, m$$

Considering the standard cross-efficiency (Eq. (16)) and standard DEA/AHP (Eqs. (17) and (18)), the modified DEA cross-efficiency/AHP evaluation is proposed as:

$$\theta_{kk}^{*} = \theta_{kk} = max \ \sum_{r=1}^{s} u_{rk} y_{rk} \tag{36}$$

subject to:

$$\sum_{i=1}^{m} v_{ik} x_{ik} = 1$$

$$\sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} = 0 \qquad j = 1, \dots, n$$

$$u_{rk}, v_{ik} \geq 0, \quad r = 1, \dots, s \quad i = 1, \dots, m$$

The second constraint of the standard DEA/AHP (Eq. (17)) demonstrates that a top portion of its objective characteristic is excluded to offer the possibility of an overall assessment of two DMUs without restricting the evolving ranking. As , when this restriction remains, the final efficiency scores are often equal, proper differences between the DMUs cannot be observed. An additional modification is the inequality in the last constraint in Eq. (17) and the second in Eq. (35) which is changed to equality in Eq. (36). If the inequality in Eq. (35) remains in its original format in

Eq. (36), it would certainly remain an equality for every option in Eq. (36). Since only the optimal solutions to Eq. (36) need to be considered, that constraint can be considered an equality.

Employing the same theory for Eq. (17) and Eq. (35), as well as omitting the second demand in Eq. (18), i.e., a top portion of the objective characteristic, the following modified condition is demonstrated for Eq. (18):

$$\theta_{hk} = max \sum_{r=1}^{s} u_{rh} y_{rh} \qquad h = 1, \dots, n \tag{37}$$

subject to:

$$\sum_{i=1}^{m} v_{ih} x_{ih} = 1$$

$$\sum_{r=1}^{s} u_{rh} y_{rk} - \theta_{kk}^{*} \sum_{i=1}^{m} v_{ih} x_{ik} = 0$$

$$u_{rh}, v_{ih} \geq 0, \quad r = 1, \dots, s \quad i = 1, \dots, m$$

In some cases, constructing a pair-wise comparison matrix using Eq. (20) of Sinuany-Stern et al. (2000) is problematic as applying this approach may comprise many elements with 'one' values (Guo et al., 2006; Oral et al., 1991; Sinuany-Stern et al., 2000; Zhang et al., 2005). An outcome of 'one' for a pair-wise assessment signifies that the DMUs are not seen as different. Consequently, many DMUs in a pair-wise assessment matrix might influence the assessment and ranking of DMUs since the rating weights generated from this matrix might be similar or even identical to each another. Therefore, unlike Eq. (20), an $n \times n$ matrix of the entries ($A = [a_{kj}]$) is constructed by:

$$a_{kj} = \theta_{kj} \tag{38}$$

5.1.4.2. **Phase 2:** ranking using AHP method

In this phase:

a. In a pair-wise assessment matrix, the sum of each column has to be calculated.
b. Each element in the column's sum is divided and a new matrix called a normalised matrix is generated.
c. Balancing the data and AHP mean normalisation of data is the next step for ensuring that the information is similar across the assessments and in units, and contains no

misalignment, with this mean indicating the ranking weight of each DMU. There are two steps for normalising the mean: firstly, the mean of the information group for every input and output must be identified, with the mean of the elements in each row of the normalised matrix estimated as:

$$\bar{M}_i = \frac{\sum_{n=1}^{N} M_{ni}}{N} \tag{39}$$

where:

$\bar{M}_i$ = mean value for column i;

N = number of DMUs; and

M_{ni} = value of DMU n for the input or output i.

In the next stage, all the values in an individual column are divided by the total mean values in each line, with the formula to be applied for every single unit:

$$MNorm_{ni} = \frac{M_{ni}}{\bar{M}_i} \tag{40}$$

where:

$MNorm_{ni}$ is the normalised significance for the value related to DMU_n as well as the input or output in column i.

5.1.4.3. **Phase 3:** consistency ratio test

Finally, for the objectivity of the results to be identified as a numerical value and to a specific standard degree of an option, a consistency test needs to be conducted using the AHP. Saaty (1980b) suggested a Consistency Index (CI) which is applied to show how consistent the pair-wise comparison matrices and, for an assessment matrix, is estimated as:

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{41}$$

where:

λ_{max} = greatest eigenvalue of the assessment matrix; and

n = size of the matrix.

The Consistency Ratio (CR) (Saaty, 1980b) is known as the ratio between the consistency of an individual assessment matrix and that of a random one as:

$$CR = \frac{CI}{RI(n)} \tag{42}$$

where *RI(n)* is a random index (Saaty, 1977) that relies on *n*, as demonstrated in Table 38.

Table 38. Random Index (RI)

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

As suggested by Saaty (1980b), if the CR of an assessment matrix is equivalent to or even lower than 0.1 (10%), it will be a reliable result for ranking and can be accepted while, if not, there is no consistency and the initial data set should be fixed.

5.1.5. Step 5 – Testing Portfolio's Efficiency Results

5.1.5.1. Phase 1 – Portfolio's actual risk and return

The original purpose of portfolio development is to diversify non-systematic risks. The actual portfolio return is described as:

$$R_p = \sum_{i=1}^{N} x_i R_i$$

It can also be calculated by multiplying all the expected return values by their weights and then summing them.

The following formula describes the portfolio risk calculation explained in Eq. (4):

$$\sigma^2 = \sum_{i=1}^{n} P_i \, [R_i - E(R_p)]^2$$

Firstly, the correlations among the DMUs need to be estimated for which the CORREL function in Excel can be used. To simplify the evaluation, more matrices need to be evaluated based on

Eq. (4), including the share, weights multiplication, risk and risk multiplication matrices. Once their values are identified, the value of correlation, weights multiplication, and risk multiplication matrices are multiplied to develop the final multiplication matrix. The total result of all the DMUs in the final multiplication matrix yields σ^2 and, to obtain the portfolio risk, the following square root is required.

$$\sigma = \sqrt{\sigma^2}$$

5.1.5.2. **Phase 2 -** Checking Sharpe Ratio (*SR*)

The *SR* is indicative of the additional profit over risk as:

$$SR = \frac{E(R_p) - R_f}{\sigma}$$

As a risk-free rate, the ten-year treasury yield at the end of the year is divided into the total of week's number; for example, assuming that this yield at the end of 2014 is equal to 1.98% and the number of our weekly data is 50, a risk-free rate can be calculated by:

$$R_f = \frac{1.98\%}{50} = 0.039\%$$

This coefficient is calculated for all the DMUs in the portfolio. It is suggested that DMs select the portfolios with the largest *SR* since it considers a greater return for risk.

5.1.5.3. **Phase 3 -** Checking Beta (β)

β details the connection between a project/asset and its portfolio/market returns as:

$$\beta_a = \frac{Cov\ (r_a - r_p)}{Var\ (r_p)} \qquad (43)$$

where:

R_a is the return of the asset/project;

R_p the return of the portfolio/market;

Cov the covariance of the asset/project and portfolio/market return; and

Var the portfolio/market variance.

This study uses the COVAR and VAR functions in Excel to calculate the covariance and variance, respectively, and β for each DMU and portfolio.

The value for the project/asset shifts correspondingly like the portfolio/market factor whenever β is equal to one. On the other hand, there is no connection between the project/asset and portfolio/market when β is zero. In the event that β is equal to minus one, the project/asset and portfolio/market values are shifted in opposite directions. If β is greater than one, the value of the project/asset increases by 1% for each 1% portfolio/market movement. When β is less than one, the value of the project/asset drops by 1% whenever the portfolio/market value increases by 1%; but increases by 1% whenever the portfolio/market decreases by 1%.

5.1.5.4. **Phase 4 -** Decision Making

Finally, DMs are able to review the provided portfolios along with the trade-off between level of return, risk of the portfolio with efficiency score in addition to select the portfolio with highest efficiency and level of return with a minimum risk. Individual DMs might select different ways of efficiency selection between portfolios. To minimise the variance related to a specified expected return, R_{min} must be considered:

$$min\,\sigma^2 \tag{44}$$

subject to:

$$E(R_p) \geq R_{min}$$

$$\sum_{i=1}^{n} x_i = 1$$

$$x_i \geq 0 \qquad i = 1, \dots, n$$

or, in order to maximise the expected return provided a specified variance:

$$max\ E(R_p) \tag{45}$$

subject to:

$$\sigma^2 \leq \sigma_{max}$$

$$\sum_{i=1}^{n} x_i = 1$$

$$x_i \geq 0 \qquad i = 1, \dots, n$$

5.2. INTRODUCTION TO DECISION SUPPORT SYSTEM

Organisations have various means by which individual projects can be reported and analysed at the portfolio level. Portfolio assessments are reported through the organisational hierarchy up to the Senior Executive and then to the Corporate Committee. However, as the data used to report on projects/programs are derived from various source systems, there are usually many DMs with different opinions. Therefore, an organisation needs a simple but powerful decision support system to positively transform planned objectives into decisions. A system's functionality is related to its business functionality and efficiency as well as the quality of DMs' decisions. The capability to present proper instruction and management procedures is essential for businesses, without which, there is absolutely no obligation or, perhaps, appropriate portfolio decisions. In large organisations with many committees, a lack of clarity in responsibilities may lead to inadequate processes or judgements. How an organisation undertakes choices and the way in which they adopt them are important drivers of organisational functionality. The capability to transform organisational goals into successful decisions is a key aspect of a successful business. Therefore, the procedure a business employs to establish its decision process is the foundation of business governance while the quality of decisions has a significant influence on an organisation's capabilities in all its aspects.

5.2.1. EXISTING GAP

The first step in assessing an organisation's functions is to select an appropriate assessment model and present the results comprehensively to assist DMs to accurately examine the functions. Inadequate data management along with the insufficient use of decision-making methods and the lack of visibility and transparency of the cost and risk, significantly impacts on the portfolio's final results. Although these visibilities are critical when the presentation of projects/programs/investments is required to demonstrate portfolio efficiency, there is still no effective decision-making tool.

Although many organisations have tried to deal with these issues, they are limited by highly complicated methods for estimating portfolio efficiency. Consequently, there are no really effective systems for comprehensively providing decision options to DMs for simultaneously applying to a model portfolio's challenges, risks, profits and efficiencies of its projects/programs/investments. Therefore, systems intended to be primarily for PPM decision making still have problems with a lack of information and direction which means that they are of little use in practice. Similarly, there are only a few decision-making applications that can assist in the collection of information and suggesting decision options to DMs. In fact, it seems that organisations concentrate more on data administration than decision supervision. Considering the current complications in the information setting processes of most complex organisations and the requirement to rationalise the considerable amounts of individual decision applications used in a variety of portfolios equally, little work has been conducted recently on developing comprehensive decision-making applications or finding effective supervision processes for determining decision options.

Although there are many portfolio management procedures and templates, they do not support a decision-making function for selecting more effective projects/programs and do not encourage the agile decisions required by a strategic portfolio management life cycle. Moreover, decision-making systems and their functionality have not been extensively discussed.

Instead of investigating the methods and tools through which judgements are made, most assessments focus on the procedures for organisational decision-making. Only a few studies have assessed methods for selecting a portfolio's efficient options, providing ways of presenting recommendations and options to DMs or investigating the possibility of generating options and reports to track a portfolio's final results; for example, the ISO9000 Standard clearly describes good management practice but does not state how procedures and controls should be operated. It is very flexible and designed to be tailored to suit an organisation, recognising variations in its portfolios, programs and projects. A major function of a decision-making process is to provide greater efficiency and ensure that the quality of the system is properly maintained and continually developed. Therefore, a decision-support system that can outline the key elements of a portfolio noting that, by definition, each project will be different, is required.

As the majority of large organisations have complex portfolio management systems with their own strengths and weaknesses, there is concern about the need for a highly effective strategic decision-making system. Existing systems are under pressure and their lack of a capability to fully deal with portfolio challenges impacts on businesses' reputations and may result in poor outcomes. Current situations can consist of delivery problems for projects, inadequate procurement judgements, and poor budget management and decision making when handling daily activities. Moreover, current portfolio agreements increase executives' management strengths by limiting a DM's capability to manage portfolio decisions and performance in selecting projects/programs. This will probably impact on the visibility of the supervision and perhaps monitoring of projects/programs under investigation in a total portfolio.

There are some decision-support systems to manage decisions; however, most of those systems are intended to deal with specific characteristics, environments or problems at a specific industry. Moreover, the majority of organisations are searching for a decision-making system that could have the capacity to fulfil the specifications of different types of portfolio decisions. This study intends to support organisations with that requirement.

Therefore, for several reasons, strategic portfolio management and decision-support systems should become more responsive, effective and easier to use. As improvements in a portfolio's efficiency and decision making will help to eliminate its risks, an effective decision-making system is required to assist DMs.

5.2.2. Possible Solution

Data visualisation is a powerful format for presenting data to assist both strategic decision making and DMs to manage their portfolios more comprehensively. An executive project portfolio dashboard can demonstrate complicated components of selected issues in an organisation in a simple and highly effective manner (Meyer, 1991). A mixture of DMs' abilities and visual representations of information can provide a powerful perspective of the decision issue which will help to improve PPM decision making. Data visualisations have been proven to improve the examination and data, and strategic thinking and planning processes (Mikkola, 2001; Warglien & Jacobides, 2010). As stated by Ware (2005): '*the power of a visualisation originates from the idea that it is likely to have a far more complex concept structure represented externally in a visual display rather than might be organised in visual and verbal working memories*'.

Recent studies have found that data visualisation can assist in both the consideration and maintenance of strategic data (Kernbach & Eppler, 2010). Advancements in information technology and computer science, especially software-based tools, have provided many new options for collecting and presenting information (Dansereau & Simpson, 2009). Computer-based applications with visual interfaces, such as pattern finding, incorporate the advantages of methods with DMs' ideas (Tergan & Keller, 2005).

As few studies explain the application of PPM data visualisations, more research is required to identify how PPM MCDM selection methods are applied in reality and what forms of visualisation enhance decisions.

Decision-making methods must recognise that an organisation's services are seen collectively and strive for organisational cohesion. However, current decision-making applications do not present a simple preference system or decision path that can easily extend from a portfolio to operational (project/investment) level. Organisations could establish more robust portfolio decision-making and proper portfolio decision options through the following approaches.

1. Having committees with individual ownership focused on supporting DMs' liability.
2. Having a suitable MCDM methodology for PPM.
3. Establishing a mechanism for improving the quality of key decisions in a non-adversarial way by visualising and estimating portfolio variables for the efficient assessment of options.

This study begins with the premise that any new decision-support approaches for dealing with the current challenges must fulfil the following specifications.

- A new model should assist the development of a portfolio structure that consistently and carefully immediately identifies the cause of inefficiency.
- A new model should be simple and transparent in relation to determining which projects/programs/investments are more effective in a portfolio.
- The system must be capable of providing a structure for comparing, ranking and weighting data and distributing these findings and data over multiple departments to receive contextual information collected from several sources including divisions, PMO offices and Head Offices. This information will then enable a de-centralised distribution algorithm to make decisions on exactly how the framework is allocated over the areas.
- A new model must provide the best possible, clear and simple decision-making structure by providing the correct data for DMs to enable them to guarantee efficient decisions in portfolios with large numbers of variables and difficult selection options.

This study aims to propose a decision-making model that supports individuals in setting specific, measurable, achievable and relevant decision outcomes. It applies an integrated MCDM method for PPM that highlights errors as soon as they arise in a portfolio and provides the appropriate information to the DMs responsible to assist them in decision making. It also aims to provide DMs with a tool they can use to view both summary and detailed data to help them interpret and understand the constituent elements (projects/programs/investments) of a portfolio. This new tool will provide a clear and timely understanding of emerging issues and risks in the delivery of a portfolio by highlighting them so that organisations can respond in an effective, efficient and coordinated manner to guide remedial actions. This will provide organisations with the capability to receive timely and specific identification of significant exceptions, make suitable decisions and then manage effective remediation with the support of senior management. In keeping with the primary goal of this study, the focus is on highlighting underperforming projects/programs/investments in a portfolio. By identifying and remediating issues early in its life cycle, the proposed tool aims to prevent a portfolio from becoming a matter of concern.

CHAPTER V provided DMs with the business logic and portfolio methodology for interpreting the data presented in the new decision making system. An in-depth review of PPM, MCDM methods and the proposed integrated PPM MCDM approach are provided in CHAPTER II, CHAPTER III, and CHAPTER IV of this study.

5.3. PROPOSED STRATEGIC PORTFOLIO MANAGEMENT TOOL (SPMT)

The SPMT is a decision-support system designed specifically to assist DMs in complex portfolio decision making. It maps all portfolios' alternatives and compares them to identify their efficiency scores. It highlights the business need to provide DMs and project personnel with clear metrics to track the performances of their projects/programs in a portfolio in terms of the organisation's goals and policies. Subsequently, it is used to assist DMs to select the most efficient projects/programs/investments for a portfolio.

The SPMT is an agile, enterprise-wide, decision-support management tool. It supports evidence-based decision making by giving DMs the ability to manage and share decisions about projects/programs during a portfolio's life cycle. As the authoritative source of information on an organisation's projects, it helps executives manage this life cycle by providing situational awareness (decision options) to DMs and other stakeholders in an organisation. It is a customised tool developed on the basis of the integrated PPM MCDM method presented in this chapter. It also supports situational awareness at portfolio levels by aggregating data across projects/programs and providing a narrative regarding the development of an appropriate business case and stakeholder commentary during various stages in the process.

5.3.1. PRIMARY GOAL OF SPMT

The primary goal of the SPMT is to serve as the central source of truth for the management of portfolio data and selection of suitable projects/programs/investments for management personnel at all levels using an integrated PPM MCDM model. Figure 13 summarises the effects expected to be supported by the SPMT and the mechanisms that will facilitate them.

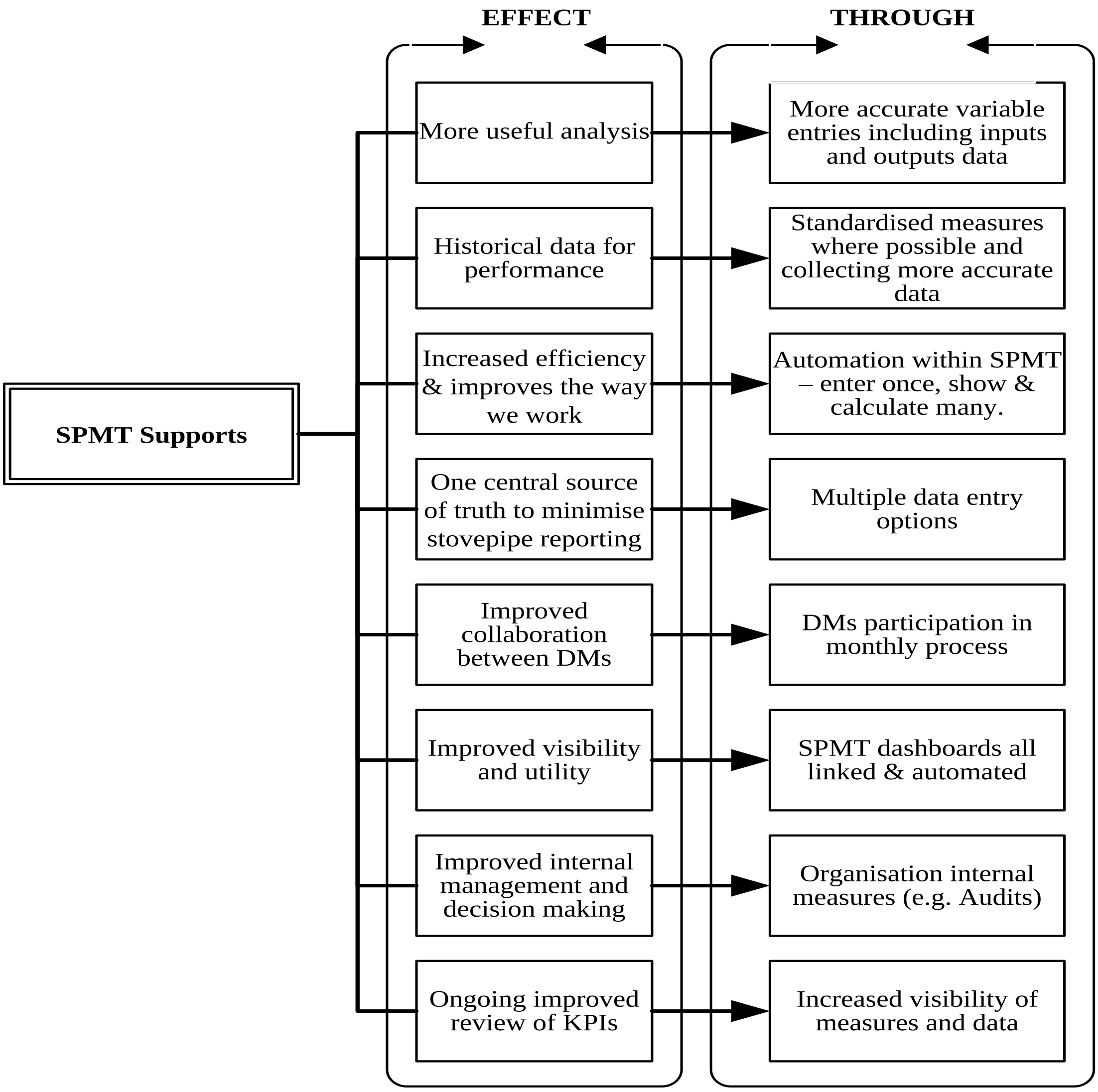

Figure 13. EXPECTED EFFECTS OF SPMT

5.3.2. STRUCTURE OF SPMT

The SPMT system requires a set of performance criteria against which projects/programs can be measured. Based on them, any inefficient projects/programs that exceed performance thresholds are reported to senior stakeholders. SPMT provides DMs with collaborative opportunities and increases the visibility of a portfolio's performance. The SPMT requires engagement with a wide range of stakeholders, such as:

- project/program/investment management teams for project/product/investment updates;
- a senior leadership team for clearance of the report;
- external stakeholders for pre-committee consultations at the working level; and
- organisational investment committee members for final clearance.

The SPMT defines the weights of each project/program/investment in a portfolio on a weekly basis (as the default) and offers the opportunity for DMs to review and provide input to the review process. In a mega-portfolio, each sub-portfolio/program measure can be assigned to a single DM (a subject-matter expert) who is responsible for that month's performance. DMs can also review the data, make decisions in groups, discuss or change these decisions and develop overall Key Performance Indicators (KPIs).

The SPMT seeks to meet the diverse needs of all stakeholders during the portfolio management process through a series of dashboards which aim to summarise the portfolio's performance. These dashboards are generated via the data entered by the DMs and their service partners. They are introduced into the SPMT to provide DMs with a brief snapshot of a portfolio's current performance. The SPMT helps DMs determine exactly which challenges should be expected regarding a portfolio's performance and details the options for resolving them which leads to the recommendation of further examination. Figure 14 presents the structure of the proposed SPMT decision-support system.

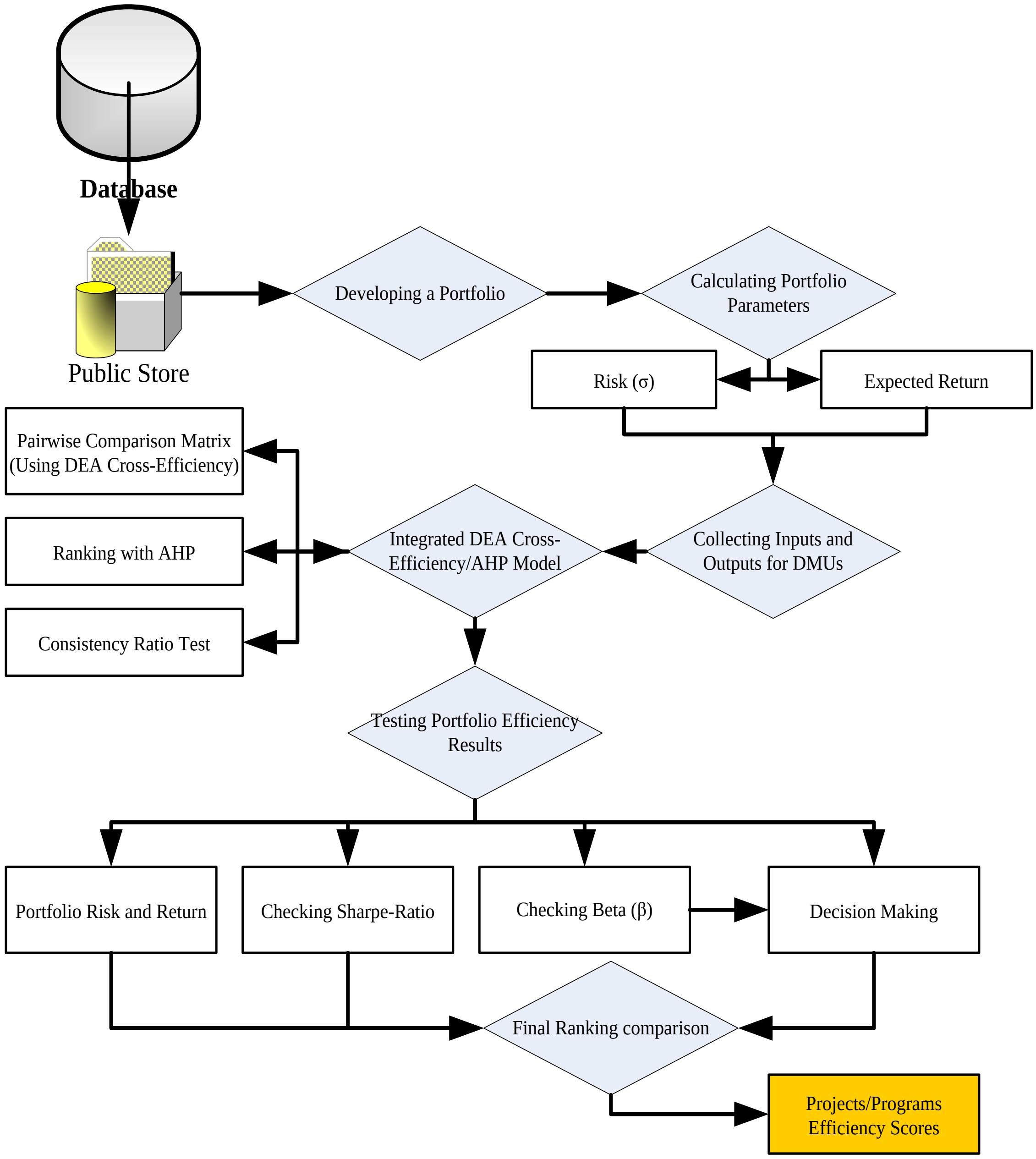

Figure 14. FLOWCHART OF SPMT DECISION PROCESS

Snapshots of the SPMT tool are presented in ANNEX H and ANNEX I.

5.4. CHAPTER V HIGHLIGHTS

This chapter proposed an integrated method combining the PT, and modified DEA-CE and AHP techniques. Also, a decision-making support tool called the SPMT was developed based on it. The key findings of CHAPTER V are:

a) the PT is used to identify the expected return and risk;
b) a modified DEA-CE scores the efficiency of DMUs;
c) the AHP is applied to conduct consistency test;
d) a comparison table is produced to enable DMs to select the best projects/assets characterised by the values of the expected return, risk, Sharpe Ratio and efficiency scores;
e) in the new method, DMs can change a portfolio (according to the outcomes of an examination) to optimise it and then verify whether the modifications enhance the efficiency of the original portfolio;
f) the results obtained from the proposed model can reveal the existing possibilities and options, or even threats, in a portfolio;
g) a decision support system (i.e., SPMT) is proposed;
h) the SPMT helps DMs to determine exactly which challenges should be expected in terms of a portfolio's performance;
i) the SPMT provides DMs with collaborative opportunities and increases the visibility of a portfolio's performance; and
j) the SPMT can engage with a wide range of stakeholders.

Although a new method and supporting tool are presented in this chapter, the final, and perhaps most important, question is: How can we ensure that the proposed method works well?. CHAPTER VI answers this question through conducting a series of real case studies to demonstrate how well the proposed method works in comparison of existing standard methods. Figure 15 presents a snapshot of the key findings of CHAPTER V and outlines the above question that is investigated in CHAPTER VI.

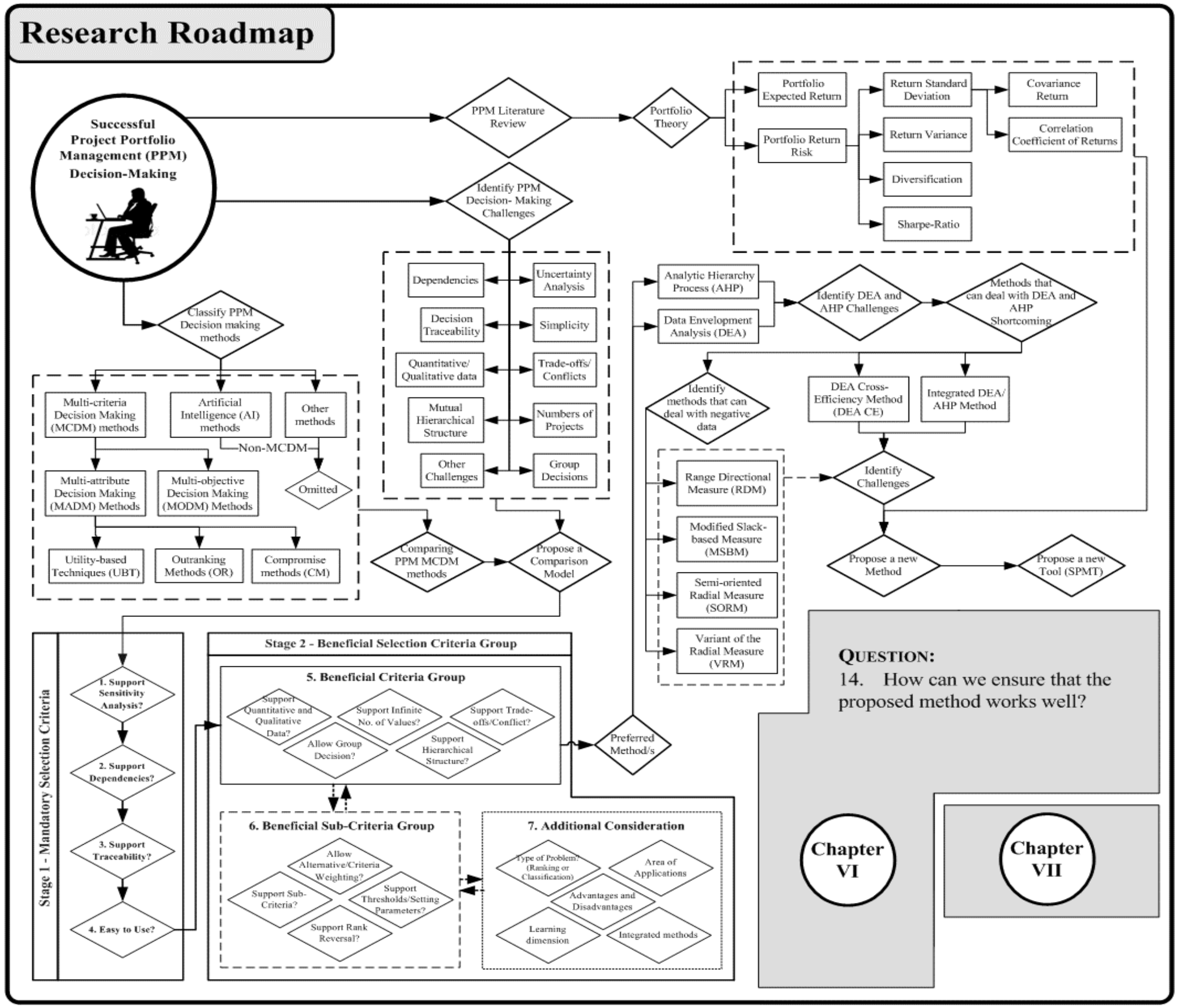

Figure 15. RESEARCH ROADMAP – CHAPTER V

CHAPTER VI

6. Executive Summary

In this chapter, case studies which clearly demonstrate how well the newly proposed MCDM method and SPMT tool presented in CHAPTER V work in comparison with existing standard models and the show the ability to use the proposed method in a predictive manner dealing with PPM problems in different portfolio scenarios are discussed.

Case Study 1, which presents a decision scenario in a project portfolio environment, proves that the proposed model can deal with PPM issues. A detailed list of the Australian Resources and Energy Major Projects for 2015 published by The Australian Government's Department of Industry, Innovation and Science (Penney, Witteveen, Bernie, Hatt, & Nguyen, 2015) is used for this case study to allocate the efficiency scores of projects/programs. The results from the proposed model and existing standard MCDM models are compared to check their accuracy.

As mentioned in CHAPTER IV, standard models cannot deal with negative data. Therefore, a portfolio of investments with negative data is presented in Case Study 2 to test the proposed model and to demonstrate its capability to be used in a predictive manner in a financial environment. This case study involves ten of the largest Australian companies on the Australian stock market with the data required for estimating their stocks obtained from the Yahoo (2016) Finance and Australian Securities Exchange (AXS, 2016) for the period 2014-15. Also, the results are compared with those obtained from standard methods designed to deal with negative data to demonstrate how well the proposed method can replicate standard methods results.

Finally, this chapter presents Case Study 3 which shows how the SPMT can calculate efficiency levels in only one click considering the existing challenges in portfolios and PPM requirements.

A comprehensive explanation of the principles of the calculation for the proposed model has been provided in CHAPTER V. We avoid repeating the steps in this chapter; however, a snapshot of all steps in the proposed model is presented below for a better understanding of the model and to avoid any confusions.

Step 1 - Developing Portfolio

$$One\text{ week growth} = 100 \times \left(\left(\frac{v_2}{v_1}\right) - 1\right)$$

where:

$v_2 =$ current week's amount; and

$v_1 =$ previous week's amount.

Step 2 - Calculating Portfolio's Parameters

$$min \sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \rho_{ij} \sigma_i \sigma_j$$

subject to:

$$\sum_{i=1}^{n} x_i E(R_i) \geq R_{min}$$

$$\sum_{i=1}^{n} x_i = 1$$

$$x_i \geq 0 \qquad i = 1, \dots, n$$

$$E(R_p) = \sum_{i=1}^{n} x_i E(R_i) = the\ expected\ return\ on\ the\ investment\ in\ a\ portfolio$$

where:

$$\sum_{i=1}^{n} x_i = 1$$

$$\sigma^2 = \sum_{i=1}^{n} P_i \, [R_i - E(R_p)]^2$$

$$\sigma = \sqrt{\sigma^2} = variance$$

Step 3 – Collecting Input and Output Data for DMUs

Step 4 – Proposed Integrated DEA Cross-efficiency/AHP Model

Phase 1: pair-wise comparison matrix

$$\theta_{kk}^{*} = \theta_{kk} = max \ \textstyle\sum_{r=1}^{s} u_{rk} y_{rk}$$

subject to:

$$\sum_{i=1}^{m} v_{ik} x_{ik} = 1$$

$$\sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} = 0 \qquad j = 1, \ldots, n$$

$$u_{rk}, v_{ik} \geq 0, \quad r = 1, \ldots, s \quad i = 1, \ldots, m$$

$$\theta_{hk} = max \sum_{r=1}^{s} u_{rh} y_{rh} \qquad\qquad h = 1, \ldots, n$$

subject to:

$$\sum_{i=1}^{m} v_{ih} x_{ih} = 1$$

$$\sum_{r=1}^{s} u_{rh} y_{rk} - \ \theta_{kk}^{*} \sum_{i=1}^{m} v_{ih} x_{ik} = 0$$

$$u_{rh}, v_{ih} \geq 0, \quad r = 1, \ldots, s \quad i = 1, \ldots, m$$

$$\mathrm{a_{kj}} = \theta_{\mathrm{kj}}$$

Phase 2: ranking using AHP method

$$\bar{M}_i = \frac{\sum_{n=1}^{N} M_{ni}}{N}$$

where:

$\bar{M}_i$ = mean value for column *i*;

N = number of DMUs; and

M_{ni} = value of DMU *n* for the input or output *i*.

$$\mathrm{MNorm_{ni}} = \frac{\mathrm{M_{ni}}}{\mathrm{\bar{M}_i}} = \textit{the total mean values}$$

where:

$MNorm_{ni}$ is the normalised significance for the value related to DMU_n as well as the input or output in column *i*.

Phase 3: consistency ratio test

$\mathrm{CI} = \frac{\lambda_{\max} - \mathrm{n}}{\mathrm{n}-1}$ = Consistency Index

where:

λ_{max}= greatest eigenvalue of the assessment matrix; and

n = size of the matrix.

$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI(n)}}$ = Consistency Ratio

RANDOM INDEX (RI)

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

Step 5 – Testing Portfolio's Efficiency Results

Phase 1 – Portfolio's actual risk and return

$$R_p = \sum_{i=1}^{N} x_i R_i = \ The\ actual\ portfolio\ return$$

$$\sigma^2 = \sum_{i=1}^{n} P_i\ [R_i - E(R_p)]^2 = \ the\ portfolio\ risk$$

$$\sigma = \sqrt{\sigma^2}$$

Phase 2 - Checking Sharpe Ratio (*SR*)

$$SR = \frac{E(R_p) - R_f}{\sigma}$$

$$R_f = \frac{the\ ten - year\ treasury\ yield}{the\ total\ of\ week's\ number} = \text{ risk free rate}$$

Phase 3 - Checking Beta (β)

$$\beta_a = \frac{Cov\ (r_a - r_p)}{Var\ (r_p)}$$

where:

R_a is the return of the asset/project;

R_p the return of the portfolio/market;

Cov the covariance of the asset/project and portfolio/market return; and

Var the portfolio/market variance.

Phase 4 - Decision Making

To minimise the variance related to a specified expected return:

$min\, \sigma^2$

subject to:

$E(R_p) \geq R_{min}$

$$\sum_{i=1}^{n} x_i = 1$$

$x_i \geq 0 \qquad i = 1, \dots, n$

or, in order to maximise the expected return provided a specified variance:

$$\max E(R_p)$$

subject to:

$$\sigma^2 \leq \sigma_{max}$$

$$\sum_{i=1}^{n} x_i = 1$$

$$x_i \geq 0 \qquad i = 1, \dots, n$$

6.1. Case Study 1: Australia's Resources and Energy Major Projects

The Resources and Energy Major Projects report published by the Australian Government's Department of Industry, Innovation and Science (Penney et al., 2015) presents an analysis of the major infrastructure projects that boost the performances of mineral and energy products in Australia. This document is presented in the following four-stage investment pipeline model.

A project with an uncertain development path or, perhaps, prior to its commencement (i.e., a pre-feasibility study) is included in the publicly announced Stage 1 from which not every project will progress this stage to an operational phase. In Stage 2 (feasibility), additional examinations are carried out to finalise the efficient projects that can obtain positive decisions from DMs. The projects in Stage 3 (committed) have gained both the necessary approvals and required funding because they have obtained positive decisions from DMs and are either under construction/development or about to be started. Finally, in Stage 4 (completed), as the projects are mainly completed, and commercial activities can be begun at the business level.

The focus of this case study is on measuring the efficiency of projects/programs at the portfolio level using the integrated PPM MCDM decision-making method in CHAPTER V and presenting an examination of the main developments and challenges of portfolio quality. Therefore, the data from the feasibility stage reported over the period of April 2015 to October 2015 are collected for further investigation to identify the effective project/programs that should be selected to commence construction.

Figure 16 describes a portfolio's structure in the feasibility stage for the year 2015 broken down into 127 major projects with a total value of $182 billion.

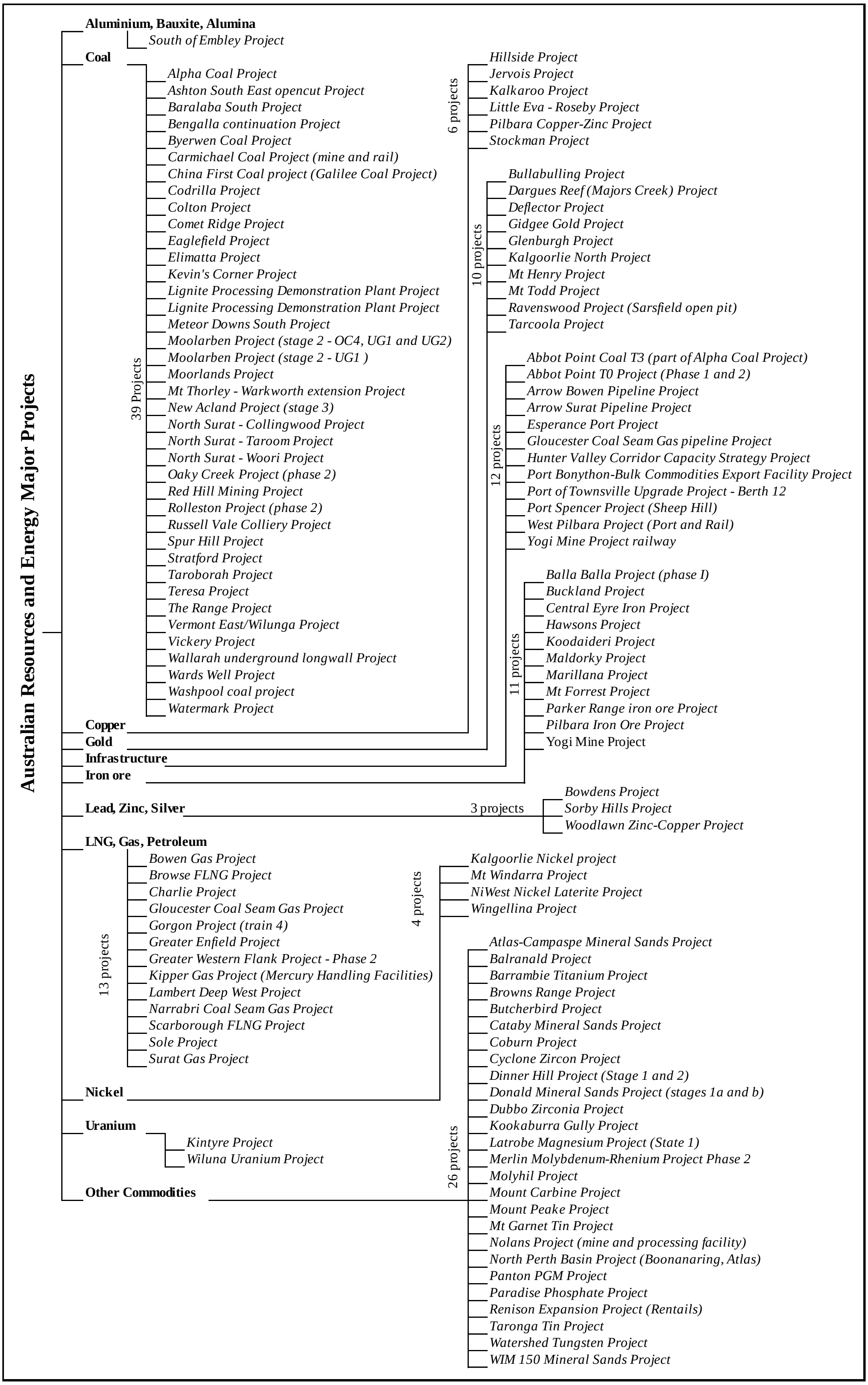

Figure 16. BREAKDOWN OF PORTFOLIO'S STRUCTURE

Two parameters identified for this case study are the numbers of projects as inputs and project cost as outputs, as presented in Table 39.

Table 39. Portfolio INPUT/OUTPUT DATA

Feasibility Stage – Oct. 2015		**Input**	**Output**
DMUs	**Programs**	**Project No.**	**Cost $m**
1	Aluminium, Bauxite, Alumina	1	1,500
2	Coal	39	57,447
3	Copper	6	1,899
4	Gold	10	2,138
5	Infrastructure	12	13,630
6	Iron ore	11	16,826
7	Lead, Zinc, Silver	3	560
8	LNG, Gas, Petroleum	13	74,600
9	Nickel	4	3,629
10	Uranium	2	915
11	Other Commodities	26	9,071
	Total	127	182,215

Using Eqs. (36), (37) and (38), we develop the comparison matrix in Table 40.

Table 40. COMPARISON MATRIX

DMUs	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	1.000	1.018	4.739	7.016	1.321	0.981	8.036	0.261	1.653	3.279	4.299
2	0.982	1.000	4.654	6.890	1.297	0.963	7.891	0.257	1.624	3.220	4.222
3	0.211	0.215	1.000	1.480	0.279	0.207	1.696	0.055	0.349	0.692	0.907
4	0.143	0.145	0.676	1.000	0.188	0.140	1.145	0.037	0.236	0.467	0.613
5	0.757	0.771	3.589	5.313	1.000	0.743	6.085	0.198	1.252	2.483	3.256
6	1.020	1.039	4.833	7.155	1.347	1.000	8.195	0.267	1.686	3.344	4.384
7	0.124	0.127	0.590	0.873	0.164	0.122	1.000	0.033	0.206	0.408	0.535
8	3.826	3.896	18.131	26.840	5.052	3.752	30.742	1.000	6.325	12.543	16.448
9	0.605	0.616	2.867	4.244	0.799	0.593	4.860	0.158	1.000	1.983	2.600
10	0.305	0.311	1.446	2.140	0.403	0.299	2.451	0.080	0.504	1.000	1.311
11	0.233	0.237	1.102	1.632	0.307	0.228	1.869	0.061	0.385	0.763	1.000
Total	9.205	9.374	43.626	64.582	12.156	9.027	73.969	2.406	15.219	30.180	39.576

The AHP mean normalisation matrix using Eqs. (39) and (40) is shown in Table 41.

Table 41. AHP Mean Normalisation Matrix

DMU	1	2	3	4	5	6	7	8	9	10	11
1	0.109	0.109	0.109	0.109	0.109	0.109	0.109	0.109	0.109	0.109	0.109
2	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107
3	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
4	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016
5	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082
6	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.111
7	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014
8	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416
9	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066
10	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033
11	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
Total	1.195	1.173	0.252	0.170	0.905	1.219	0.149	4.572	0.723	0.364	0.278
Efficiency	0.109	0.107	0.023	0.015	0.082	0.111	0.014	0.416	0.066	0.033	0.025
Consistency	10	10	10	10	10	10	10	10	10	10	10
Rank	3	4	9	10	5	2	11	1	6	7	8

A consistency test of the above results is conducted using Eq. (41):

CI = (11-11)/(10-1) = 0

As the consistency test performed using Eq. (42) results in a total consistency ratio (*CR*) of zero which is much less than the upper boundary of 10% suggested by Saaty (1980b), we can rely on the rankings.

According to the Resources and Energy Major Projects Report (Penney et al., 2015), *the outlook for investment in the resources and energy sectors in Australia remains broadly unchanged from April 2015. The value of committed projects has declined and it is clear that this decline will not be offset by new investments coming through the pipeline in the short to medium term.*

There are currently more projects in the feasibility stage condition, 127 compared with 125 in April 2015. In October 2015, nine projects with a total value of $48 billion obtained positive decisions and, at the end of that month, there were 36 projects with a total value of $221 billion in the committed stage, as shown in Table 42.

Table 42. Portfolio Data in Committed Stage (October 2015)

Programs	Project No.	Cost $m
Aluminium, Bauxite, Alumina	0	0
Coal	6	4,701
Copper	0	0
Gold	4	971
Infrastructure	4	4,864
Iron ore	3	11,416
Lead, Zinc, Silver	3	2,029
LNG, Gas, Petroleum	11	195,000
Nickel	1	443
Uranium	0	0
Other Commodities	4	1,372
Total	36	220796

All exploration expenditure, such as for minerals and petroleum, are 23% less than that of $5.4 billion in 2013-14. Investment decisions regarding petroleum exploration totalled $3.8 billion, down 21% while those for minerals exploration also decreased considerably, by 25%, to $1.6 billion (Penney et al., 2015).

As mentioned in CHAPTER IV, DMs face some challenges for identifying a portfolio's efficiency scores in the presence of negative data; for example, they need to make decisions based on the differences between the data presented in the feasibility and committed stages in October 2015 to improve a portfolio's performance. As defined in Table 43, both the inputs and outputs contain negative data.

Table 43. Portfolio Data - Feasibility and Committed Stage Differences (October 2015)

	Input	Output		
Programs	**Project No.**	**Cost $m**	**Efficiency**	**Ranks**
Aluminium, Bauxite, Alumina	-1	-1,500	0.00010	3
Coal	-33	-52,746	0.00011	2
Copper	-6	-1,899	0.00002	9
Gold	-6	-1,167	0.00001	10
Infrastructure	-8	-8,766	0.00007	4
Iron ore	-8	-5,410	0.00005	6
Lead, Zinc, Silver	0	1,469	1.00362	1

LNG, Gas, Petroleum	-2	120,400	-0.00411	11
Nickel	-3	-3,186	0.00007	5
Uranium	-2	-915	0.00003	7
Other Commodities	-22	-7,699	0.00002	8
Total	-91	38,581		

Although the proposed model can identify efficient and inefficient projects/programs with negative inputs and outputs, other standard DEA methods cannot estimate their efficiency using the same data. To prove this claim, the same data presented in Table 43 are applied 34 times to the following standard methods.

1. Standard DEA Input-oriented (I) Constant Returns to Scale (CRS)
2. Standard DEA I Variance Returns to Scale (VRS)
3. Basic Radial Models (BRM) Envelopment Forms (EV) I-CRS
4. BRM I EV-VRS
5. BRM Output-oriented (O) EV-CRS
6. BRM O EV-VRS
7. BRM Multiplier Forms (MP) I-CRS
8. BRM MP O-CRS
9. BRM MP I-VRS
10. BRM MP O-VRS
11. Scale Efficiency Measure (SEM) I
12. SEM O
13. Radial Supper-efficiency Model (RSEM) I-CRS
14. RSEM O-CRS
15. RSEM I-VRS
16. RSEM O-VRS
17. Radial Models with Value Judgements (RMVJ) I-CRS
18. RMVJ O-CRS
19. RMVJ I-VRS
20. RMVJ O-VRS
21. Free Disposal Hull Models (FDHM) CRS
22. FDHM VRS
23. Additive Models (AM) I-CRS
24. AM I-VRS
25. Range Directional Measure (RDM)+

26. RDM-
27. Variant of Radial Measure (VRM) I-CRS
28. VRM O-CRS
29. VRM I-VRS
30. VRM O-VRS
31. Cost-efficiency Models (CEM) CRS
32. CEM VRS
33. Slack-based Model (SBM)
34. Modified Slack-based Model (MSBM)

The above methods are incapable of estimating portfolio efficiency using the data presented in Table 43 as all the input values (numbers of projects) are not semi-positive although they should have a minimum of one positive input and one positive output to be used in standard models.

To be able to clearly show how well the newly proposed method works in comparison with existing standard methods and its capability to be used in a predictive manner, a financial portfolio case study is presented in the next section.

6.2. CASE STUDY 2: AUSTRALIA'S TEN LARGEST COMPANIES

Australia's exports of resource and energy commodities have increased substantially over the last few years, supported by approximately $400 billion in investment between 2003 and 2014. Also, seven mega-projects with a total value of more than $40 billion are currently under development in Australia. Once these projects enter production, they will be another boost to Australia's exports of resource and energy services.

A case study involving the ten largest Australian companies outlined on the Australian stock market and Forbes (2016) listed in Table 44 is conducted to identify the best-performing ones that could provide the foundations of economic growth.

Table 44. TEN LARGEST FIRMS IN AUSTRALIA (FY2014-15)

	Company Name	**Code**
1	BHP Billiton Ltd	BHP.AX
2	National Australia Bank Ltd	NAB.AX
3	Commonwealth Bank of Australia	CBA.AX
4	Rio Tinto Ltd	RIO.AX
5	ANZ Banking Group Ltd	ANZ.AX
6	Westpac Banking Corp.	WBC.AX
7	Telstra Corp Ltd	TLS.AX
8	Macquarie Group Ltd	MQG.AX
9	Woolworths Ltd	WOW.AX
10	AMP Ltd	AMP.AX

6.2.1. Step 1 - Developing Portfolio

As a first step, a portfolio consisting of the ten firms needs to be created using the 2014 weekly data required to estimate their stocks and are obtained from the financial records accessed through Yahoo Finance (Yahoo, 2016) and the Australian Securities Exchange (AXS, 2016) (for the period 01 January 2014 to 29 December 2014). Later, the portfolio determined by the outcomes of the examination is adjusted to optimise it and verify whether the modifications assisted in enhancing the efficiency of the original portfolio and compared with the S&P factor in 2015. As outlined in Wikinvest (2016), the "*S&P/ASX 200 Index is the investable benchmark for the Australian Securities Exchange. It measures the performance of the 200 largest index eligible* *stocks listed on the exchange. The index is float-adjusted, covering approximately 80% of Australian equity market capitalisation*".

This study examines the companies' weekly records shown in Table 45 with the intention of developing a portfolio for one week.

Table 45. COMPANIES' 2014 FINANCIAL AND S&P/ASX DATA

No.	Date	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP	S&P/AXS 200
1	1/1/14	35.29	33.00	77.16	68.36	32.21	32.12	5.27	55.00	34.00	4.39	5350.10
2	6/1/14	34.05	32.89	77.18	63.65	31.56	32.00	5.26	54.81	34.36	4.43	5312.40
3	13/1/14	35.41	32.10	75.06	66.32	31.03	31.39	5.24	53.96	34.19	4.49	5305.90
4	20/1/14	34.61	32.17	74.34	65.16	30.65	30.91	5.15	55.88	33.98	4.33	5240.90
5	27/1/14	34.17	31.63	73.83	65.64	30.13	30.66	5.14	54.09	34.07	4.27	5190.00
6	3/2/14	33.72	31.18	73.12	65.96	29.45	31.04	5.01	54.87	34.97	4.24	5166.50
7	10/2/14	35.24	32.46	75.58	67.90	31.34	32.53	5.20	55.36	35.50	4.52	5356.30
8	17/2/14	36.60	32.86	74.77	70.23	31.82	33.08	5.25	55.34	36.32	5.00	5438.70
9	24/2/14	35.86	33.05	74.26	66.84	32.14	33.24	5.05	56.27	36.07	4.83	5404.80
10	3/3/14	35.25	33.05	75.59	64.94	32.58	33.67	5.07	56.84	36.36	5.00	5462.30
11	10/3/14	33.32	32.66	74.84	61.50	31.87	33.42	5.01	54.25	36.32	4.92	5329.40
12	17/3/14	33.25	32.98	75.25	61.37	32.25	33.37	5.00	54.83	35.80	4.92	5338.10
13	24/3/14	33.77	33.60	76.72	63.24	32.82	34.20	5.03	57.65	35.60	4.96	5366.90
14	31/3/14	35.28	33.66	76.57	63.72	33.37	34.37	5.06	57.96	35.96	5.06	5422.80
15	7/4/14	35.15	33.61	76.94	64.11	33.85	34.43	5.05	56.37	36.04	5.14	5428.60
16	14/4/14	35.60	33.64	77.15	63.37	33.88	34.70	5.13	55.97	37.09	5.18	5454.20
17	21/4/14	35.77	34.07	78.46	62.98	34.67	35.54	5.18	56.54	37.74	5.16	5531.00
18	28/4/14	34.83	32.88	78.71	60.98	34.34	34.63	5.20	58.70	36.60	5.13	5458.10
19	5/5/14	34.89	32.71	79.07	60.95	32.72	34.70	5.22	60.12	36.84	5.25	5460.80
20	12/5/14	35.58	31.86	79.97	61.95	32.94	34.05	5.29	58.88	37.10	5.33	5479.00
21	19/5/14	35.18	31.93	80.87	60.54	33.60	33.96	5.38	59.30	37.57	5.26	5492.80
22	26/5/14	34.58	31.86	81.15	59.30	33.49	34.19	5.34	60.03	37.53	5.29	5492.50
23	2/6/14	33.86	31.90	81.33	59.40	33.67	34.32	5.23	60.10	37.04	5.34	5464.00
24	9/6/14	32.98	31.59	81.29	57.60	33.75	34.03	5.21	59.98	36.48	5.35	5405.10
25	16/6/14	33.59	31.52	80.98	58.51	33.98	33.92	5.17	60.50	35.40	5.34	5419.50
26	23/6/14	34.03	31.42	81.03	60.06	33.60	33.94	5.26	60.46	35.66	5.36	5445.10
27	30/6/14	35.11	32.09	81.51	62.60	33.78	34.17	5.34	60.44	36.42	5.41	5525.00
28	7/7/14	35.12	32.03	80.79	62.14	33.35	33.72	5.33	59.26	35.97	5.39	5486.80
29	14/7/14	35.87	32.51	80.83	64.29	33.42	33.67	5.43	60.00	35.95	5.27	5531.70
30	21/7/14	36.44	32.90	81.84	65.09	33.75	34.05	5.45	58.62	36.00	5.42	5583.50

31	28/7/14	35.89	33.23	82.37	65.40	33.56	33.82	5.44	57.71	36.46	5.37	5556.40
32	4/8/14	35.27	32.17	79.70	66.43	32.26	32.81	5.39	55.65	35.67	5.23	5435.30
33	11/8/14	36.49	33.00	80.76	65.29	32.39	33.86	5.58	57.03	36.12	5.37	5566.50
34	18/8/14	35.32	32.78	80.18	65.40	33.47	34.65	5.71	58.38	37.02	5.77	5645.60
35	25/8/14	34.27	33.49	80.88	62.63	33.43	34.80	5.56	58.30	36.16	5.88	5625.90
36	1/9/14	33.31	33.14	80.86	61.30	33.34	34.52	5.64	57.75	36.31	5.66	5598.70
37	8/9/14	33.44	32.58	79.80	61.89	32.83	34.02	5.54	57.95	35.25	5.57	5531.10
38	15/9/14	33.15	32.25	77.39	61.59	31.92	32.95	5.41	58.42	35.07	5.59	5433.10
39	22/9/14	31.92	31.11	74.85	60.11	30.99	31.67	5.31	57.79	34.50	5.62	5313.40
40	29/9/14	31.26	31.36	76.24	58.80	31.64	32.37	5.39	57.22	34.45	5.46	5318.20
41	6/10/14	30.19	30.36	74.40	57.26	31.22	32.03	5.29	55.83	33.73	5.22	5188.30
42	13/10/14	31.21	31.54	76.13	59.37	31.93	32.88	5.38	57.49	34.76	5.16	5271.70
43	20/10/14	31.53	32.60	78.35	60.05	33.02	33.98	5.50	59.75	34.83	5.56	5412.20
44	27/10/14	31.73	33.29	80.05	60.41	33.50	34.54	5.63	61.17	36.00	5.85	5526.60
45	3/11/14	32.23	31.60	82.31	60.70	32.88	34.60	5.77	62.36	34.48	5.90	5549.10
46	10/11/14	31.07	31.10	81.33	60.05	32.33	32.81	5.80	60.34	33.72	5.75	5454.30
47	17/11/14	29.62	30.70	79.66	56.41	31.82	32.03	5.65	58.45	31.60	5.56	5304.30
48	24/11/14	28.89	31.01	80.29	59.10	31.92	32.33	5.69	58.43	31.12	5.64	5313.00
49	1/12/14	28.43	30.82	81.20	57.14	32.10	32.79	5.67	60.40	30.84	5.68	5335.30
50	8/12/14	26.59	30.39	81.30	53.67	31.00	31.83	5.70	58.30	29.86	5.42	5219.60
51	15/12/14	27.08	31.07	83.26	56.29	31.68	32.26	5.89	57.82	30.00	5.48	5338.60
52	22/12/14	27.07	31.75	84.46	56.59	32.00	32.68	5.91	58.35	30.50	5.47	5394.50
53	29/12/14	27.44	31.96	85.19	58.00	32.09	32.94	5.97	58.29	30.68	5.50	5411.00

One week's average growth (Eq. (31)) is the simple growth over the previous week expressed as a percentage as:

1 week growth = 100*((V2/V1)-1)

Considering the company BHP, its one-week growth from 1/1/2014 (V1=35.29) to 6/1/2014 (V2=34.05) is:

100*((34.05/ 35.29)-1) = -3.5%

The portfolio information for the ten companies is presented in Table 46:

Table 46. PORTFOLIO DATA

Company	Acronym	Last price (as at 29/12/14)	No. of Shares	Position	Shares
BHP Billiton	BHP	$27.44	45.619	$1,252	14.89%
National Australia Bank	NAB	$31.96	34.638	$1,107	13.17%
Commonwealth Bank	CBA	$85.19	16.517	$1,407	16.74%
Rio Tinto	RIO	$58.00	10.483	$608	7.23%
ANZ Banking Group	ANZ	$32.09	30.19	$969	11.52%
Westpac Banking Corp.	WBC	$32.94	37.095	$1,222	14.53%
Telstra Corp Ltd	TLS	$5.97	116.451	$695	8.27%
Macquarie Group	MQG	$58.29	6.031	$352	4.18%
Woolworths	WOW	$30.68	21.107	$648	7.70%
AMP	AMP	$5.50	26.862	$148	1.76%
Total				**$8,407**	**100.0%**

Where:

The number of shares (volume at 29/12/2014) is the quantity of stocks managed in a portfolio over a particular time frame. (Note: '*Volume is an important indicator in technical analysis as it is used to measure the worth of a market move. If the markets have made a strong price move either up or down, the perceived strength of that move depends on the volume for that period. The higher the volume during that price move, the more significant the move*'(Investopedia, 2016)).

6.2.2. Step 2 - Calculating Portfolio Parameters

Weekly share values, S&P indices and weekly changes for all DMUs are measured, with the values of the expected return, risk and variance identified using Eqs. (1), (2) and (37). As a simple example, those of the expected return are the average weekly returns of the companies and those of the risks the standard deviations of these returns calculated using the STDEV function in Excel. Table 47 lists the portfolios' parameters.

Table 47. PORTFOLIO PARAMETERS

Company	Shares	Expected Return (Re)	Risk (σ)	Variance (σ^2)
BHP Billiton	14.89%	-0.45%	2.63%	0.07%
National Australia Bank	13.17%	-0.04%	1.93%	0.04%

Commonwealth Bank	16.74%	0.20%	1.57%	0.02%
Rio Tinto	7.23%	-0.27%	2.91%	0.08%
ANZ Banking Group	11.52%	0.01%	2.04%	0.04%
Westpac Banking Corp.	14.53%	0.07%	1.94%	0.04%
Telstra Corp Ltd	8.27%	0.25%	1.70%	0.03%
Macquarie Group	4.18%	0.14%	2.18%	0.05%
Woolworths	7.70%	-0.18%	1.96%	0.04%
AMP	1.76%	0.48%	3.04%	0.09%
S&P		**0.03%**	**1.42%**	**0.02%**

6.2.3. Step 3 – Collecting Input and Output Data for DMUs

To rate the sampled businesses, the two factors considered are the two financial parameters, the expected return and variance considered as the output and input respectively, as shown in Table 48.

Table 48. INPUT/OUTPUT DATA

DMUs	Company	Input 1 (Variance)	Output 1 (Expected Return)
1	BHP Billiton	0.689124	-4.48616
2	National Australia Bank	0.373543	-0.43002
3	Commonwealth Bank	0.246631	2.026055
4	Rio Tinto	0.844466	-2.73763
5	ANZ Banking Group	0.416069	0.131739
6	Westpac Banking Corp.	0.376906	0.667096
7	Telstra Corp Ltd	0.287517	2.542196
8	Macquarie Group	0.476039	1.351179
9	Woolworths	0.386048	-1.78282
10	AMP	0.925884	4.78745

6.2.4. Step 4 – Proposed Integrated DEA Cross-efficiency/AHP Model

Using Eqs. (36), (37) and (38), we develop the following comparison matrix (Table 49):

Table 49. COMPARISON MATRIX

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10
DMU1	1.000	5.655	-0.792	2.008	-20.560	-3.678	-0.736	-2.294	1.410	-1.259
DMU2	0.177	1.000	-0.140	0.355	-3.636	-0.650	-0.130	-0.406	0.249	-0.223
DMU3	-1.262	-7.136	1.000	-2.534	25.945	4.641	0.929	2.894	-1.779	1.589
DMU4	0.498	2.816	-0.395	1.000	-10.239	-1.832	-0.367	-1.142	0.702	-0.627
DMU5	-0.049	-0.275	0.039	-0.098	1.000	0.179	0.036	0.112	-0.069	0.061
DMU6	-0.272	-1.537	0.215	-0.546	5.590	1.000	0.200	0.624	-0.383	0.342
DMU7	-1.358	-7.681	1.076	-2.727	27.925	4.996	1.000	3.115	-1.915	1.710
DMU8	-0.436	-2.466	0.346	-0.876	8.964	1.604	0.321	1.000	-0.615	0.549
DMU9	0.709	4.012	-0.562	1.425	-14.585	-2.609	-0.522	-1.627	1.000	-0.893
DMU10	-0.794	-4.492	0.629	-1.595	16.330	2.921	0.585	1.822	-1.120	1.000
Total	**-1.787**	**-10.10**	**1.416**	**-3.588**	**36.735**	**6.572**	**1.315**	**4.098**	**-2.519**	**2.249**

Eqs. (39) and (40) are applied to develop the AHP mean normalisation matrix shown in Table 50:

Table 50. AHP MEAN NORMALISATION MATRIX

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10
DMU1	-0.560	-0.560	-0.560	-0.560	-0.560	-0.560	-0.560	-0.560	-0.560	-0.560
DMU2	-0.099	-0.099	-0.099	-0.099	-0.099	-0.099	-0.099	-0.099	-0.099	-0.099
DMU3	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706
DMU4	-0.279	-0.279	-0.279	-0.279	-0.279	-0.279	-0.279	-0.279	-0.279	-0.279
DMU5	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027
DMU6	0.152	0.152	0.152	0.152	0.152	0.152	0.152	0.152	0.152	0.152
DMU7	0.760	0.760	0.760	0.760	0.760	0.760	0.760	0.760	0.760	0.760
DMU8	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244
DMU9	-0.397	-0.397	-0.397	-0.397	-0.397	-0.397	-0.397	-0.397	-0.397	-0.397
DMU10	0.445	0.445	0.445	0.445	0.445	0.445	0.445	0.445	0.445	0.445
Total	-5.597	-0.990	7.063	-2.787	0.272	1.522	7.602	2.440	-3.970	4.445
Efficiency	-0.560	-0.099	0.706	-0.279	0.027	0.152	0.760	0.244	-0.397	0.445
Consistency	10	10	10	10	10	10	10	10	10	10
Rank	10	7	2	8	6	5	1	4	9	3

A consistency test of the above results is conducted using Eq. (41):

CI = (10-10)/(10-1) = 0

As, according to Table 38, the random index (RI)) for 10 DMUs is equal to 1.49, the consistency ratio is:

CR=0/1.49 = 0

0% <= 10% OK

The consistency test using Eq. (42) is performed and a total consistency ratio of zero obtained which cannot often be ensured to work with a mixed professional group. As this result is much less than the upper boundary of 10% suggested by Saaty (1980b), we can rely on the ranking result and select the alternative 'DMU 7 - Telstra Corp Ltd' as the best company with the lowest possible risk and highest return on investment.

6.2.5. Step 5 – Testing Portfolio Efficiency Results

6.2.5.1. Phase 1 - actual risk and return of portfolio

The actual portfolio return can be found using Eq. (2):

$$R_p = -0.03\%$$

As the estimated portfolio return is below the S&P return of 0.03% and the portfolio is unable to defeat this index on a weekly basis, the risk is calculated using Eq. (4). However, the correlations between the shares should be determined as a first step and are shown in Table 51.

Table 51. Correlation Matrix

	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	1.000	0.433	0.369	0.749	0.455	0.497	0.520	0.334	0.445	0.480
NAB	0.433	1.000	0.603	0.319	0.689	0.729	0.392	0.360	0.534	0.385
CBA	0.369	0.603	1.000	0.215	0.656	0.730	0.663	0.444	0.342	0.349
RIO	0.749	0.319	0.215	1.000	0.327	0.316	0.447	0.168	0.352	0.375
ANZ	0.455	0.689	0.656	0.327	1.000	0.752	0.517	0.369	0.435	0.505
WBC	0.497	0.729	0.730	0.316	0.752	1.000	0.507	0.520	0.576	0.560
TLS	0.520	0.392	0.663	0.447	0.517	0.507	1.000	0.219	0.455	0.439
MQG	0.334	0.360	0.444	0.168	0.369	0.520	0.219	1.000	0.246	0.339
WOW	0.445	0.534	0.342	0.352	0.435	0.576	0.455	0.246	1.000	0.450
AMP	0.480	0.385	0.349	0.375	0.505	0.560	0.439	0.339	0.450	1.000

Considering ANZ and BHP as examples and applying Eq. (31), the changes in returns for ANZ and BHP are estimated as:

$$\text{BHP's one} - \text{ week growth} = 100 \times \left(\left(\frac{v_2}{v_1}\right) - 1\right)$$

…

$$\text{BHP's one} - \text{ week growth} = 100 \times \left(\left(\frac{v_{53}}{v_{52}}\right) - 1\right)$$

Using the CORREL function in Excel, the following correlation matrix can be developed.

$$= CORREL\big((BHP_1 : BHP_{53}), (ANZ_1 : ANZ_{53})\big) = 0.455$$

To simplify a valuation, five more matrices are examined based on the portfolio risk formula in Eq. (4) and the results shown in Table 52 to Table 56.

The share values of each firm can be obtained from Table 47.

Table 52. SHARES MATRIX

BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%

Using the values in this matrix, the weights multiplication one is created and the results shown in Table 53. Considering the CBA and BHP firms as examples, their weights multiplication values are estimated using the following process.

$$\text{The weights multiplication values of CBA and BHP} = 0.1489 \times 0.1674 = 0.0249$$

Table 53. WEIGHTS MULTIPLICATION MATRIX

	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	0.022	0.020	0.025	0.011	0.017	0.022	0.012	0.006	0.011	0.003
NAB	0.020	0.017	0.022	0.010	0.015	0.019	0.011	0.006	0.010	0.002
CBA	0.025	0.022	0.028	0.012	0.019	0.024	0.014	0.007	0.013	0.003
RIO	0.011	0.010	0.012	0.005	0.008	0.011	0.006	0.003	0.006	0.001
ANZ	0.017	0.015	0.019	0.008	0.013	0.017	0.010	0.005	0.009	0.002
WBC	0.022	0.019	0.024	0.011	0.017	0.021	0.012	0.006	0.011	0.003
TLS	0.012	0.011	0.014	0.006	0.010	0.012	0.007	0.003	0.006	0.001
MQG	0.006	0.006	0.007	0.003	0.005	0.006	0.003	0.002	0.003	0.001
WOW	0.011	0.010	0.013	0.006	0.009	0.011	0.006	0.003	0.006	0.001
AMP	0.003	0.002	0.003	0.001	0.002	0.003	0.001	0.001	0.001	0.000

Table 54 presents the risk matrix created using the risk values identified in Table 47.

Table 54. RISK MATRIX

BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%

The risk multiplication matrix (Table 55) is created using the values identified in Table 54. Considering the ANZ and RIO firms as examples, their risk multiplication values are estimated using the following process.

The risk multiplication values of ANZ and RIO $= 0.029 \times 0.020 = 0.001$

Table 55. RISK MULTIPLICATION MATRIX

	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	0.001	0.001	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.001
NAB	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
CBA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RIO	0.001	0.001	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.001
ANZ	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
WBC	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
TLS	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
MQG	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
WOW	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
AMP	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001

At this point, the values of the correlation, weights multiplication and risk multiplication matrices are multiplied to develop the final matrix presented in Table 56. Considering the WBC and CBA firms as examples, their final multiplication values are estimated by:

$$\text{The final multiplication values of WBC and CBA} = 0.7299 \times 0.0243 \times 0.0003 = 0.00001$$

Table 56. FINAL MULTIPLICATION MATRIX

	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	0.00002	0.00000	0.00000	0.00001	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
NAB	0.00000	0.00001	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
CBA	0.00000	0.00000	0.00001	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
RIO	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
ANZ	0.00000	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000
WBC	0.00001	0.00001	0.00001	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
TLS	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
MQG	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
WOW	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
AMP	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Then, the total of all the values in Table 56 are calculated to find σ^2, that is:
σ^2 = 0.00024

The square root of Eq. (6) is estimated to obtain the portfolio risk as:

$$\sigma = \sqrt{\sigma^2} = 1.5\%$$

It is obvious that the portfolio risk exceeds the S&P index of 1.42%.

6.2.5.2. Phase 2 - Checking Sharpe Ratio (*SR*)

In this step, we calculate the *SR* of the return to risk, as:

$$SR = \frac{E(R_p) - R_f}{\sigma}$$

This study obtains ten years of Australian treasury yield value for the *SR* right to the end of 2014 (Investing, 2016) and breaks it into the total weeks value of a portfolio recorded to obtain:

$$R_f = 1.98\% \,/\, 53 = 0.03736\%$$

Then, the coefficient for every share in the portfolio and the S&P index are measured, as shown in Table 57.

Table 57. Portfolio Coefficient

Company	**Expected Return (R_e)**	**Risk (σ)**	**Risk-free rate (R_f)**	**Sharpe Ratio (*SR*)**
BHP Billiton	-0.449%	2.625%	0.037%	-18.512%
National Australia Bank	-0.043%	1.933%	0.037%	-4.158%
Commonwealth Bank	0.203%	1.570%	0.037%	10.522%
Rio Tinto	-0.274%	2.906%	0.037%	-10.706%
ANZ Banking Group	0.013%	2.040%	0.037%	-1.186%
Westpac Banking Corp.	0.067%	1.941%	0.037%	1.512%
Telstra Corp Ltd	0.254%	1.696%	0.037%	12.789%
Macquarie Group	0.135%	2.182%	0.037%	4.481%
Woolworths	-0.178%	1.965%	0.037%	-10.975%
AMP	0.479%	3.043%	0.037%	14.506%
Portfolio	**-0.026%**	**1.542%**	**0.037%**	**-4.095%**
S&P index	**0.032%**	**1.418%**	**0.037%**	**-0.405%**

It is suggested that DMs select the portfolios with the maximum possible *SRs* since it is considered that they have a larger excess return for risk. Considering this theory, at this stage, AMP appears to be the best option and BHP the worst.

6.2.5.3. Phase 3 - Checking Beta (β)

In this stage, to determine the connection between the returns of a project/asset and portfolio/market, Beta (β) is estimated using Eq. (43), with the results shown in Table 58.

Table 58. BETA (β) CALCULATIONS

Company	Covariance	Variance	Beta
BHP Billiton	0.00027	0.00020	1.34
National Australia Bank	0.00019	0.00020	0.96
Commonwealth Bank	0.00016	0.00020	0.82
Rio Tinto	0.00022	0.00020	1.11
ANZ Banking Group	0.00022	0.00020	1.10
Westpac Banking Corp.	0.00023	0.00020	1.13
Telstra Corp Ltd	0.00018	0.00020	0.87
Macquarie Group	0.00015	0.00020	0.77
Woolworths	0.00017	0.00020	0.86
AMP	0.00029	0.00020	1.45
Portfolio	**0.00021**	**0.00020**	**1.04**

6.2.5.4. Phase 4 - Decision Making

Details of all the parameters are presented in Table 59.

Table 59. CALCULATED PARAMETERS

Company	Shares	Expected Return (Re)	Risk (σ)	Sharpe Ratio	Beta
BHP Billiton	14.9%	-0.4%	2.6%	-0.19	1.34
National Australia Bank	13.2%	0.0%	1.9%	-0.04	0.96
Commonwealth Bank	16.7%	0.2%	1.6%	0.11	0.82
Rio Tinto	7.2%	-0.3%	2.9%	-0.11	1.11
ANZ Banking Group	11.5%	0.0%	2.0%	-0.01	1.10

Westpac Banking Corp.	14.5%	0.1%	1.9%	0.02	1.13
Telstra Corp Ltd	8.3%	0.3%	1.7%	0.13	0.87
Macquarie Group	4.2%	0.1%	2.2%	0.04	0.77
Woolworths	7.7%	-0.2%	2.0%	-0.11	0.86
AMP	1.8%	0.5%	3.0%	0.15	1.45
Portfolio		**-0.03%**	**1.54%**	**-0.041**	**1.040**
S&P index		**0.03%**	**1.42%**	**-0.004**	

The first point to note is that the *SR* is below the S&P value which implies that the latter offers a more desirable connection between the return and risk. Also, as the portfolio possesses a Beta equivalent of 1.04, once the portfolio/market improves, our portfolio improves much faster.

The following adjustments are made based on the values extracted from Table 59.

- The values of shares with the lowest *SR*s are reduced (BHP, RIO and WOW).
- The value of a share with the largest Beta value is maximised (AMP).
- The value of a share with the largest *SR* is maximised (also AMP).
- The other values shown in Table 46 are retained.

The portfolio presented in this case study is also tested with data collected from 2015. Applying the above adjustments to Table 46, a new modified version of this table is presented in Table 60, including the adjustments to the numbers of shares for BHP, RIO, WOW and AMP.

Table 60. NEW PORTFOLIO WITH MODIFIED SHARE VALUES

Company	**Synonym**	**Last price (as at 2014)**	**Shares No.**	**Position**	**Shares**
BHP Billiton	BHP	$27.4445	**7**	$192	2.3%
National Australia Bank	NAB	$31.9631	34.638	$1,107	13.2%
Commonwealth Bank	CBA	$85.1885	16.517	$1,407	16.7%
Rio Tinto	RIO	$58	**3.5**	$203	2.4%
ANZ Banking Group	ANZ	$32.09	30.19	$969	11.5%
Westpac Banking Corp.	WBC	$32.9358	37.095	$1,222	14.5%
Telstra Corp Ltd	TLS	$5.97	116.451	$695	8.3%
Macquarie Group	MQG	$58.29	6.031	$352	4.2%
Woolworths	WOW	$30.68	**5**	$153	1.8%

AMP	AMP	$5.5	**383**	$2,107	25.1%
Portfolio				**$8,407**	**100%**

The share quantities for BHP, RIO, WOW and AMP are modified to obtain ones almost equal to the totals in Table 46. In this step, the weekly returns for the current as well as newly modified portfolios are estimated with the average ones and results for the S&P index shown in Table 61.

Table 61. AVERAGE WEEKLY RETURNS

	OLD	**NEW**	**S&P index**
2015 average weekly return	-0.157%	0.003%	-0.026%

There is no doubt that the improvements help as the new portfolio demonstrates better performance than the old one and outperforms the S&P index. Table 62 refers to the average weekly performances of the shares in 2014:

Table 62. AVERAGE WEEKLY PERFORMANCES IN 2014

Company	**Change (2014)**
BHP Billiton	-0.45%
National Australia Bank	-0.04%
Commonwealth Bank	**0.20%**
Rio Tinto	-0.27%
ANZ Banking Group	**0.01%**
Westpac Banking Corp.	**0.07%**
Telstra Corp Ltd	**0.25%**
Macquarie Group	**0.14%**
Woolworths	-0.18%
AMP	**0.48%**

The weight of AMP is improved and, surprisingly it is among the preferred portfolios together with MQG, CBA and WBC. The weights of BHP, RIO and WOW are decreased and BHP is the worst-performing stock followed by RIO and WOW.

The expected return, risk, *SR* and efficiency of each portfolio are compared based on Eqs. (44) and (45) assumptions, as presented in Table 63 and Table 64.

In this step, DMs review the portfolios' values and the trade-offs between their expected return, risk, *SR* and efficiency scores and can select the portfolio with the highest possible return and lowest possible risk while considering the efficiency scores. These values are shown in Table 63.

Table 63. COMPARISON OF RESULTS

DMUs No.	Company	Expected Return (Re)	Risk (σ)	Sharpe Ratio	Efficiency Score
1	BHP Billiton	-0.4%	2.6%	-0.19	-0.5597
2	National Australia Bank	0.0%	1.9%	-0.04	-0.0990
3	Commonwealth Bank	0.2%	1.6%	0.11	0.7063
4	Rio Tinto	-0.3%	2.9%	-0.11	-0.2787
5	ANZ Banking Group	0.0%	2.0%	-0.01	0.0272
6	Westpac Banking Corp.	0.1%	1.9%	0.02	0.1522
7	Telstra Corp Ltd	0.3%	1.7%	0.13	0.7602
8	Macquarie Group	0.1%	2.2%	0.04	0.2440
9	Woolworths	-0.2%	2.0%	-0.11	-0.3970
10	AMP	0.5%	3.0%	0.15	0.4445

Table 64. RANKING SCORES

DMUs No.	Company	Expected Return (Re)	Risk (σ) (1=low, 10=high)	Sharpe Ratio	Efficiency Score
1	BHP Billiton	10	8	10	10
2	National Australia Bank	6	3	7	7
3	Commonwealth Bank	3	1	3	2
4	Rio Tinto	9	9	8	8
5	ANZ Banking Group	6	6	6	6
6	Westpac Banking Corp.	4	4	5	5
7	Telstra Corp Ltd	2	2	2	1
8	Macquarie Group	4	7	4	4
9	Woolworths	8	5	9	9
10	AMP	1	10	1	3

World demand for Australian resource and energy exports remains strong and, for most products, is expected to increase in coming years. However, the ongoing downturn in production and trading costs has led many finance, resource and energy organisations to apply expense reduction policies to remain successful, with limiting their exploration funds undoubtedly one principal approach. The focus of companies has clearly shifted from developing new projects to ensuring the commercial viability of existing assets. Australia's total exploration expenses in 2014-15 (i.e., minerals and petroleum) reduced by 22% from $5.4 billion in 2013-14.

In an environment of tight finances and falling prices, companies have been forced to re-evaluate their project development plans in order to identify cost savings. The result is a downward trend in the number and value of both committed and uncommitted projects in Australia over the last four years. The benefits of agreed projects are declining which, in turn, are not mitigated by new forthcoming funds and are being significantly delayed as a result of undesirable market situations.

The slowing growth in demand in key markets and the increasing supply of most products have led to lower product prices in 2015. This trend has impacted on the finance and development of resource and energy projects in Australia. According to empirical results from this case study, in December 2014, six companies (CBA, ANZ, WBC, TCL, MQG and AMP) with a combined average weekly performance value of 1.15% progressed to be the top six companies with higher average weekly performance; this is two companies more and 0.15% higher than recorded in December 2015. This decrease in value is due to the closure of some major projects, especially in the mining industry, and different cost reduction policies used in many organisations to remain profitable. Business investment is cyclical and, although the level of investment in the resource and energy sectors in Australia is decreasing, there are significant opportunities for investment in coming years. Advances in technology and the ongoing growth in demand in highly populated emerging economies will continue to support the higher consumption of commodities, such as base metals, rare earth elements, gold, silver and uranium, in future. However, Australia must remain competitive with other countries to guarantee continuing financial investment and ensure that it remains one of the best places for attracting capital.

The result from the case study shows that eight companies have lower performance scores than Telstra Corp Ltd and Commonwealth Bank of Australia which suggests that, in particular, they must enhance their expected returns while focusing on possible risks. It is clear that the proposed model has the capacity to select the portfolio with the highest efficiency while considering the *SR* and risk factor at a given expected return, as proven in Table 64. The majority of DMUs resulting from the proposed model are identical with the results from the PT *SR*s. Although the efficiency results for DMUs 3, 7 and 10 are different, the proposed model scores all DMUs by simultaneously considering the risk, expected return and *SR* and identifying the best companies with the highest expected returns and *SR*s, and lowest possible risks.

6.3. COMPARING RESULTS FROM STANDARD METHODS AND PROPOSED MODEL

In this step, this study compares and tests the standard ranking methods discussed in this study with the new proposed method in parallel using the same data presented in our case study.

This study selected portfolios 49 times using different methods by applying:

1. Standard DEA Input-oriented (I) Constant Returns to Scale (CRS)
2. DEA I-CRS Cross-efficiency (CE)
3. DEA Output-oriented (O) - CRS
4. DEA I- Variant Returns to Scale (VRS)
5. DEA O-VRS
6. Range Directional Measure (RDM)+
7. RDM-
8. Slack-based Model (SBM)
9. Modified Slack-based Model (MSBM)
10. Semi-oriented Radial Measure (SORM) I-CRS
11. SORM O-CRS
12. SORM I-VRS
13. SORM O-VRS
14. Variant of the Radial Measure (VRM) I-CRS
15. VRM O-CRS
16. VRM I-VRS
17. VRM O-VRS
18. Radial Supper-efficiency Model (RSEM) I-CRS
19. RSEM O-CRS
20. RSEM I-VRS
21. RSEM O-VRS
22. Scale Efficiency Measure (SEM) I-VRS
23. SEM O-VRS
24. Radial Models with Value Judgements (RMVJ) I-CRS
25. RMVJ O-CRS
26. RMVJ I-VRS
27. RMVJ O-VRS

28. Additive Model (AM) I-CRS
29. AM I-VRS
30. Free Disposal Hull Models (FDHM) I-CRS
31. FDHM I-VRS
32. Cost Efficiency Models (CEM) O-CRS Cost Efficiency
33. CEM O-CRS Technical Efficiency
34. CEM O-CRS Allocative Efficiency
35. CEM O-CRS Profit Efficiency
36. CEM O-CRS Revenue Efficiency
37. CEM O-VRS Cost Efficiency
38. CEM O-VRS Technical Efficiency
39. CEM O-VRS Allocative Efficiency
40. CEM O-VRS Profit Efficiency
41. CEM O-VRS Revenue Efficiency
42. Standard DEA/AHP Linear Programming (LP)
43. Standard DEA/AHP Average Efficiency (Avg.)
44. Standard DEA/AHP Total
45. Proposed DEA CE/AHP Model Avg. with 2 Criteria
46. Proposed DEA CE/AHP Total with 2 Criteria
47. Proposed DEA CE/AHP LP with 3 Criteria
48. Proposed DEA CE/AHP Avg. with 3 Criteria
49. Proposed DEA CE/AHP Total with 3 Criteria

Although the proposed model can identify efficient and inefficient DMUs using only two criteria (variance as input and expected return with negative data as output), other standard DEA methods are not able to estimate efficiency among DMUs using these criteria. DMUs 1, 2, 4, 9 are not semi-positive and should have a minimum of one positive input as well as one positive output to be used in the standard models.

If both the variance and expected return values are considered outputs, a minimum of one input is necessary as DEA methods cannot be completely created with outputs. A dummy input with a value equal to one for all the DMUs and the expected return and variance as two outputs are considered for comparing other standard methods, as demonstrated in Table 65:

Table 65. INPUT/ OUTPUT DATA WITH DUMMY INPUTS

Company	**Input**	**Output 1** (Expected Return)	**Output 2** (Variance)
BHP Billiton	1	-4.48616	0.689124
National Australia Bank	1	-0.43002	0.373543
Commonwealth Bank	1	2.026055	0.246631
Rio Tinto	1	-2.73763	0.844466
ANZ Banking Group	1	0.131739	0.416069
Westpac Banking Corp.	1	0.667096	0.376906
Telstra Corp Ltd	1	2.542196	0.287517
Macquarie Group	1	1.351179	0.476039
Woolworths	1	-1.78282	0.386048
AMP	1	4.78745	0.925884

The expected return is often treated as an output since more of this variable is desired and can become negative for the respective period whereas the variance involves only the variables in the model that take non-negative values. Although some methods can score efficiency using the above three criteria (RDM, SORM, VRM and MSBM), the rest cannot deal with negative data. While we also apply these criteria to the proposed model, the results are far from the reality. Considering only the Consistency Ratio (CR) clearly shows that this arrangement of the criteria needs to be changed as the CR for our proposed model using them is 53.3% which is far greater than the acceptable one of 10% proposed by Saaty (1980b) in Eq. (42). The DMUs' ranking scores are neither acceptable nor justifiable as they are not even close to the results we identified from the PT; for example, based on them, BHP is the second-best company compared with the others in terms of efficiency, with the results from the PT and proposed model clearly showing a huge discrepancy.

As standard DEA methods cannot handle non-positive data, there is a need for a solution to this issue. A possible and, perhaps, simplest approach is to treat negative outputs as positive inputs and vice versa (e.g., Scheel, 2001; Seiford & Zhu, 2002). Therefore, the negative inputs/outputs in the proposed model are shifted to positive values by changing the original results obtained from a new problem (Cooper et al., 2007). Then, modified positive input/output data are presented for further investigation.

Drawing upon the above-described approach, if a vector of input or output data consists of a mix of positive and negative numbers, this approach will require dividing this vector into two sub-vectors. One will hold the positive numbers and replace the negative values with zeroes (or very small positive values) while the other one will retain the absolute values of the negative elements and substitute zeroes (or very small positive values) for positive numbers. Then, the context will dictate which sub-vector needs to be maximised (minimised) and reside on the output (input) side.

To deal with the negative data from Output 1 (the expected return) in Table 65, these data are shifted to positive values by changing the original results in a new problem (Input 2). Modified positive input/output data are shown in Table 66.

Table 66. INPUT/OUTPUT DATA WITH POSITIVE VALUES

Company	**Input 1**	**Input 2**	**Output 1** (Expected Return)	**Output 2** (Variance)
BHP Billiton	1	4.48616	0	0.689124
National Australia Bank	1	0.43002	0	0.373543
Commonwealth Bank	1	0	2.026055	0.246631
Rio Tinto	1	2.73763	0	0.844466
ANZ Banking Group	1	0	0.131739	0.416069
Westpac Banking Corp.	1	0	0.667096	0.376906
Telstra Corp Ltd	1	0	2.542196	0.287517
Macquarie Group	1	0	1.351179	0.476039
Woolworths	1	1.78282	0	0.386048
AMP	1	0	4.78745	0.925884

Although applying the data in Table 66 to the remaining models shows that they can estimate efficiency scores, some models are infeasible. Numerical errors may lead to some minor changes in model constraints that can cause Linear Programming (LP) to become infeasible. In this case, we need to scale the data or change the tolerance value to reduce numerical errors. Moreover, some models are not always feasible; for example the Radial Super-efficiency Model (RSEM)-VRS or any models with weight restrictions. There are also other restrictions, such as epsilon which limits the lower bound of the LP variables, with the results are not justifiable in this scenario.

The results have been compared as shown in Table 67 and discussed in the followings. A detailed calculation of each method is available in ANNEX F.

Table 67. Comparison of results from Standard Models

Models	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10
1	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
2	0.521	0.282	0.313	0.638	0.323	0.327	0.377	0.445	0.292	1.000
3	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
4	1	1	1	1	1	1	1	1	1	1
5	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
7	93.461	64.412	66.730	99.227	69.681	64.844	78.005	76.395	66.005	0.000
8	0.000	0.202	0.000	1.000	0.620	0.579	0.474	0.679	0.613	1.000
9	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	1.000
10	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
11	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
12	1	1	1	1	1	1	1	1	1	1
13	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
14	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
15	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
16	1	1	1	1	1	1	1	1	1	1
17	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
18	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	2.440
19	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	2.440
20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
21	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	2.440
22	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
23	1	1	1	1	1	1	1	1	1	1
24	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
25	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
26	1	1	1	1	1	1	1	1	1	1
27	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
28	9.510	5.770	3.441	7.606	5.166	4.669	2.884	3.886	7.110	0.000
29	9.510	5.770	3.441	7.606	5.166	4.669	2.884	3.886	7.110	0.000
30	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
31	1	1	1	1	1	1	1	1	1	1
32	0.035	0.138	0.423	0.069	0.449	0.407	0.531	0.514	0.046	1.000
33	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
34	0.047	0.341	1.000	0.075	1.000	1.000	1.000	1.000	0.111	1.000
35	76.656	18.296	5.419	38.469	4.385	5.024	4.172	3.611	57.860	1.000
36	0.744	0.403	0.266	0.912	0.449	0.407	0.311	0.514	0.417	1.000

37	0.047	0.341	1.000	0.075	1.000	1.000	1.000	1.000	0.111	1.000
38	1	1	1	1	1	1	1	1	1	1
39	0.047	0.341	1.000	0.075	1.000	1.000	1.000	1.000	0.111	1.000
40	57.054	7.381	2.293	35.086	1.971	2.045	2.215	1.856	24.125	1.000
41	0.744	0.403	0.266	0.912	0.449	0.407	0.311	0.514	0.417	1.000
42	0.091	0.086	0.088	0.100	0.090	0.087	0.092	0.099	0.084	0.182
43	1.057	1.188	1.153	0.961	1.120	1.171	1.074	1.021	1.213	0.580
44	0.093	0.086	0.088	0.103	0.090	0.087	0.092	0.098	0.083	0.180
45	-0.179	-1.010	0.142	-0.359	3.673	0.657	0.132	0.410	-0.252	0.225
46	-0.560	-0.099	0.706	-0.279	0.027	0.152	0.760	0.244	-0.397	0.445
47	0.114	0.038	0.104	0.104	0.042	0.056	0.129	0.091	0.054	0.268
48	0.729	2.925	2.045	0.696	9.285	2.424	1.747	1.441	1.374	0.580
49	0.151	0.057	0.073	0.142	0.063	0.062	0.089	0.085	0.072	0.207

There are several methods that produce identical ranking scores in the same order for the DMUs under consideration; for example, Methods 1 (DEA I-CRS), 3 (DEA I-CRS), 5 (DEA O-VRS), 10 (SORM I-CRS), 11 (SORM O-CRS), 13 (SORM O-VRS), 14 (VRM I-CRS), 15 (VRM O-CRS), 17 (VRM O-VRS), 22 (SEM I-VRS), 24 (RMVJ I-CRS), 25 (RMVJ O-CRS), 27 (RMVJ O-VRS), 30 (FDHM I-CRS) and 33 (CEM O-CRS Tech.Effic).

Also, Methods 18 (RSEM I-CRS), 19 (RSEM O-CRS) and 21 (RSEM O-VRS) have the same ranking scores as do Methods 36 (CEM O-CRS Rev.Effic) and 41 (CEM O-VRS Rev.Effic). The efficiency results obtained from these methods are also very close to those from the previous groups of models, that is, Methods 28 (AM I-CRS) and 29 (AM I-VRS) in one group and 34 (CEM O-CRS Alloc.Effic), 37 (CEM O-VRS Cost.Effic) and 39 (CEM O-VRS Alloc.Effic) in another.

Moreover, the efficiency levels of DMUs cannot be estimated by some methods which estimate zero values for them; for instance, Methods 6 (RDM+) and 20 (RSEM I-VRS) consider all the DMUs inefficient (zero) while Methods 7 (RDM-), 8 (SBM), 28 (AM I-CRS) and 29 (AM I-VRS) identify the values for DMUs 1, 3 and 10 as zero. As the efficiency results for all DMUs in Methods 4 (DEA I-VRS), 12 (SORM I-VRS), 16 (VRM VRS IO), 23 (SEM O-VRS), 26 (RMVJ I-VRS), 31 (FDHM I-VRS) and 38 (CEM O-VRS Tech.Effic) are equal to one, because these DMUs cannot be considered different, they are viewed as equally efficient.

Only the results obtained from 36 of the 49 methods (1, 2, 3, 5, 9, 10, 11, 13, 14, 15, 17, 18, 19, 21, 22, 24, 25, 27, 30, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48 and 49) are considered for further investigation. Those that cannot estimate the efficiency of DMUs (zero values) and those incapable of differentiating between DMUs (equally efficient with values of one) are omitted from further investigation.

There are significant differences between the proposed method and the other standard models concerning their performance scores for effective organisations. The above results demonstrate that the proposed approach is a promising tool for portfolio selection as a means of fundamental analysis. Our results also show that the DEA cross-efficiency approach in the new method is more effective than that based on the simple use of cross-efficiency scores, at least for this particular application. Overall, our findings consistently support the effectiveness of our approach.

6.4. Case Study 3: Innovative Strategic Portfolio Management Tool/SPMT

The proposed SPMT decision-support system is based on the processes described in Figure 14 which prioritise the efficiency of DMUs for selecting the appropriate projects/programs/investments in portfolios as follows.

In the first step, the data required to create a portfolio of several DMUs are collected, with the primary source for the SPMT the Yahoo (2016) finance reporting system which includes weekly/monthly online reporting and projects/programs values. These data are populated every day and can be classified and modified by the relevant assets or country codes before being used in the system and, if required, be inserted manually.

Using the PT method of Markowitz (1952), the expected return (on investment) and risk are identified to calculate a portfolio's parameters. Two criteria, the expected return and variance, are used to rank the efficiency levels of DMUs and a pair-wise comparison matrix formed using the modified DEA cross-efficiency assessment presented in CHAPTER V. This integrated method is then applied through three phases. Phase 1 develops a pair-wise comparison matrix and then, in Phase 2, all the DMUs are ranked using the AHP method proposed by Saaty (1980c) and a new normalised matrix generated using the AHP model. To ensure that the information is similar across assessment and in units, and there is no misalignment in the information collected, the AHP is able to balance the data with a mean normalisation of them conducted in the same phase. Then, a consistency test is carried out in Phase 3 using the AHP method to identify the objectivity of the results. By multiplying the expected return values by their weights and then summing them, the system identifies the actual portfolio return. Likewise, the connection between the asset and market returns (β factor) and *SR* is determined using the PT method. Finally, the DMs can review the portfolios and trade-off between the levels of return and the risk of the portfolio according to the efficiency score to select the portfolio with the highest efficiency and return level and minimum risk.

To test the applicability of the new system, the top five largest portfolios presented in the Dog-of-the-Dow (2016) for the 2015-2016 year are selected to identify the most efficient. A list of the portfolios used in this case study is presented in Table 68 and the related financial data (from 02 January 2015 to 28 December 2015) in Table 69.

Table 68. PROGRAM NAMES (2015-16)

	Program Name	**Synonym**
1	Apple	AAPL
2	Alphabet	GOOGL
3	Microsoft	MSFT
4	Berkshire Hathaway	BRK-A
5	Amazon.com	AMZN

Table 69. PORTFOLIO DATA (PERIOD 02 JAN 2015 TO 28 DECEMBER 2015)

Date	AAPL	GOOGL	MSFT	BRK-A	AMZN	S&P 500
2/01/2015	109.33	529.55	46.76	223600	308.52	2058.2
5/01/2015	112.01	500.72	47.19	224675	296.93	2044.81
12/01/2015	105.99	510.46	46.24	223615	290.74	2019.42
20/01/2015	112.98	541.95	47.18	223751	312.39	2051.82
26/01/2015	117.16	537.55	40.4	215865	354.53	1994.99
2/02/2015	118.93	533.88	42.41	224880	374.28	2055.47
9/02/2015	127.08	551.16	43.87	222555	381.83	2096.99
17/02/2015	129.5	541.8	43.86	223100	383.66	2110.3
23/02/2015	128.46	562.63	43.85	221180	380.16	2104.5
2/03/2015	126.6	572.9	42.36	218811	380.09	2071.26
9/03/2015	123.59	553	41.38	217118	370.58	2053.4
16/03/2015	125.9	564.95	42.88	218300	378.49	2108.1
23/03/2015	123.25	557.55	40.97	217000	370.56	2061.02
30/03/2015	125.32	541.31	40.29	216500	372.25	2066.96
6/04/2015	127.1	548.54	41.72	215211	382.65	2102.06
13/04/2015	124.75	532.74	41.62	212982	375.56	2081.18
20/04/2015	130.28	573.66	47.87	214490	445.1	2117.69
27/04/2015	128.95	551.16	48.66	215800	422.87	2108.29
4/05/2015	127.62	548.95	47.75	222880	433.69	2116.1
11/05/2015	128.77	546.49	48.3	218640	426	2122.73
18/05/2015	132.54	554.52	46.9	217000	427.63	2126.06
26/05/2015	130.28	545.32	46.86	214800	429.23	2107.39
1/06/2015	128.65	549.53	46.14	211560	426.95	2092.83
8/06/2015	127.17	547.47	45.97	210760	429.92	2094.11
15/06/2015	126.6	557.52	46.1	212200	434.92	2109.99
22/06/2015	126.75	553.06	45.26	209900	438.1	2101.49
29/06/2015	126.44	547.34	44.4	205923	437.71	2076.78
6/07/2015	123.28	556.11	44.61	209800	443.51	2076.62

13/07/2015	129.62	699.62	46.62	215960	483.01	2126.64
20/07/2015	124.5	654.77	45.94	212032	529.42	2079.65
27/07/2015	121.3	657.5	46.7	214000	536.15	2103.84
3/08/2015	115.52	664.39	46.74	215463	522.62	2077.57
10/08/2015	115.96	689.37	47	213981	531.52	2091.54
17/08/2015	105.76	644.03	43.07	202500	494.47	1970.89
24/08/2015	113.29	659.69	43.93	205344	518.01	1988.87
31/08/2015	109.27	628.96	42.61	196501	499	1921.22
8/09/2015	114.21	655.3	43.48	198329	529.44	1961.05
14/09/2015	113.45	660.92	43.48	192200	540.26	1958.03
21/09/2015	114.71	640.15	43.94	194620	524.25	1931.34
28/09/2015	110.38	656.99	45.57	195500	532.54	1951.36
5/10/2015	112.12	671.24	47.11	199650	539.8	2014.89
12/10/2015	111.04	695.32	47.51	200469	570.76	2033.11
19/10/2015	119.08	719.33	52.87	206584	599.03	2075.15
26/10/2015	119.5	737.39	52.64	204596	625.9	2079.36
2/11/2015	121.06	761.6	54.92	203100	659.37	2099.2
9/11/2015	112.34	740.07	52.84	197825	642.35	2023.04
16/11/2015	119.3	777	54.19	204600	668.45	2089.17
23/11/2015	117.81	771.97	53.93	201624	673.26	2090.11
30/11/2015	119.03	779.21	55.91	204500	672.64	2091.69
7/12/2015	113.18	750.42	54.06	195757	640.15	2012.37
14/12/2015	106.03	756.85	54.13	194720	664.14	2005.55
21/12/2015	108.03	765.84	55.67	201137	662.79	2060.99
28/12/2015	105.26	778.01	55.48	197800	675.89	2043.94

As all the programs presented in this case study are US-based, unlike Case Study 2, it uses the 10Y US Treasury yield (U.S.Government, 2016) at the end of 2015 (2.24% as at 28/12/2015) and divides it by the number of weeks in a year to obtain a weekly risk-free return.

Snapshots of the SPMT reports, including the efficiency results for the programs studied, are presented in Table 70, Table 71, Table 72 and Figure 17.

Table 70. PORTFOLIO PARAMETERS

Program	**Budget $ (end 2015)**	**Number of Projects**	**Position $**	**Share in portfolio**
AAPL	$105.26	30871100	$3,249,492,048	37.02%
GOOGL	$778.01	1634200	$1,271,423,958	14.49%

MSFT	$55.48	24605900	$1,365,135,332	15.55%
BRK-A	$197800	300	$59,340,000	0.68%
AMZN	$675.89	4188900	$2,831,235,684	32.26%
Portfolio			**$8,776,627,022**	**100.0%**

Table 71. PORTFOLIO INPUTS AND OUTPUTS

DMUs	Program	Input (σ²)	Output (Re)
1	AAPL	1.345621	-0.069013
2	GOOGL	2.195640	8.417433
3	MSFT	1.763206	4.157062
4	BRK-A	0.406220	-2.154931
5	AMZN	2.074424	16.164779

Programs	Share in portfolio	Expected return (*Re*)	Risk (*σ*)	Sharpe ratio (*SR*)	Beta	Efficiency
Apple	37.02%	-0.007%	3.668%	-0.013	1.331	-0.0059
Alphabet	14.49%	0.842%	4.686%	0.171	1.400	0.4443
Microsoft	15.55%	0.416%	4.199%	0.089	1.581	0.2733
Berkshire Hathaway	0.68%	-0.215%	2.015%	-0.128	0.817	-0.6149
Amazon	32.26%	1.616%	4.555%	0.346	1.077	0.9032
Portfolio		**0.704%**	**3.31%**	**0.200**	**1.301**	**1.000**
S&P index		**0.004%**	**1.89%**	**-0.020**		

Figure 17. PORTFOLIO RESULTS

Table 72. PORTFOLIO RANKING SCORES

Programs	Expected return (Re)	Risk (σ)	SR	Efficiency
AAPL	4	2	4	4
GOOGL	2	5	2	2
MSFT	3	3	3	3
BRK-A	5	1	5	5
AMZN	1	4	1	1

5.1. RESULTS

The results shown in Figure 17 and Table 72 illustrate that four programs have lower performance scores than AMZN in our portfolio.

To gain a sense of the efficiency scores and the level of improvement applied to this portfolio, a chart is generated using Yahoo (2016) for the period of this case study (2015-2016). All five programs are included to demonstrate how well the proposed system can estimate the efficiency scores while suggesting future necessary improvements and adjustments to the portfolio.

Figure 18 clearly shows that the program efficiency orders in this chart are identical to the results presented in Table 72.

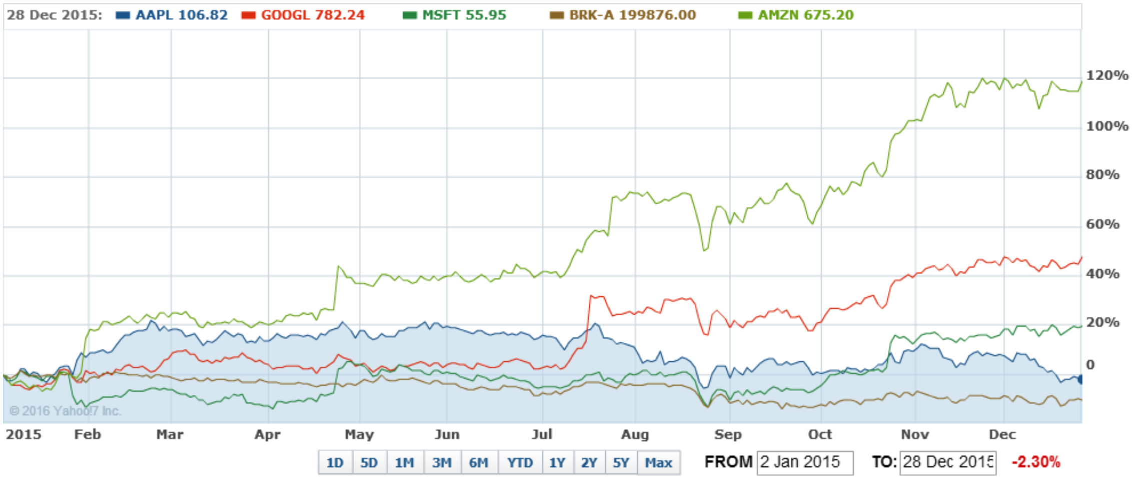

Figure 18. PORTFOLIO COMPARISON CHART (PERIOD 2/1/2015 TO 28/12/2015)

In Figure 17, the SPMT identified that the lowest *SR* of -0.128 and lowest Beta value of 0.817 belong to the BRK-A program, the AMZN program has the largest *SR* value of 0.346 and the MSFT program has the largest Beta value of 1.581. As a result of these investigations and to improve the existing portfolio, the number of projects in the BRK-A program is reduced while those in the AMZN and MSFT programs are increased.

To check the accuracy of the decision and changes made to improve the portfolio in 2015, a chart comparing all five programs is generated for 2016 using Yahoo (2016). The results show that the three programs improved in 2016 (AMZN, BRK-A and MSFT) are among the top three programs in the portfolio. Therefore, the proposed SPMT is fully capable of selecting the programs that require improvement; for example, while the BRK-A program is ranked fifth in the 2015 portfolio, it is the second most effective program in 2016. It can be concluded that the decision option proposed by SPMT, suggesting the adjustment in the number of projects in the BRK-A program in 2015 to improve it in 2016, is completely correct, accurate and necessary to improve the entire portfolio. This SPMT recommendation also ensured that the AMZN and MSFT programs remained among the top three most effective programs in the 2016 portfolio. Figure 19 shows a comparison of the portfolios of all five programs in 2016, including their performance orders.

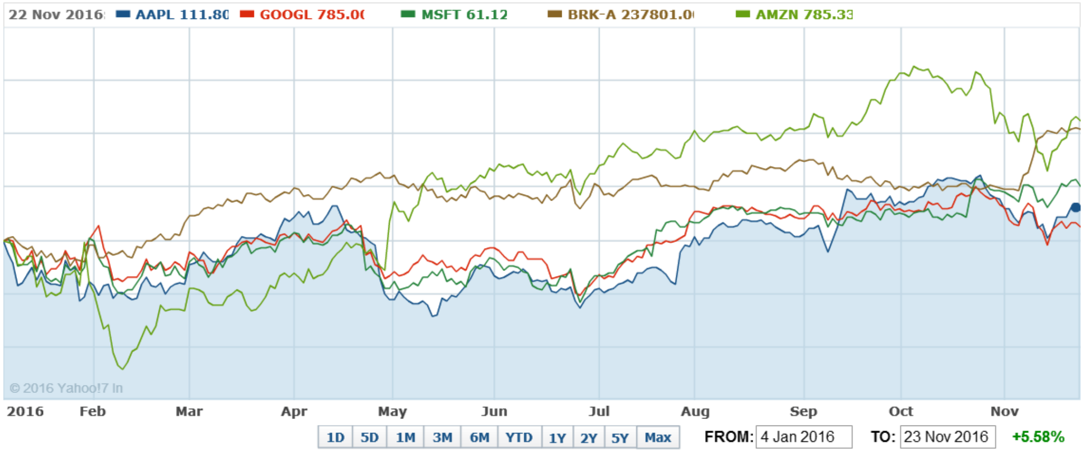

Figure 19. Portfolio Comparison Chart (Period 4/1/2016 to 23/11/2016)

6.5. CHAPTER VI Conclusions

To effectively perform PPM, organisations should revise their strategies and prioritise their targets in their business plans to make good portfolio decisions. They should map their candidate programs/projects/investments to the objective(s) and prioritise them against all other portfolio elements. The evaluation and comparison of an organisation's portfolios must be conducted effectively and the results represent a correct picture of their performances.

This study tried to improve the way in which organisations select major projects/programs/investments in a portfolio, including improvements to their decision-making systems to strengthen the connection between their objectives and decision functionality as well as enhance their cost estimations. The proposed system not only reduces the amount of effort required to reduce portfolio expenses but is more focused on providing a better decision capability at a lower cost by enhancing the PPM decision making and selection processes to eliminate waste.

This study proposed a model based on the PT, standard DEA cross-efficiency and standard DEA/AHP methods. It simultaneously takes into account the efficiency, expected return, *SR* and risk of a portfolio. Moreover, the AHP and PT models are considered tools for testing efficiency to check the accuracy of the proposed model.

The proposed model is inspired by considering that the standard basic use of DEA scores in portfolio selection per se suffers from the problem of the resultant portfolios not being well diversified which is exacerbated by the DEA cross-efficiency evaluation being integrated with the AHP. This study discovered that this problem is due to the basic utilisation of DEA assessment in portfolio selection not taking into account shifts or improvements in weights. This issue is addressed by integrating a modified DEA cross-efficiency and AHP assessment into the PT method in which those risks are simultaneously taken into consideration.

As standard DEA methods presume positive inputs/outputs for DMUs, the DEA models for non-negative data in the literature cannot be employed to establish the cross-efficiency of these DMUs. All existing methods for measuring efficiency with negative data have some disadvantages whereas the proposed model evaluates the Pareto-Koopmans efficiency of DMUs when the inputs and outputs can be either positive or negative.

As an illustration of the recommended method, a case study using the actual financial data from 2014 to 2015 of Australia's 10 largest companies in the Australian share market were taken into consideration. Its fundamental aim was neither to provide perspectives of those companies nor present grading advice but to concentrate on explicitly representing an integrated method for rating those organisations according to a variety of factors. The accuracy of the proposed model has been defined by comparing the results obtained from 49 standard main and sub-models including the proposed method, with the outcomes revealing that the proposed model presents much better efficiency scores with higher accuracy. It scores efficient DMUs with much better ranking levels than inefficient ones. Therefore, there is certainly better agreement among its rankings and the efficiency specifications taken from the DEA, that is, the proposed model scores effective DMUs which cannot be considered by standard models. Simultaneously, it scores inefficient DMUs while ensuring that efficient ones have better ranking levels.

The results obtained using this method show the accuracy and clarity of the weights generated. They appear to be much more reasonable with financial and organisational clarity since this study used a modified DEA cross-efficiency evaluation instead of a standard DEA method. The proposed model perceives the subjective and objective aspects and makes the options far more practical and, in general, provides better objectives than the available methods presented in the literature review.

SPMT provides a simple approach for improving portfolio decisions in an organisation and generates major savings options for reinvesting to establish a highly effective organisation which are crucial for guaranteeing the delivery of organisational targets.

SPMT enables DMs to work smarter rather than harder and can generate automatic reports via the click of a button. It provides valid and verifiable decision information through several reports and dashboards. DMs can easily generate management, project, program and portfolio reports on a range of issues, such as risks and benefits, using historical data, decision scores and funding. This improves situational awareness, facilitates the analysis and presentation of information, and supports timely and informed decision making at the project, program and portfolio levels. A SPMT system can provide valuable information to support portfolio management decisions, such as: project/program risks and issues, benefits, funding, and project dependencies. It can deal with a very large number of DMUs and takes the interdependencies of the criteria into account based on the weight of each criterion during the evaluation process, and supports both quantitative and qualitative information. Most importantly, it can handle both positive and negative data, an option not available in most decision-support systems. It can also drive organisational improvements through increasing performance transparency and improving decisions in project/program reporting to senior stakeholders, combining improved data quality with more independent analyses, and focusing on improving collaboration between DMs and their end-users.

SPMT provides a reliable direction for portfolio management which can present the main cost and risk factors. It can simply enhance PPM decisions to establish superior processes for selecting projects with greater possibilities of returning benefits. It can present the best possible portfolio advice based on which organisations can select the best projects/programs in which to invest their money. The proposed system guarantees the facilitation of data and appropriately enables DMs to generate the most suitable decisions regarding an organisation’s capital investments. SPMT applies the most suitable PPM methods for minimising waste, selecting effective projects/programs, boosting portfolio delivery and decreasing the cost of risk.

SPMT provides DMs with greater authority to manage their portfolios by applying an integrated MCDM approach that improves decision-making options. It offers DMs adequate rankings, vision and power to adjust and modify a standard portfolio to select the most suitable projects/programs and reduce an organisation’s costs.

The proposed method in CHAPTER V can function very well using the proposed tool (i.e., SPMT) and is capable of dealing with a large number of projects and variables. In addition, negative data can be applied to it and there is no limit regarding different decision criteria and options. SPMT can produce specific project/program-related profit benchmarks, generate portfolio efficiency scores and illustrate those findings in different reports. The proposed decision tool can simply present PPM performances and determine projects/programs that are not functioning well. By including the applicable values and advantages of every project/program, DMs are able to immediately recognise those with higher efficiency with their levels of risk and benefits. Using these capabilities, DMs can make innovative and practical decisions regarding the essential modifications of and corrections to a portfolio.

6.6. CHAPTER VI HIGHLIGHTS

This chapter presented three case studies to describe the applicability of the proposed model and its supporting tool (i.e., SPMT). Each was precisely investigated which elicited the following key findings.

a) The proposed method simultaneously considers the efficiency, expected return, *SR* and risk of a portfolio.
b) The proposed method provides a better decision capability at a lower cost than other techniques by enhancing the PPM decision making and selection processes for eliminating waste.
c) The outcomes from the case studies reveal that the proposed model presents much better efficiency scores with greater accuracy than other standard methods.
d) The proposed model scores the efficient DMUs in a much better ranking level compared to the inefficient DMUs.
e) The proposed tool supports both quantitative and qualitative information.
f) SPMT can support both positive and negative data, an option not available in most decision-support systems.
g) SPMT applies the most suitable PPM methods for minimising waste, selecting effective projects/programs, boosting portfolio delivery and decreasing the cost of risk.
h) SPMT has no limit in terms of applying different decision criteria and/or options.
i) Using SPMT, DMs are able to immediately recognise projects with higher levels of efficiency and associated risks and benefits.

Figure 20 presents a snapshot of the key findings from CHAPTER VI.

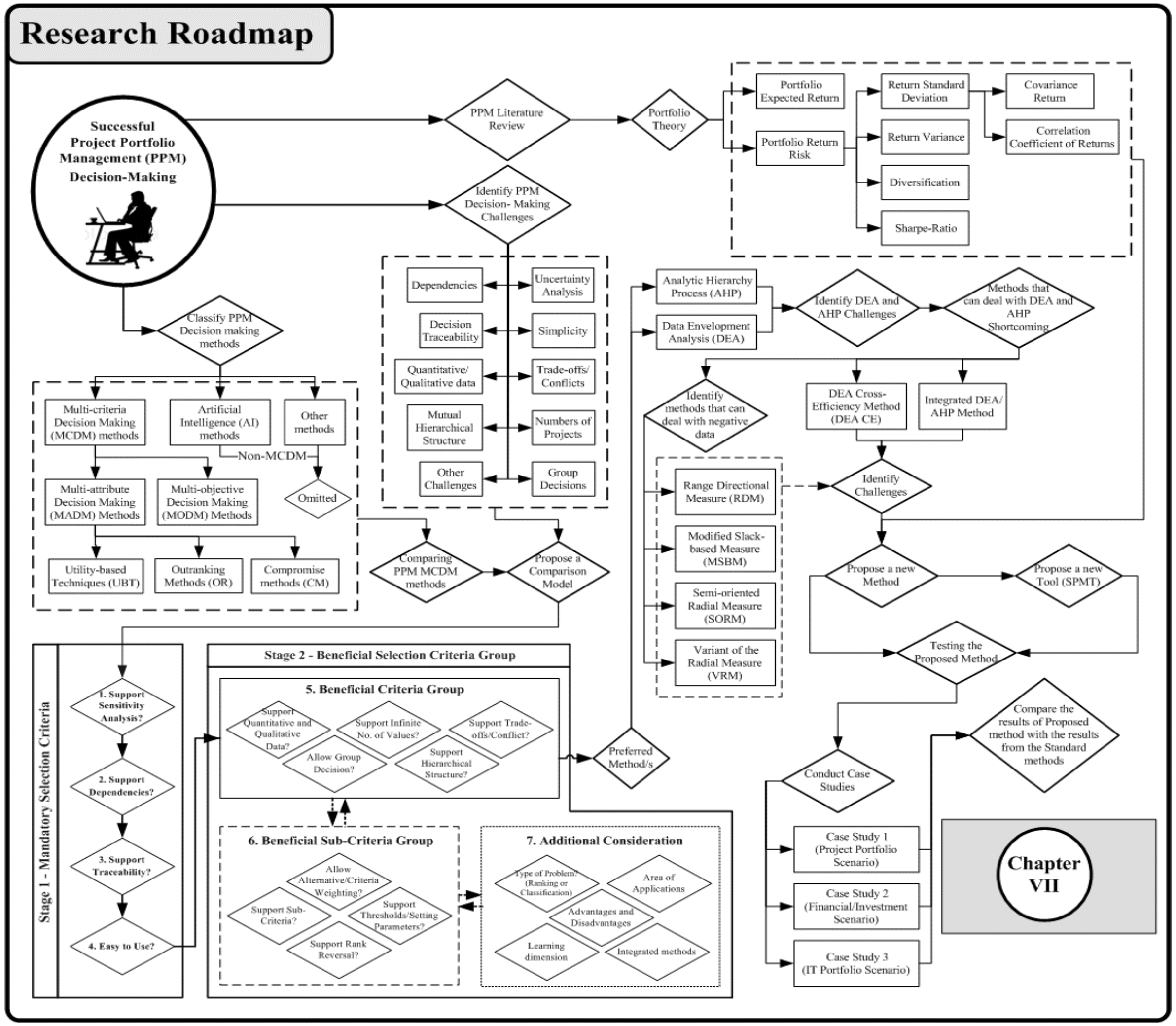

Figure 20. RESEARCH ROADMAP – CHAPTER VI

CHAPTER VII

7.1. CONCLUSION

To perform PPM more effectively, an organisation should revise its strategy and prioritise the targets in its strategic plan to make effective portfolio decisions. It should map its candidate projects to its strategic objective(s) and prioritise them against all other projects. Therefore, the prime intention of this study was to establish the most effective decision-making model for PPM.

More than 1400 publications on decision making for organisational and portfolio management were reviewed to highlight the key challenges of PPM and related MCDM methods. This is probably the first study that benchmarked PPM MCDM methods on this scale. The key failure factors of PPM were identified and applied to propose a comparison model for down-selecting useful MCDM techniques, with the main PPM challenges conducting a sensitivity analysis, and determining the interdependencies among projects/programs/portfolios, traceability, simplicity, supporting quantitative and qualitative data, project quantity, trade-offs, group decision making and mutual links between portfolio levels. To overcome them, this study analysed the literature and established a variety of conditions that must exist in cases in which a technique is to be successful in practice. It also considered the selection paradigm of Deason and White (1984), choice algorithm of Gershon (1981), selection model of Tecle (1988) and hierarchical process for portfolio selection of Cooper (2005) to present a model for comparing MCDM methods for PPM decision making according to their suitability in terms of their handling of PPM challenges, comprehensiveness and relatively simple delivery.

For the purpose of this study, several MCDM techniques are analysed to determine which fulfils as many criteria/specifications as possible and categorised based on the set of seven comparison criteria (factors/groups) listed in Table 3 suggested as essential by several authors (e.g. Antunes, 2012; Buchholz, Rametsteiner, Volk, & Luzadis, 2009; Munda, 2005, 2008; Polatidis, Haralambopoulos, Munda, & Vreeker, 2006; Rowley et al., 2012; Sadok et al., 2009; Sala, Farioli, & Zamagni, 2013; Teghem, Delhaye, & Kunsch, 1989).

To shortlist the appropriate PPM-related MCDM methods, of more than the 100 identified in the literature, a pre-selection stage (Classification of Decision-making Methods) is conducted to eliminate those designed for a specific industry/situation and unsuitable for PPM decision making or not included in the MCDM categories in Figure 6 (i.e., MADM and MODM) which are classified according to their types of data input. All Artificial Intelligence (AI) techniques are omitted from this study since they are normally employed to provide approximate answers and options for difficult optimisation conditions; for example, a genetic algorithm (GA) method is incapable of ensuring a truly ideal solution to a complex optimisation problem (Xu & Ding, 2011). Others, such as the Chance Constrained and GA (CCGA) (Azadeh & Alem, 2010) and Numerical Taxonomy (NT) (Sokal & Sneath, 1963), are designed for a specific industry or situation and may not be suitable for many real-life challenges, including general PPM decision making; for example, CCGA is a genetic model and NT a classification method in biological systematics which involves grouping numerical types of taxonomic units according to their characteristics. The characteristics and differences in behaviour associated with these techniques are examined and the techniques that comply with this study's essential requirements defined in Stage 2 identified for further investigation. The consecutive use of the associated requirements results in eliminating many of the MCDM methods.

Although more than 100 MCDM methods were identified as being related to PPM challenges, finding the one most suitable for dealing with PPM issues was a significant task. In almost all the available literature, the selection of MCDM techniques relied on knowledge of and affinity with the method instead of the decision-making circumstances of interest. A common issue with the majority of these studies was that most failed to present a clear reason for selecting a particular method. The authors' selection processes were based mainly on random choices, the most widely used methods, one created by themselves or one with which they had had experience. Some just referenced other people's work, or in some cases, the number of articles published in the particular area was the basis for selecting a specific model.

The results obtained from these studies also differed, with some showing that the rankings for all the methods tested did not differ greatly and others that no method was more suitable or preferred. In most of the comparison studies, each method produced different solutions for the same option which suggested that a combination of techniques would select and manage projects better. However, some concluded that no individual technique could determine the ideal option while some left the final decision to their readers. The authors' comparison processes were conducted based on the limited numbers of methods they most preferred themselves without any explanation as to why they were selected, with some presented in only the authors' publications and including no practical case studies to justify them.

Therefore, MCDM techniques from various groups were classified and examined in this study. Of more than 100 MCDM methods in over 1400 articles presented in ANNEX A, over 40 found to be irrelevant or unsuitable for this study's direction are eliminated while only 46 of the others can adequately manage 'uncertainty'. Many methods are identified as being very complicated and requiring large amounts of input information, with the number of those for consideration significantly decreasing once the 'dependency' factor is included. Therefore, only 28 are assessed as being capable of supporting interdependencies among projects or not needing to support them while only 11 of the remaining 28 support the 'traceability' function, with three of the remainder very complicated or not following an organised structure.

A total of eight MCDM methods (AHP, ANP, DEA, DRSA, ELECTRE, VIKOR, PROMETHEE and TOPSIS) are selected for a final investigation to identify a preferred one. They are identified to be more appropriate for decision making for PPM due to their capabilities for dealing with any kind of judgement considerations, their simple outcomes, low complexity for managing criteria and the decisions they contain. Furthermore, all have been employed to address various real-life challenges, are simple in concept and computation and are applicable to multi-level hierarchies. The challenge now was to identify which of these techniques is considered the most suitable for applying to solve the challenges on which this study is focused.

In summary, this investigation demonstrated that specific MCDM techniques are better suited to, and designed for, particular circumstances/scenarios while other applications need to completely ignore them. Also, it was study determined that there is no single standard MCDM method that can both support a PPM's strategic decision making and deal with all its challenges. Moreover, not all portfolio decision-making specifications can be accomplished using current techniques. A few, such as those working with both quantitative and qualitative values might be achieved in the case of a customised application. This review indicated that using particular techniques significantly increases a planning procedure's performance and it would be better to apply more than one MCDM technique or even a hybrid method, with those more useful for PPM problems a combination of MADM and MODM techniques.

The capabilities of the AHP and DEA methods to deal with any type of judgement specifications or factors with both quantitative and qualitative data, the simplicity of their outcomes and their relatively low levels of complexity when managing preferences leads to the conclusion that they are the most effective approaches for the targeted process. They can provide better solutions related to PPM decisions and, in particular, offer the prospect of re-evaluation. Some techniques take significant amounts of a DM's time and usually are not capable of ranking options. The ANP, DRSA, ELECTRE, PROMETHEE, TOPSIS and VIKOR methods were omitted given that, despite the fact that they may take even less time than the AHP or DEA, their solution procedures would still be complicated for a large group of targets while their procedures for a sensitivity examination would be challenging. The evaluation results showed that the AHP and DEA are slightly easier to use than the other methods but, to apply the former for the purpose of PPM decision making would require modifications to it or possibly its integration with other methods that can support both infinite and qualitative data.

Two specified for overcoming the challenges of PPM selection, namely DEA and AHP, which had some limitations, were studied and the issues involved in using each individually identified. Standard DEA models presume that the values of each of the inputs or outputs of DMUs are only positive; in other words, they cannot examine non-positive data. To eliminate this issue, a number of models have been designed with the intention of enhancing the distinguishing factor of DEA. Although the abovementioned methods might be employed as a way of dealing with negative data, they have shortcomings. Therefore, the standard input-/output-oriented radial models produce inaccurate and problematic results because of their disadvantages when determining the significance of negative information in the optimisation procedure. AHP requires many pair-wise comparisons to identify units' efficiency scores and cannot individually support strategic decision-making for a complex PPM.

This study determined that an integrated DEA/AHP method was beneficial and avoided each model's limitations although using a basic DEA model led to the effective units not being reasonably distinguished. In turn, this justified incorporating a peer evaluation mode into the standard DEA model, with a cross-efficiency examination presented by Sexton et al. (1986) included. While applications of cross-efficiency in portfolio assessments have been reported to show significant advantages over approaches based on the standard DEA, some challenges have emerged.

Although Sinuany-Stern et al. (2000) presented a combined DEA/AHP method for arranging DMUs, the selection method could not obtain efficient/inefficient ratings when several inputs and outputs were involved, thereby unreasonably selecting an efficient DMU from inefficient ones. The pair-wise assessment matrix established by Eq. (20) of Sinuany-Stern et al. (2000) consisted of many 'one' variables signifies that a pair of DMUs is regarded as equally efficient. Consequently, many similarities in a pair-wise assessment matrix can cause strict selection of DMUs since the rating weights generated from this matrix can be similar, or even identical, to those of other DMUs. Standard DEA/AHP models are not able to use negative values or simultaneously obtain an efficiency ranking that can be easily employed to assess DMUs. Also, the basic application of only cross-efficiency ranking in portfolio decisions may lead to inadequately expanded portfolios in terms of their efficiency regarding several input/output aspects. Moreover, as a performance analysis using DEA involves both inputs and outputs, a decision matrix of $n \times n$ requires *n* DMUs and *n* outputs. The results are regarded as outputs since they have the features of outputs and a DMU obtaining a high score is preferable to those with lower ones. As a DEA cannot be generated by only outputs, it needs a minimum of one input.

An overview of the integrated AHP/DEA model, cross-efficiency and other methods that can deal with negative variables was conducted. Their drawbacks were identified and a new model, which applied PT to identify the expected return and risk, as well as a modified DEA-CE for properly scoring the efficiency of a DMU using AHP were proposed to deal with them. The portfolio's performance was then combined with the standard PT. A comparison table was produced to enable DMs to select the best assets characterised by the values of the expected return, risk, Sharpe ratio (*SR*) and efficiency scores. Then, based on the outcomes of an examination, a DM could optimise and enhance the efficiency of the original portfolio. The concept of the proposed model is simple: the portfolio with the lowest risk at a given expected return (on investment) can be found with a higher efficiency rank. Using the PT, this study developed a model that enables DMs to modify the expected return and obtain the best portfolio with a minimum risk for that amount which guarantees efficient ratings once negative values are applied. The proposed model determines the cross-efficiency of the DMUs and generates a pair-wise assessment matrix in accordance with each DMU's weights and the outcomes of the assessments of two DMUs. Then, it is normalised using the AHP to produce the final efficiency ranks. Also, it provides objectives which are much easier to obtain than those of other approaches.

The proposed model is inspired by considering that the standard basic use of DEA scores in portfolio selection per se suffers from the problem of the resultant portfolios not being well diversified which is exacerbated by the DEA cross-efficiency evaluation being integrated with the AHP. This study discovered that this problem is due to the basic utilisation of DEA assessment in portfolio selection not taking into account shifts or improvements in weights. This issue is addressed by integrating a modified DEA cross-efficiency and AHP assessment into the PT method in which those risks are simultaneously taken into consideration. All existing methods for measuring efficiency with negative data have some disadvantages whereas the proposed model evaluates the Pareto-Koopmans efficiency of DMUs when the inputs and outputs can be either positive or negative.

A real-life case study consisting of Australia's ten largest companies was also presented to describe the application, accuracy and functionality level of the proposed model with which the results obtained from standard models were also reviewed and compared. Their performance scores revealed significant differences among them, with the proposed model demonstrated to be a promising tool for portfolio selection, and the DEA cross-efficiency approach in the new method more effective than that based on simply using cross-efficiency scores. Also, a decision-support system called the Strategic Portfolio Management Tool (SPMT) was developed to assist DMs to identify the most effective projects/programs in a portfolio. The proposed system not only reduces the amount of effort required to reduce portfolio expenses but is more focused on providing a better decision capability at a lower cost by enhancing the PPM decision making and selection processes to eliminate waste. It simultaneously takes into account the efficiency, expected return, SR and risk of a portfolio. Moreover, the AHP and PT models are considered tools for testing efficiency to check the accuracy of the proposed model. It can deal with a very large number of DMUs and takes the interdependencies of the criteria into account based on the weight of each criterion during the evaluation process, and supports both quantitative and qualitative information. Most importantly, it can handle both positive and negative data, an option not available in most decision-support systems. It can also drive organisational improvements through increasing performance transparency and improving decisions in project/program reporting to senior stakeholders, combining improved data quality with more independent analyses, and focusing on improving collaboration between DMs and their end-users.

The results obtained from this study indicated that applying the proposed model in the contemporary industrial scenario is feasible and adoptable for simultaneously analysing profit, risks and proficiency. The proposed model perceives the subjective and objective aspects and makes the options far more practical and, in general, provides better objectives than the available methods presented in the literature review. Figure 21 presents the full progress of this study from the preliminary literature review and initial research stage to the proposition of a new model for dealing with PPM challenges and selecting the most effective projects/assets in a portfolio.

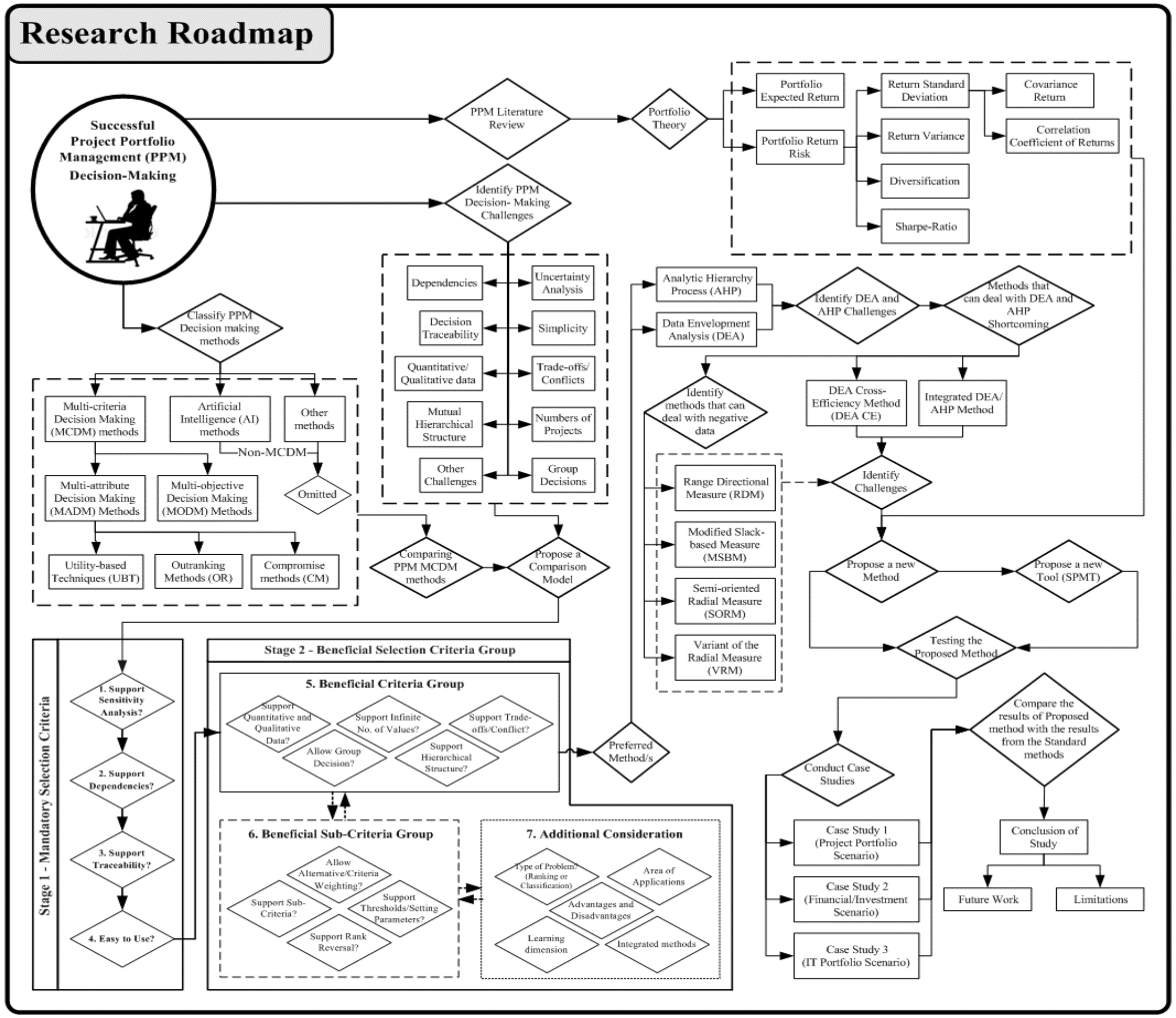

Figure 21. RESEARCH ROADMAP - CHAPTER VII

7.2. LIMITATIONS

That DMs are simply ready to take higher levels of risk given considerably better than expected returns is often contradicted by their decisions. Usually, investment methods require that they undertake an investment considered risky to minimise the total risk with no noticeable improvement in expected returns (McClure, 2010). Moreover, DMs possess particular powers which could outweigh considerations regarding the delivery of returns.

The PT presumes all the data from DMs regarding their investments are regularly received. However, in fact, world markets represent data irregularly and some DMs may be much better informed than others (Bofah, unknown) which may explain why organisations usually purchase below market value.

Another key idea is that DMs have an almost infinite capability to lend at a risk-free interest rate. In reality, each DM carries credit limitations and only the government can frequently access interest-free funds (Morien, unknown). The PT aims to minimise the risk on returns while taking no notice of environmental or strategic aspects. In reality, there is no factor called a risk-free asset (McClure, 2010).

Although the PT considers the possibility of choosing portfolios with different efficiencies than others, market records verified that there are no tools for accomplishing this (McClure, 2010).

A company's investment outlook is based on a project-level analysis of a number of factors to assess the probability that a project moves to the development stage. Usually, case studies draw on projects currently in the development phase or being assessed as having a good possibility of progressing to closure. Projects for which information can be obtained are evaluated according to their positions in terms of applicable management expenses and their internal return levels. Given that an examination is possibility-dependent, there is some doubt regarding the results of the projects considered and their progression to the closing phase. Moreover, typically, estimates created at a project level may not be incorporated since some of the data employed may be addressed as commercial-in-confidence.

7.3. FUTURE WORK

This study might be extended in several potential ways, as summarised in the following.

1- Even if the case study presented in this document empirically promotes the success and ability of the suggested method for portfolio selection, other sorts of objectives or perhaps restrictions may be included in future models (e.g. skewness and kurtosis).

2- It is likely to choose only DMUs with at least moderately good performances for all measures and exclude those with good performances on only a subset. As this leads to the selection of a specialised portfolio comprising similar DMUs, it lacks diversification. As Tofallis (1996) demonstrated, in the event that two DMUs obtain the same variable degrees, they will use the same weights and increase each other's cross-efficiency ranking. If the remaining DMUs do not have similar variable degrees, they will be disadvantaged since they are separated in the cross-efficiency assessment. Consequently, either one or both DMUs might become the more efficient given that they successfully provide large ranks to one another. If one DMU's factor levels are very different from those of the others, it has significantly less potential to become efficient. This phenomenon is aggravated as the distribution of DMUs' locations is skewed which, again, leads to the selection of a specialised portfolio consisting of relatively similar DMUs that, in turn, lacks diversification.

3- For an in-depth view of risk, a Monte Carlo simulation consisting of an organised process of sensitivity investigation that clearly includes the uncertainties in methods, such as financial estimations or schedules, in which statistical computations often turn out to be complex or unrealistic when the quantity of tasks increases, might be employed (Cooper et al., 2001a). Rather than conducted as an examination, a Monte Carlo simulation may be applied like a random sampling technique to approximate values. According to several approximated results and their specific likelihoods, such a simulation operates on many random, feasible what-if situations in an iterative loop to display possibilities. Its obtained outcome forms the technique's overall submission which is why it is very easy to understand (Schuyler, 2001).

4- As the quality of the outcomes of the DEA is dependent on its collected inputs/outputs, quality measures, such as satisfaction and/or awareness levels, may also be incorporated in the model. As the DEA uses a variety of inputs/outputs, collecting these parameters is a challenging task. Although this is referred to mainly as a DM's personal decision, as there may be better ways of selecting the input/output factors for an efficient examination, experts may establish a structure for this task.

5- As not every new portfolio can be implemented from development to closure, only those in the probability phases may be selected for further investigation. More research on the quality of a company’s finances, resources and operating costs, and its capability to attract finance and returns on investment would be beneficial for determining the possibility of each project providing the prospect of obtaining future investment from the particular industry’s market.

6- SPMT identifies projects/programs/investments at the portfolio level. If any other sub-projects within it are deemed reportable, investigations are required by the business to adjust any anomalies. A SPMT solution will enable DMs to adjust the number of projects/programs/investments in a portfolio and it is also beneficial to add comments to their performance reports which include cost and/or schedule variations.

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ANNEX A - MCDM METHODS REFERENCES

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Data Envelopment Analysis (DEA) (e.g., Cooper, Seiford, & Zhu, 2004a); Decision EXpert (DEX) (e.g., Bohanec & Rajkovič, 1990); Decision matrix (DM) (e.g., Hawass, 1997); Dependence-based Interval-valued ER (DIER) (e.g., Fu & Yang, 2012); Dominance-based Rough Set Approach (DRSA) (e.g., Greco, Matarazzo, & Słowiński, 2007); ELimination and Choice Translating REality (ELECTRE) (e.g., Figueira, Mousseau, et al., 2005); Evidence Reasoning (ER) (e.g., Zhang, Da Xu, Zhang, & Li, 2003); Evidential Reasoning approach (ERA) (e.g., Yang & Singh, 1994); Failure Mode and Effect Analysis (FMEA) (e.g., Hollenback, 1977); Fuzzy Set Theory (FST) (e.g., Zimmermann, 2010); Genetic Algorithm (GA) (e.g., Tanaka, Watanabe, Furukawa, & Tanino, 1995); GAIA (e.g., Hayez, Mareschal, & De Smet, 2009; Lidouh, De Smet, & Zimányi, 2009); Goal Programming (GP) (e.g., Lee, 1972); Grey Relation Analysis (GRA) (e.g., Hsia & Wu, 1998); Hasse Diagram Technique (HDT) (e.g., Bruggemann & Voigt, 2008; Simon, Kübler, & Böhner, 2007); House of Quality (HOQ) (e.g., er Tapke, son Muller, Johnson, & Sieck, 1997); Index Decomposition Analysis (IDA) (e.g., Ang & Zhang, 2000); Inner Product of Vectors (IPV) (e.g., Wang, Yang, Waters, & Zhang, 2011); Integer Linear Programming (ILP) (e.g., Abara, 1989); Interactive Minimax Reference Point (IMRP) (e.g., Yang, Xu, & Yang, 2012); Interpretive Structural Modeling (ISM) (e.g., Malone, 1975); IRIS (e.g., Dias, Mousseau, Figueira, Clímaco, & Silva, 2002); Lexicographic Goal Programming (LGP) (e.g., Rees, Clayton, & Taylor, 1985); Linear Programming (LP) (e.g., Dantzig, 1998); Linear Programming Techniques for Multidimensional Analysis of Preference (LINMAP) (e.g., Srinivasan & Shocker, 1973); Measuring Attractiveness by a categorical Based Evaluation Technique (MACBETH) (e.g., Bana e Costa, Corte, & Vansnick, 2011); Multicriterion Q-analysis (MCQA) (e.g., Duckstein, Kempf, & Casti, 1984; Eder, Duckstein, & Nachtnebel, 1997); Meta-heuristics (MH) (e.g., Osman & Kelly, 1996); Mixed Integer Programming (MIP) (e.g., Wolsey, 2008); Monte Carlo Simulation (MCS) (e.g., Mooney, 1997); Multi-attribute Global Inference of Quality (MAGIQ) (e.g., McCaffrey, 2005); Multi-attribute Utility Theory (MAUT) (e.g., Mateo, 2012); Multi-attribute Value Theory (MAVT) (e.g., Hostmann, Bernauer, Mosler, Reichert, & Truffer, 2005); Multicriterion Analysis of Preferences by means of Pairwise Alternatives and Criterion comparisons (MAPPAC) (e.g., Matarazzo, 1984); Multi-objective Optimization by Ratio Analysis plus Full Multiplicative Form (MULTIMOORA) (e.g., Brauers & Zavadskas, 2010); Multi-objective Optimization on the basis of Ratio Analysis (MOORA) (e.g., Brauers & Zavadskas, 2006); Multi-objective Programming (MOP) (e.g., Zografos & Davis, 1989); Multiplicative Exponent Weighting (MEW) (e.g., Zhengkun, L. et al. 2012); Novel Approach to Imprecise Assessment and Decision Environment (NAIDE) (e.g., Cancelliere, Giuliano, & Longheu, 2003; Naidu, Sawhney, & Li, 2008); Nonlinear Programming Model (NLP) (e.g., Tyteca, 1981); Ordered Weighted Averaging (OWA) (e.g., Yager, 1988); Organization, Rangement Et Synthese De Donnes Relationnelles (ORESTE) (e.g., Chatterjee & Chakraborty, 2013); Potentially All Pairwise Rankings of all possible alternatives (PAPRIKA) (e.g., Dalgaard, Heikkilae, & Koskinen, 2014); Preemptive Goal Programming (PGP) (e.g., Wang & Parkan, 2007); Preference Ranking Global frequencies in Multicriterion Analysis (PRAGMA) (e.g., Matarazzo, 1988); Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) (e.g., Mareschal, Brans, & Vincke, 1984); Principal Component Analysis (PCA) (e.g., Jolliffe, 1986); Pugh Evaluation Matrix (PEM) (e.g., Pugh & Clausing, 1996); Quality function deployment (QFD) (e.g., Chan & Wu, 2002); REMBRANDT (e.g., Lootsma, 1992); Rough Set Approach (RSA) (e.g., Pawlak & Sowinski, 1994); Simple Additive Weighting (SAW) (e.g., Afshari, Mojahed, & Yusuff, 2010); Stochastic Multi-criteria Acceptability Analysis (SMAA) (e.g., Lahdelma & Salminen, 2001); Simple Multi-attribute Rating Technique (SMART) (e.g., Valiris, Chytas, & Glykas, 2005); Stochastic Programming (SP) (e.g., Birge & Louveaux, 2011); Superiority and Inferiority Ranking (SIR) (e.g., Jian-qiang, 2004); Total Cost of Ownership (TCO) (e.g., Ellram & Siferd, 1998; Ferrin & Plank, 2002); Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (e.g., Chen, 2000); Theory of Inventive Problem Solving (TRIZ) (e.g., Altshuller & Shulyak, 1996); Tratement des Actions Compte Tenu de l'Importance des Crite'res (TACTIC) (e.g., Vansnick, 1986); Utility Theory Additive (UTA) (e.g., Jacquet-Lagreze & Siskos, 1982); Value Analysis (VA) (e.g., Miles, 1961); Value Engineering (VE) (e.g., Caijiang, Kehua, & Yongmei, 2002); VIP (e.g., Dias & Clímaco, 2000); VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (e.g., El-Santawy, 2012); Weighted Linear Assignment Method (WLAM) (e.g., Zhou, Jia, Xie, Chang, & Tang, 2012); Weighted Product Model (WPM) (e.g., Savitha & Chandrasekar, 2011b); Weighted Sum Model

(WSM) (e.g., Goh, Tung, & Cheng, 1996); ZAPROS (e.g., Larichev, 2001; Tamanini & Pinheiro, 2008); Zero-One Goal Programming (ZOGP) (e.g., GAME & TWO-PERSON, 1996) and Z-W (e.g., Fang, 2008).

ANNEX B - DOWN-SELECTION OF DECISION-MAKING METHODS

List of all decision-making methods used in this study
Activity Based Costing (ABC), Additive Ratio Assessment (ARAS), Aggregated Indices Randomization Method (AIRM), Analysis of Variance (ANOVA), Analytic hierarchy process (AHP), Analytic Network Process (ANP), Ant colony algorithm (ACA), ARGUS, Artificial Neural Network (ANN), Association Rule (AR), Axiomatic design (AD), Balanced Scorecard (BSC), Bayesian Networks (BN), Best Worst Method (BWM), Canonical Correlation Analysis (CCA), Cased Based Reasoning (CBR), Cellular Automata (CA), Chance Constrained and Genetic Algorithm (CCGA), Chance Constraint DEA (CCDEA), Characteristic Objects METhod (COMET), Choosing By Advantages (CBA), COmplex Proportional ASsessment (COPRAS), Comprehensive Algorithm (CA), Compromise programming (CP), Constant Return to Scale (CRS), Corrected Ordinary Least Squares (COLS), Data Envelopment Analysis (DEA), Decision EXpert (DEX), Decision Making Trial and Evaluation Laboratory (DEMATEL), Decision matrix (DM), Decision tree (DT), Delphi, Dempster–Shafer theory (DST), Dependence-based Interval-valued ER (DIER), Design for X (DFX), Disaggregation – Aggregation Approaches (UTA*, UTAII, UTADIS), Dominance-based Rough Set Approach (DRSA), ELimination and Choice Translating REality (ELECTRE), Evidence Reasoning (ER), Evidential Reasoning approach (ERA), Failure Mode and Effect Analysis (FMEA), Fuzzy Set Theory (FST), Fuzzy Synthetic Evaluation Method (FSEM), Genetic Algorithm (GA), Goal Programming (GP), Grey Relation Analysis (GRA), Grey System Theory (GST), Group Support Systems (GSS), House of Quality (HOQ), Index Decomposition Analysis (IDA), Inner Product of Vectors (IPV), Integer Linear Programming (ILP), Interactive Minimax Reference Point (IMRP), Interpretive Structural Modeling (ISM), IRIS, Just-In-Time (JIT), Knapsack , Knowledge Communities (KC), Lexicographic Goal Programming (LGP), Linear Programming (LP), Linear Programming Techniques for Multidimensional Analysis of Preference (LINMAP), Logarithmic Mean Divisia Index (LMDI), Measuring Attractiveness by a categorical Based Evaluation Technique (MACBETH), Meta-heuristics (MH), Mixed Integer Programming (MIP), Monte Carlo Simulation (MCS), Multi-attribute Global Inference of Quality (MAGIQ), Multi-attribute Utility Theory (MAUT), Multi-attribute Value Theory (MAVT), Multicriterion Analysis of Preferences by means of Pairwise Alternatives and Criterion comparisons (MAPPAC), Multi-objective Optimization by Ratio Analysis plus Full Multiplicative Form (MULTIMOORA), Multi-objective Optimization on the basis of Ratio Analysis (MOORA), Multi-objective Programming (MOP), Multiplicative Exponent Weighting (MEW), Neural Networks (NN), New Approach to Appraisal (NATA), Nonlinear Programming Model (NLP), Nonliner Mathematical Programme (NLMP), Nonstructural Fuzzy Decision Support System (NSFDSS), Numerical Taxonomy (NT), Optimization Techniques (OP), Ordered Weighted Averaging (OWA), Organization, Rangement Et Synthese De Donnes

Relationnelles (ORESTE), Particle Swarm Optimization (PSO), Potentially All Pairwise Rankings of all possible alternatives (PAPRIKA), Preemptive Goal Programming (PGP), Preference Ranking Global frequencies in Multicriterion Analysis (PRAGMA), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Principal Component Analysis (PCA), Pugh Evaluation Matrix (PEM), Quality function deployment (QFD), REMBRANDT, Robust design (RD), Rough Set Approach (RSA), Rough Set Theory (RST), Simple Additive Weighting (SAW), Simple Multi-attribute Rating Technique (SMART), Stochastic Frontier Analysis (SFA), Stochastic Multi-criteria Acceptability Analysis (SMAA), Stochastic Programming (SP), Strength Weakness Opportunity Threats (SWOT), Structural Equation Modeling (SEM), Superiority and Inferiority Ranking (SIR), Supply Chain Operations Reference (SCOR), Support Vector Machine (SVM), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Theory of Inventive Problem Solving (TRIZ), Total Cost of Ownership (TCO), Tratement des Actions Compte Tenu de l'Importance des Crite'res (TACTIC), Utility Theory Additive (UTA), Value Analysis (VA), Value Engineering (VE), Variable Returns to Scale (VRS), VIP, VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Weighted Product Model (WPM), Weighted Sum Model (WSM), and Zero-One Goal Programming (ZOGP).	
Criteria 1: Only MCDM methods (MADM and MODM)	**78 methods identified**
MADM Methods	**44 methods identified**
UBT Methods	24 methods identified
Additive Ratio Assessment (ARAS), Analytic hierarchy process (AHP), Analytic Network Process (ANP), Artificial Neural Network (ANN), COmplex Proportional ASsessment (COPRAS), Decision matrix (DM), Dependence-based Interval-valued ER (DIER), Evidence Reasoning (ER), Evidential Reasoning approach (ERA), Inner Product of Vectors (IPV), Linear Programming Techniques for Multidimensional Analysis of Preference (LINMAP), Measuring Attractiveness by a categorical Based Evaluation Technique (MACBETH), Multi-attribute Utility Theory (MAUT), Multi-attribute Value Theory (MAVT), Multicriterion Analysis of Preferences by means of Pairwise Alternatives and Criterion comparisons (MAPPAC), Multi-objective Optimization by Ratio Analysis plus Full Multiplicative Form (MULTIMOORA), Multi-objective Optimization on the basis of Ratio Analysis (MOORA), Preference Ranking Global frequencies in Multicriterion Analysis (PRAGMA), Pugh Evaluation Matrix (PEM), REMBRANDT, Simple Additive Weighting (SAW), Utility Theory Additive (UTA), Weighted Product Model (WPM), and Weighted Sum Model (WSM).	
OR Methods	16 methods identified

Aggregated Indices Randomization Method (AIRM), ARGUS, Best Worst Method (BWM) , Choosing By Advantages (CBA), Dominance-based Rough Set Approach (DRSA), ELimination and Choice Translating REality (ELECTRE), IRIS, Multiplicative Exponent Weighting (MEW), Ordered Weighted Averaging (OWA) Organization, Rangement Et Synthese De Donnes Relationnelles (ORESTE), Potentially All Pairwise Rankings of all possible alternatives (PAPRIKA), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Quality function deployment (QFD), Superiority and Inferiority Ranking (SIR), Tratement des Actions Compte Tenu de l'Importance des Crite'res (TACTIC), and VIP.	
CM Methods	4 methods identified
Comprehensive Algorithm (CA), Compromise programming (CP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR).	
MODM Methods	**34 methods identified**
MP Methods	34 methods identified
Axiomatic design (AD), Balanced Scorecard (BSC), Chance Constraint DEA (CCDEA), Characteristic Objects METhod (COMET), Corrected Ordinary Least Squares (COLS), Data Envelopment Analysis (DEA), Decision EXpert (DEX), Failure Mode and Effect Analysis (FMEA), Fuzzy Set Theory (FST), Goal Programming (GP) Grey Relation Analysis (GRA), House of Quality (HOQ), Index Decomposition Analysis (IDA), Integer Linear Programming (ILP), Interactive Minimax Reference Point (IMRP), Interpretive Structural Modeling (ISM), Lexicographic Goal Programming (LGP), Linear Programming (LP), Meta-heuristics (MH), Mixed Integer Programming (MIP), Monte Carlo Simulation (MCS), Multi-attribute Global Inference of Quality (MAGIQ), Multi-objective Programming (MOP), Nonlinear Programming Model (NLP), Nonliner Mathematical Programme (NLMP), Preemptive Goal Programming (PGP), Principal Component Analysis (PCA), Rough Set Approach (RSA), Stochastic Multi-criteria Acceptability Analysis (SMAA), Stochastic Programming (SP), Theory of Inventive Problem Solving (TRIZ), Value Analysis (VA), Value Engineering (VE), and Zero-One Goal Programming (ZOGP).	
Criteria 2: Only those supporting Sensitivity Analysis	**46 methods identified**
Aggregated Indices Randomization Method (AIRM), Analytic hierarchy process (AHP), Analytic Network Process (ANP), Artificial Neural Network (ANN), Balanced Scorecard (BSC), Chance Constraint DEA (CCDEA), Choosing By Advantages (CBA), COmplex Proportional ASsessment	

(COPRAS), Data Envelopment Analysis (DEA), Decision matrix (DM), Dependence-based Interval-valued ER (DIER), Dominance-based Rough Set Approach (DRSA), ELimination and Choice Translating REality (ELECTRE), Evidence Reasoning (ER), Evidential Reasoning approach (ERA), Fuzzy Set Theory (FST), Goal Programming (GP), Integer Linear Programming (ILP), Interactive Minimax Reference Point (IMRP), Lexicographic Goal Programming (LGP), Linear Programming (LP), Measuring Attractiveness by a categorical Based Evaluation Technique (MACBETH), Mixed Integer Programming (MIP), Monte Carlo Simulation (MCS), Multi-attribute Utility Theory (MAUT), Multi-attribute Value Theory (MAVT), Multi-objective Optimization by Ratio Analysis plus Full Multiplicative Form (MULTIMOORA), Multi-objective Optimization on the basis of Ratio Analysis (MOORA), Multi-objective Programming (MOP), Nonlinear Programming Model (NLP), Nonliner Mathematical Programme (NLMP), Ordered Weighted Averaging (OWA), Organization, Rangement Et Synthese De Donnes Relationnelles (ORESTE), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Quality function deployment (QFD), Rough Set Approach (RSA), Simple Additive Weighting (SAW), Stochastic Multi-criteria Acceptability Analysis (SMAA), Stochastic Programming (SP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Utility Theory Additive (UTA), Value Analysis (VA), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Weighted Product Model (WPM), Weighted Sum Model (WSM), and Zero-One Goal Programming (ZOGP).	
Criteria 3: Only those supporting dependencies or does not require dependencies	**28 methods identified**
Analytic hierarchy process (AHP), Analytic Network Process (ANP), Artificial Neural Network (ANN), Balanced Scorecard (BSC), Chance Constraint DEA (CCDEA), Choosing By Advantages (CBA), COmplex Proportional ASsessment (COPRAS), Data Envelopment Analysis (DEA), Decision matrix (DM), Dependence-based Interval-valued ER (DIER), Dominance-based Rough Set Approach (DRSA), ELimination and Choice Translating REality (ELECTRE), Evidential Reasoning approach (ERA), Goal Programming (GP), Interactive Minimax Reference Point (IMRP), Multi-attribute Utility Theory (MAUT), Multi-attribute Value Theory (MAVT), Multi-objective Optimization on the basis of Ratio Analysis (MOORA), Nonlinear Programming Model (NLP), Nonliner Mathematical Programme (NLMP), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Stochastic Multi-criteria Acceptability Analysis (SMAA), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Utility Theory Additive (UTA), Value Analysis (VA), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Weighted Sum Model (WSM), and Zero-One Goal Programming (ZOGP).	
Criteria 4: Only those supporting decision traceability	**11 methods identified**

Analytic hierarchy process (AHP), Analytic Network Process (ANP), Artificial Neural Network (ANN), Complex Proportional ASsessment (COPRAS), Data Envelopment Analysis (DEA), Dominance-based Rough Set Approach (DRSA), ELimination and Choice Translating REality (ELECTRE), Multi-attribute Utility Theory (MAUT), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR).	
Criteria 5: Only Simple or moderate methods	**8 methods identified**
Analytic hierarchy process (AHP), Analytic Network Process (ANP), Data Envelopment Analysis (DEA), Dominance-based Rough Set Approach (DRSA), ELimination and Choice Translating REality (ELECTRE), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR).	

ANNEX C - TOP EIGHT PPM MCDM METHODS COMPARISON TABLE

		Requirements	AHP	ANP	DEA	DRSA	ELECTRE	PROMETHEE	TOPSIS	VIKOR
Main Criteria	1	*Supporting Sensitivity Analysis* [1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes and No
	2	*Supporting Dependencies* [2]	Yes	Yes	Yes	Yes and No	Yes	Yes	Yes	Yes
	3	*Supporting Decision Traceability*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	4	*Simplicity Level* [3]	3	2	3	2	1	2	1	1
Beneficial Criteria	5.1	*Supporting Quantitative Data*	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
	5.1	*Supporting Qualitative Data*	No	No	Yes	Yes	No	No	No	No
	5.2	*Supporting Infinite number of values*	No	No	Yes	No	No	No	No	No
	5.3	*Supporting Tradeoffs / Conflict*	No	No	Yes	No	No	No	No	No
	5.4	*Supporting Group Decision*	No	Yes	Yes	No	No	No	No	No
	5.5	*Supporting Hierarchical Structure*	Yes	Yes	No	No	No	No	No	No
Beneficial Sub-criteria	6.1	*Supporting Thresholds/Setting Parameters* [4]	No	No	Yes	Yes	Yes	Yes	No	Yes
	6.2	*Allowing criteria weighting* [5]	Yes	Yes and No	Yes	No	No	Yes	Yes	Yes
	6.2	*Allowing alternative weighting* [5]	Yes	Yes and No	Yes	No	No	No	No	No
	6.3	*Supporting rank reversal*	No	No	Yes	No	No	No	No	No
	6.4	*Supporting sub-criteria*	Yes	Yes	Yes	No	No	Yes	No	Yes
Additional consideration during the selection process	7.1	*Type of Problem*	Ranking	Ranking	Ranking / Classification	Classification	Ranking / Classification	Ranking	Ranking	Ranking
	7.2	*Some Advantages*	Can be used in almost any type of subject; Easy to use; scalable; hierarchy structure can easily adjust to fit many sized problems; lots of tools are available; not data intensive.	Can get ranking of a set of alternatives in terms of a finite number of decision criteria. Allows grouping of criteria.	It does not require pre-estimated variables. It is capable of handling multiple inputs and outputs; efficiency can be analysed and quantified; weights assigned to outputs and inputs are not allocated by users.	Handles missing values and qualitative and qualitative data. The method is not limited to a specific field and could be used for a wide variety of real-life problems; does not require any data transformation; and is able to handle uncertainty.	They avoid compensation between criteria and any normalization process. Takes uncertainty and vagueness into account. Does not need criteria weights.	Easy to use; does not require assumption that criteria are proportionate; allows to operate directly on the variables included in the decision matrix without requiring any normalisation; User friendly tools available.	Has a simple process; easy to use and program; the number of steps remains the same regardless of the number of attributes; allows selecting only one solution as the "best" one and it is able to manage each kind of variables and each type of criteria; and There are also multiple tools that support this method.	Evaluates several possible alternatives according to multiple conflicting criteria and rank them from the worst to the best one; it is not necessary to perform consistency test; and simple to use and implement.
	7.3	*Some Disadvantages*	Problems due to interdependence between criteria and alternatives; can lead to inconsistencies between judgment and ranking criteria; rank reversal problem;only supports qualitative values; a limited number of criteria can be applied.	Only a limited number of criteria and alternatives can be applied. This method suffers from the rank reversal problem. It may be very difficult to create own implementation of ANP in Excel spreadsheet. it ignores the different effects among clusters.	Does not deal with imprecise data; assumes that all input and output are exactly known; the results can be sensitive depending on the inputs and outputs; DEA does not work with negative or zero values for inputs and outputs.	Limited by the previous experience; DRSA could suffer from rank reversal	Its process and outcome can be difficult to explain in layman's terms; sometimes is unable to identify the preferred alternative; does not have these characteristics; outranking causes the strengths and weaknesses of the alternatives to not be directly identified. Criteria Weights are not supported.	Does not provide a clear method by which to assign weights; is needed that each criterion is of the benefit type; handle only quantitative and missing values; and suffers from the rank reversal problem.	Its use of Euclidean Distance does not consider the correlation of attributes; difficult to weight and keep consistency of judgment; it does not support uncertain or missing values; and suffers from rank reversal problem.	Not tools available for this method. It is not able to handle incomplete and uncertain information. Suffers from the rank reversal problem
	7.4	*Area of Applications*	Performance-type problems, resource management, government, corporate policy and strategy, public policy, political strategy, planning, supplier selection, and…	Logistic services, services selection, manufacturing performance, IT system project selection, hazardous substance management, forest management, planning, and …	Economics, medicine, utilities, road safety, agriculture, construction, water resources, retail, business problems, banking, operational efficiency, aviation, and …	Medicine, Education, Finance, IT, Medical practice, Cryptography, IGS, and…	Energy, economics, environmental, water management, transportation problems, and …	Environmental, hydrology, water management, business and finance, chemistry, logistics and transportation, manufacturing and assembly, energy, agriculture, and …	Supply chain management and logistics, engineering, manufacturing systems, business and marketing, environmental, human resources, water resources, and …	Multi-criteria optimisation of complex systems, business management, water resources, material selection, supplier selection, forestry, land subdivisions, and …
	7.5	*Integrated methods*	ANP, DEA, ELECTRE, PROMETHEE, TOPSIS, VIKOR	AHP, DEA,PROMETHEE, TOPSIS, VIKOR	AHP, ANP, PROMETHEE, TOPSIS, VIKOR	AHP, ANP, TOPSIS	AHP, PROMETHEE	AHP, ANP, DEA, ELECTRE	AHP, ANP, DEA, VIKOR	AHP, ANP, DEA, TOPSIS
	7.6	*Learning dimension*	Difficult	Difficult	Possible	Difficult	Difficult	Possible	Possible	Difficult
References		*Literature References*	Saaty, 1980	Saaty, 2001	Charnes et al., 1994	Greco et al., 2007	Benayoum et al.1966	Mareschal et al. 1984	Lai et al. 1994	Opricovic et al. 2004

	Comparision Summary		
	Methods	Score	Rank
1	AHP	11	2
2	ANP	9	3
3	DEA	15	1
4	DRSA	7	5
5	ELECTRE	6	8
6	PROMETHEE	9	4
7	TOPSIS	6	7
8	VIKOR	7	6

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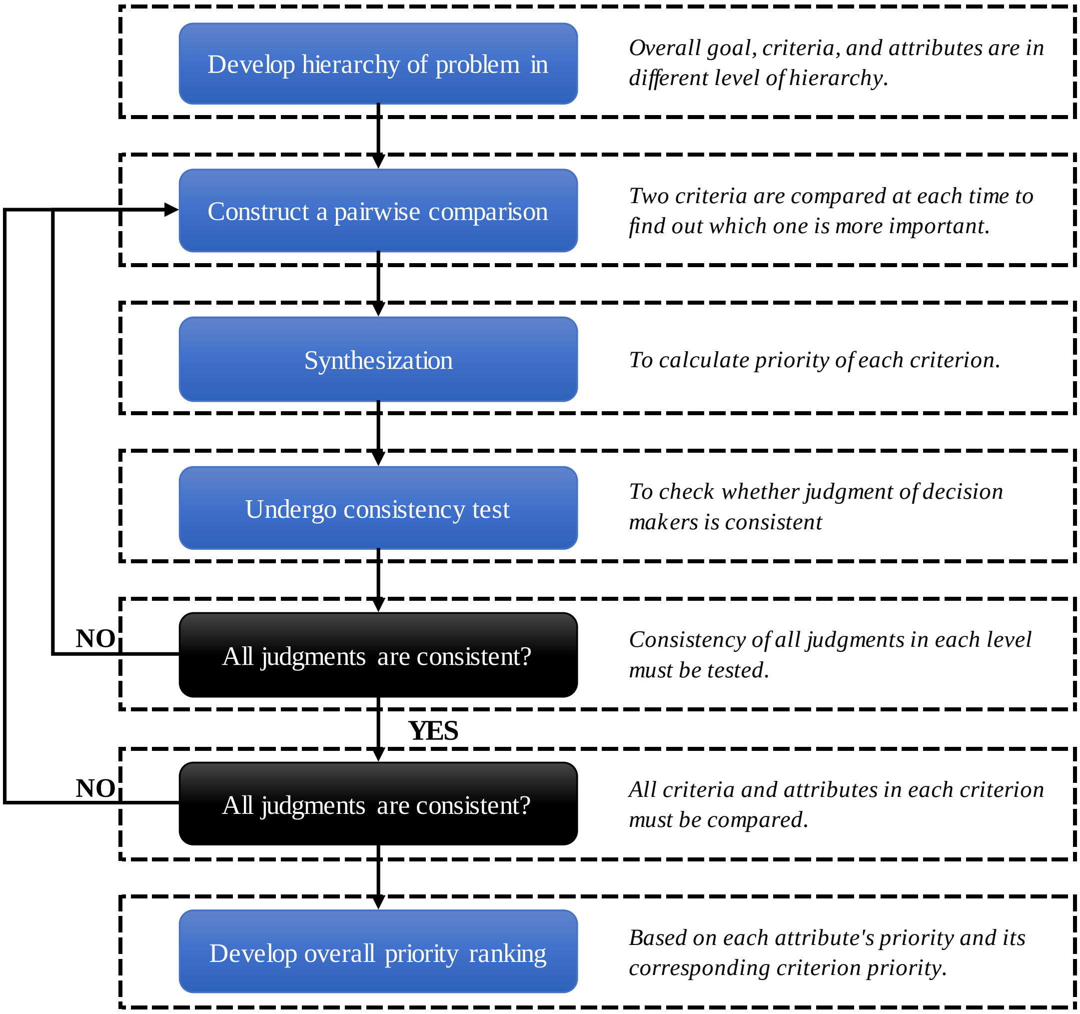
NOTE:

[1] DEA, DSRA, ELECTRE as well as PROMETHEE are able to manage unknown data better than AHP, ANP and TOPSIS through possibility distributions together with thresholds management.
[2] DRSA can only support the interdependencies between alternatives.
[3] 1= Complex; 2= Moderate; 3= Simple
[4] PROMETHEE is subject to the time-intensive thresholds verification, however it is easier to learn and apply instead of ELECTRE.
[5] ANP undermines the outcomes of weighing the clusters.

ANNEX D - AHP FLOWCHART



The flowchart of the Analytic Hierarchy Process (Ho et al., 2006).

ANNEX E - MCDM METHODS AVAILABLE SOFTWARE

Method	Software name	Links
AHP	Expert Choice:	http://www.expertchoice.com/
	Mind Decider:	http://www.minddecider.com
	HIPRE 3+:	http://sal.aalto.fi/en/resources/downloadables/hipre3
	MAkeItRational:	www.makeitrational.com/
	Transparent Choice:	www.transparentchoice.com/
	Decision Analysis Module for Excel (DAME):	http://ironcake.blogspot.com.au/p/download-dame.html
	ChoiceResults:	http://choiceresults.win7dwnld.com/
	123AHP (Online):	http://123ahp.com/Izracun.aspx
	Decisions Lens:	http://www.decisionlens.com
	Super Decisions:	http://www.superdecisions.com
ANP	ANP SOLVER:	http://kkir.simor.ntua.gr/anpsolver.html
	WEB ANP SOLVER:	http://kkir.simor.ntua.gr/web-anp-solver.html
	Decisions Lens:	http://www.decisionlens.com
	Super Decisions:	http://www.superdecisions.com
DEA	DEA-Solver-Pro:	www.saitech-inc.com
	Frontier Analyst:	www.banxia.com
	OnFront:	www.emq.com
	Warwick DEA:	www.deazone.com
	DEA Excel Solver:	www.deafrontier.com
	DEAP:	http://www.uq.edu.au/economics/cepa/deap.htm
	EMS: Efficiency Measurement System:	http://www.holger-scheel.de/ems/
	PIONEER 2:	http://faculty.smu.edu/barr/pioneer
	Win4DEAP:	http://www8.umoncton.ca/umcm-deslierres_michel/dea/install.html
	DEAFrontier:	http://www.deafrontier.net/software.html
DSRA	4eMka2:	http://idss.cs.put.poznan.pl/site/60.html#c80

	jMAF:	http://www.cs.put.poznan.pl/jblaszczynski/Site/jRS.html
ELECTRE	ELECTRE III/IV:	http://www.lamsade.dauphine.fr/~mayag/links.html
	ELECTRE TRI:	http://www.lamsade.dauphine.fr/~mayag/links.html
PROMETHEE	Visual PROMETHEE Academic:	http://www.promethee-gaia.net/software.html
	PROMETHEE:	www.smart-picker.com
TOPSIS	Triptych:	www.stat-design.com/Software/Triptych.html
VIKOR	N/A	No software available.
Multi-Software	SANA (Electre I & 3, Topsis, Promethee II):	http://nb.vse.cz/~jablon/sanna.htm
	Decision Deck:	http://www.decision-deck.org/
	DECERNS (AHP, PROMETHEE and TOPSIS):	http://deesoft.ru/lang/en

ANNEX F - STANDARD MODELS RESULTS

1. Standard Data Envelopment Analysis (DEA) Input-oriented (I) Constant Returns to Scale (CRS)

					Weights				Improvements				
DMU	**Input1**	**Input2**	**Output1**	**Output2**	**Input1**	**Input2**	**Output1**	**Output2**	**Input1**	**Input2**	**Output1**	**Output2**	**Efficiency**
DMU1	1	4.486161	0	0.689124	1.0000	0.0000	0.0000	1.080049	0.744287	0.0000	3.563239	0.68912355	74.42875
DMU2	1	0.430017	0	0.373543	1.0000	0.0000	0.0000	1.080049	0.403445	0.0000	1.931474	0.373543443	40.34454
DMU3	1	0	2.026055	0.246631	1.0000	0.0000	0.208879	0.0000	0.423201	0.0000	2.026055	0.391835082	42.32013
DMU4	1	2.737628	0	0.844466	1.0000	0.0000	0.0000	1.080049	0.912065	0.0000	4.366467	0.844466378	91.20654
DMU5	1	0	0.131739	0.416069	1.0000	0.0000	0.0000	1.080049	0.449375	0.0000	2.151359	0.416068616	44.93747
DMU6	1	0	0.667096	0.376906	1.0000	0.0000	0.0000	1.080049	0.407078	0.0000	1.948864	0.376906488	40.70776
DMU7	1	0	2.542196	0.287517	1.0000	0.0000	0.208879	0.0000	0.531013	0.0000	2.542196	0.491655872	53.10126
DMU8	1	0	1.351179	0.476039	1.0000	0.0000	0.0000	1.080049	0.514145	0.0000	2.461445	0.476038641	51.41453
DMU9	1	1.782823	0	0.386048	1.0000	0.0000	0.0000	1.080049	0.41695	0.0000	1.996129	0.386047544	41.69504
DMU10	1	0	4.78745	0.925884	1.0000	0.0000	0.208879	0.0000	1.0000	0.0000	4.78745	0.925883558	100

2. DEA I-CRS Cross-efficiency (CE)

DMU	**DMU1**	**DMU2**	**DMU3**	**DMU4**	**DMU5**	**DMU6**	**DMU7**	**DMU8**	**DMU9**	**DMU10**	**Total**	**Efficiency**
DMU1	0.744287	0.403445	0.266374	0.912065	0.449375	0.407078	0.310533	0.514145	0.41695	1.0000	5.424253	0.521001243
DMU2	0.744287	0.403445	0.266374	0.912065	0.449375	0.407078	0.310533	0.514145	0.41695	1.0000	5.424253	0.282411765
DMU3	0.0000	0.0000	0.423201	0.0000	0.027518	0.139343	0.531013	0.282234	0.0000	1.0000	2.403308	0.313421907
DMU4	0.744287	0.403445	0.266374	0.912065	0.449375	0.407078	0.310533	0.514145	0.41695	1.0000	5.424253	0.638445795
DMU5	0.744287	0.403445	0.266374	0.912065	0.449375	0.407078	0.310533	0.514145	0.41695	1.0000	5.424253	0.322817559
DMU6	0.744287	0.403445	0.266374	0.912065	0.449375	0.407078	0.310533	0.514145	0.41695	1.0000	5.424253	0.326757155
DMU7	0.0000	0.0000	0.423201	0.0000	0.027518	0.139343	0.531013	0.282234	0.0000	1.0000	2.403308	0.376676825
DMU8	0.744287	0.403445	0.266374	0.912065	0.449375	0.407078	0.310533	0.514145	0.41695	1.0000	5.424253	0.444571763
DMU9	0.744287	0.403445	0.266374	0.912065	0.449375	0.407078	0.310533	0.514145	0.41695	1.0000	5.424253	0.291865298
DMU10	0.0000	0.0000	0.423201	0.0000	0.027518	0.139343	0.531013	0.282234	0.0000	1.0000	2.403308	1.0000
Average	**0.521001**	**0.282412**	**0.313422**	**0.638446**	**0.322818**	**0.326757**	**0.376677**	**0.444572**	**0.291865**	**1**		
Total	**5.210012**	**2.824118**	**3.134219**	**6.384458**	**3.228176**	**3.267572**	**3.766768**	**4.445718**	**2.918653**	**10**		

3. DEA Output-oriented (O) – CRS

					Weights				Improvements				
DMU	**Input1**	**Input2**	**Output1**	**Output2**	**Input1**	**Input2**	**Output1**	**Output2**	**Input1**	**Input2**	**Output1**	**Output2**	**Efficiency**
DMU1	1	4.486161	0	0.689124	1.3436	0.0000	0.0000	1.4511	1.0000	0.0000	4.78745	0.925884	74.42875
DMU2	1	0.430017	0	0.373543	2.4787	0.0000	0.0000	2.6771	1.0000	0.0000	4.78745	0.925884	40.34454
DMU3	1	0	2.026055	0.246631	2.3629	0.0000	0.4936	0.0000	1.0000	0.0000	4.78745	0.925884	42.32013
DMU4	1	2.737628	0	0.844466	1.0964	0.0000	0.0000	1.1842	1.0000	0.0000	4.78745	0.925884	91.20654
DMU5	1	0	0.131739	0.416069	2.2253	0.0000	0.0000	2.4034	1.0000	0.0000	4.78745	0.925884	44.93747
DMU6	1	0	0.667096	0.376906	2.4565	0.0000	0.0000	2.6532	1.0000	0.0000	4.78745	0.925884	40.70776
DMU7	1	0	2.542196	0.287517	1.8832	0.0000	0.3934	0.0000	1.0000	0.0000	4.78745	0.925884	53.10126
DMU8	1	0	1.351179	0.476039	1.9450	0.0000	0.0000	2.1007	1.0000	0.0000	4.78745	0.925884	51.41453
DMU9	1	1.782823	0	0.386048	2.3984	0.0000	0.0000	2.5904	1.0000	0.0000	4.78745	0.925884	41.69504
DMU10	1	0	4.78745	0.925884	1.0000	0.0000	0.2089	0.0000	1.0000	0.0000	4.78745	0.925884	100

4. DEA I- Variant Returns to Scale (VRS)

					Weights				Improvements				
DMU	**Input1**	**Input2**	**Output1**	**Output2**	**Input1**	**Input2**	**Output1**	**Output2**	**Input1**	**Input2**	**Output1**	**Output2**	**Efficiency**
DMU1	1	4.486161	0	0.689124	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	4.78745	0.925884	100
DMU2	1	0.430017	0	0.373543	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	4.78745	0.925884	100
DMU3	1	0	2.026055	0.246631	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	4.78745	0.925884	100
DMU4	1	2.737628	0	0.844466	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	4.78745	0.925884	100
DMU5	1	0	0.131739	0.416069	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	4.78745	0.925884	100
DMU6	1	0	0.667096	0.376906	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	4.78745	0.925884	100
DMU7	1	0	2.542196	0.287517	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	4.78745	0.925884	100
DMU8	1	0	1.351179	0.476039	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	4.78745	0.925884	100
DMU9	1	1.782823	0	0.386048	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	4.78745	0.925884	100
DMU10	1	0	4.78745	0.925884	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	4.78745	0.925884	100

5. DEA O-VRS

					Weights				Improvements				
DMU	**Input1**	**Input2**	**Output1**	**Output2**	**Input1**	**Input2**	**Output1**	**Output2**	**Input1**	**Input2**	**Output1**	**Output2**	**Efficiency**
DMU1	1	4.486161	0	0.689124	1.3436	0.0000	0.0000	1.4511	1.0000	0.0000	4.78745	0.925884	74.42875
DMU2	1	0.430017	0	0.373543	2.4787	0.0000	0.0000	2.6771	1.0000	0.0000	4.78745	0.925884	40.34454
DMU3	1	0	2.026055	0.246631	2.3629	0.0000	0.4936	0.0000	1.0000	0.0000	4.78745	0.925884	42.32013
DMU4	1	2.737628	0	0.844466	1.0964	0.0000	0.0000	1.1842	1.0000	0.0000	4.78745	0.925884	91.20654
DMU5	1	0	0.131739	0.416069	2.2253	0.0000	0.0000	2.4034	1.0000	0.0000	4.78745	0.925884	44.93747
DMU6	1	0	0.667096	0.376906	2.4565	0.0000	0.0000	2.6532	1.0000	0.0000	4.78745	0.925884	40.70776
DMU7	1	0	2.542196	0.287517	1.8832	0.0000	0.3934	0.0000	1.0000	0.0000	4.78745	0.925884	53.10126
DMU8	1	0	1.351179	0.476039	1.9450	0.0000	0.0000	2.1007	1.0000	0.0000	4.78745	0.925884	51.41453
DMU9	1	1.782823	0	0.386048	2.3984	0.0000	0.0000	2.5904	1.0000	0.0000	4.78745	0.925884	41.69504
DMU10	1	0	4.78745	0.925884	1.0000	0.0000	0.2089	0.0000	1.0000	0.0000	4.78745	0.925884	100

6. Range Directional Measure (RDM)+

DMU	**Input1**	**Output1**	**Output2**	**RDM+**
DMU1	1	-4.48616	0.689124	0.0000
DMU2	1	-0.43002	0.373543	0.0000
DMU3	1	2.026055	0.246631	0.0000
DMU4	1	-2.73763	0.844466	0.0000
DMU5	1	0.131739	0.416069	0.0000
DMU6	1	0.667096	0.376906	0.0000
DMU7	1	2.542196	0.287517	0.0000
DMU8	1	1.351179	0.476039	0.0000
DMU9	1	-1.78282	0.386048	0.0000
DMU10	1	4.78745	0.925884	0.0000

7. RDM-

DMU	Input1	Output1	Output2	RDM-
DMU1	1	-4.48616	0.689124	93.4611
DMU2	1	-0.43002	0.373543	64.4122
DMU3	1	2.026055	0.246631	66.7303
DMU4	1	-2.73763	0.844466	99.2267
DMU5	1	0.131739	0.416069	69.6812
DMU6	1	0.667096	0.376906	64.8442
DMU7	1	2.542196	0.287517	78.0051
DMU8	1	1.351179	0.476039	76.3945
DMU9	1	-1.78282	0.386048	66.0054
DMU10	1	4.78745	0.925884	0.0000

8. Slack-based Model (SBM)

					Improvements				
DMU	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Efficiency**
DMU1	1	4.486161	0	0.689124	NaN	NaN	NaN	NaN	0.00%
DMU2	1	0.430017	0	0.373543	0.4034	0.0000	1.9315	0.3735	20.17%
DMU3	1	0	2.026055	0.246631	NaN	NaN	NaN	NaN	0.00%
DMU4	1	2.737628	0	0.844466	1.0000	2.7376	0.0000	0.8445	100.00%
DMU5	1	0	0.131739	0.416069	1.0000	0.0000	4.7874	0.9259	62.01%
DMU6	1	0	0.667096	0.376906	1.0000	0.0000	4.7874	0.9259	57.86%
DMU7	1	0	2.542196	0.287517	1.0000	0.0000	4.7874	0.9259	47.39%
DMU8	1	0	1.351179	0.476039	1.0000	0.0000	4.7874	0.9259	67.91%
DMU9	1	1.782823	0	0.386048	1.0000	1.7828	1.6697	0.9259	61.33%
DMU10	1	0	4.78745	0.925884	1.0000	0.0000	4.7874	0.9259	100.00%

9. Modified Slack-based Model (MSBM)

Where: Input1 = 0, Output1 = 0.5, Output2 = 0.5

				Improvements			SP Range of Indices			
DMU	**Input1**	**Output1**	**Output2**	**Input1**	**Output1**	**Output2**	**Input1**	**Output1**	**Output2**	**Efficiency**
DMU1	1	-4.48616	0.689124	1.0000	4.7875	0.9259	0.0000	9.2736	0.2368	50.00%
DMU2	1	-0.43002	0.373543	1.0000	4.7875	0.9259	0.0000	5.2175	0.5523	50.00%
DMU3	1	2.026055	0.246631	1.0000	4.7875	0.9259	0.0000	2.7614	0.6793	50.00%
DMU4	1	-2.73763	0.844466	1.0000	4.7875	0.9259	0.0000	7.5251	0.0814	50.00%
DMU5	1	0.131739	0.416069	1.0000	4.7875	0.9259	0.0000	4.6557	0.5098	50.00%
DMU6	1	0.667096	0.376906	1.0000	4.7875	0.9259	0.0000	4.1204	0.5490	50.00%
DMU7	1	2.542196	0.287517	1.0000	4.7875	0.9259	0.0000	2.2453	0.6384	50.00%
DMU8	1	1.351179	0.476039	1.0000	4.7875	0.9259	0.0000	3.4363	0.4498	50.00%
DMU9	1	-1.78282	0.386048	1.0000	4.7875	0.9259	0.0000	6.5703	0.5398	50.00%
DMU10	1	4.78745	0.925884	1.0000	4.7875	0.9259	0.0000	0.0000	0.0000	100.00%

10. Semi-oriented Radial Measure (SORM) I-CRS

				Improvements			
DMU	**Input1**	**Output1**	**Output2**	**Input1**	**Output1**	**Output2**	**Efficiency**
DMU1	1	-4.48616	0.689124	0.7443	3.5632	0.6891	74.43%
DMU2	1	-0.43002	0.373543	0.4034	1.9315	0.3735	40.34%
DMU3	1	2.026055	0.246631	0.4232	2.0261	0.3918	42.32%
DMU4	1	-2.73763	0.844466	0.9121	4.3665	0.8445	91.21%
DMU5	1	0.131739	0.416069	0.4494	2.1514	0.4161	44.94%
DMU6	1	0.667096	0.376906	0.4071	1.9489	0.3769	40.71%
DMU7	1	2.542196	0.287517	0.5310	2.5422	0.4917	53.10%
DMU8	1	1.351179	0.476039	0.5141	2.4614	0.4760	51.41%
DMU9	1	-1.78282	0.386048	0.4170	1.9961	0.3860	41.70%
DMU10	1	4.78745	0.925884	1.0000	4.7875	0.9259	100.00%

11. SORM O-CRS

				Improvements			
DMU	**Input1**	**Output1**	**Output2**	**Input1**	**Output1**	**Output2**	**Efficiency**
DMU1	1	-4.48616	0.689124	1.0000	4.7875	0.9259	74.43%
DMU2	1	-0.43002	0.373543	1.0000	4.7875	0.9259	40.34%
DMU3	1	2.026055	0.246631	1.0000	4.7875	0.9259	42.32%
DMU4	1	-2.73763	0.844466	1.0000	4.7875	0.9259	91.21%
DMU5	1	0.131739	0.416069	1.0000	4.7875	0.9259	44.94%
DMU6	1	0.667096	0.376906	1.0000	4.7875	0.9259	40.71%
DMU7	1	2.542196	0.287517	1.0000	4.7875	0.9259	53.10%
DMU8	1	1.351179	0.476039	1.0000	4.7875	0.9259	51.41%
DMU9	1	-1.78282	0.386048	1.0000	4.7875	0.9259	41.70%
DMU10	1	4.78745	0.925884	1.0000	4.7875	0.9259	100.00%

12. SORM I-VRS

				Improvements			
DMU	**Input1**	**Output1**	**Output2**	**Input1**	**Output1**	**Output2**	**Efficiency**
DMU1	1	-4.48616	0.689124	1.0000	-1.4998	0.6891	100.00%
DMU2	1	-0.43002	0.373543	1.0000	1.0148	0.3735	100.00%
DMU3	1	2.026055	0.246631	1.0000	2.0261	0.2466	100.00%
DMU4	1	-2.73763	0.844466	1.0000	-2.7376	0.8445	100.00%
DMU5	1	0.131739	0.416069	1.0000	0.1317	0.4161	100.00%
DMU6	1	0.667096	0.376906	1.0000	0.6671	0.3769	100.00%
DMU7	1	2.542196	0.287517	1.0000	2.5422	0.3736	100.00%
DMU8	1	1.351179	0.476039	1.0000	1.3512	0.4760	100.00%
DMU9	1	-1.78282	0.386048	1.0000	0.9151	0.3860	100.00%
DMU10	1	4.78745	0.925884	1.0000	4.7875	0.9259	100.00%

13. SORM O-VRS

				Improvements			
DMU	**Input1**	**Output1**	**Output2**	**Input1**	**Output1**	**Output2**	**Efficiency**
DMU1	1	-4.48616	0.689124	1.0000	4.7875	0.9259	74.43%
DMU2	1	-0.43002	0.373543	1.0000	4.7875	0.9259	40.34%
DMU3	1	2.026055	0.246631	1.0000	4.7875	0.9259	42.32%
DMU4	1	-2.73763	0.844466	1.0000	4.7875	0.9259	91.21%
DMU5	1	0.131739	0.416069	1.0000	4.7875	0.9259	44.94%
DMU6	1	0.667096	0.376906	1.0000	4.7875	0.9259	40.71%
DMU7	1	2.542196	0.287517	1.0000	4.7875	0.9259	53.10%
DMU8	1	1.351179	0.476039	1.0000	4.7875	0.9259	51.41%
DMU9	1	-1.78282	0.386048	1.0000	4.7875	0.9259	41.70%
DMU10	1	4.78745	0.925884	1.0000	4.7875	0.9259	100.00%

14. Variant of the Radial Measure (VRM) I-CRS

				Improvements			
DMU	**Input1**	**Output1**	**Output2**	**Input1**	**Output1**	**Output2**	**Efficiency**
DMU1	1	-4.48616	0.689124	0.7443	3.5632	0.6891	74.43%
DMU2	1	-0.43002	0.373543	0.4034	1.9315	0.3735	40.34%
DMU3	1	2.026055	0.246631	0.4232	2.0261	0.3918	42.32%
DMU4	1	-2.73763	0.844466	0.9121	4.3665	0.8445	91.21%
DMU5	1	0.131739	0.416069	0.4494	2.1514	0.4161	44.94%
DMU6	1	0.667096	0.376906	0.4071	1.9489	0.3769	40.71%
DMU7	1	2.542196	0.287517	0.5310	2.5422	0.4917	53.10%
DMU8	1	1.351179	0.476039	0.5141	2.4614	0.4760	51.41%
DMU9	1	-1.78282	0.386048	0.4170	1.9961	0.3860	41.70%
DMU10	1	4.78745	0.925884	1.0000	4.7875	0.9259	100.00%

15. VRM O-CRS

				Improvements			
DMU	**Input1**	**Output1**	**Output2**	**Input1**	**Output1**	**Output2**	**Efficiency**
DMU1	1	-4.48616	0.689124	1.0000	4.7875	0.9259	74.43%
DMU2	1	-0.43002	0.373543	1.0000	4.7875	0.9259	40.34%
DMU3	1	2.026055	0.246631	1.0000	4.7875	0.9259	42.32%
DMU4	1	-2.73763	0.844466	1.0000	4.7875	0.9259	91.21%
DMU5	1	0.131739	0.416069	1.0000	4.7875	0.9259	44.94%
DMU6	1	0.667096	0.376906	1.0000	4.7875	0.9259	40.71%
DMU7	1	2.542196	0.287517	1.0000	4.7875	0.9259	53.10%
DMU8	1	1.351179	0.476039	1.0000	4.7875	0.9259	51.41%
DMU9	1	-1.78282	0.386048	1.0000	4.7875	0.9259	41.70%
DMU10	1	4.78745	0.925884	1.0000	4.7875	0.9259	100.00%

16. VRM I-VRS

				Improvements			
DMU	**Input1**	**Output1**	**Output2**	**Input1**	**Output1**	**Output2**	**Efficiency**
DMU1	1	-4.48616	0.689124	1.0000	-1.4998	0.6891	100.00%
DMU2	1	-0.43002	0.373543	1.0000	1.0148	0.3735	100.00%
DMU3	1	2.026055	0.246631	1.0000	2.0261	0.2466	100.00%
DMU4	1	-2.73763	0.844466	1.0000	-2.7376	0.8445	100.00%
DMU5	1	0.131739	0.416069	1.0000	0.1317	0.4161	100.00%
DMU6	1	0.667096	0.376906	1.0000	0.6671	0.3769	100.00%
DMU7	1	2.542196	0.287517	1.0000	2.5422	0.3736	100.00%
DMU8	1	1.351179	0.476039	1.0000	1.3512	0.4760	100.00%
DMU9	1	-1.78282	0.386048	1.0000	0.9151	0.3860	100.00%
DMU10	1	4.78745	0.925884	1.0000	4.7875	0.9259	100.00%

17. VRM O-VRS

				Improvements			
DMU	**Input1**	**Output1**	**Output2**	**Input1**	**Output1**	**Output2**	**Efficiency**
DMU1	1	-4.48616	0.689124	1.0000	4.7875	0.9259	74.43%
DMU2	1	-0.43002	0.373543	1.0000	4.7875	0.9259	40.34%
DMU3	1	2.026055	0.246631	1.0000	4.7875	0.9259	42.32%
DMU4	1	-2.73763	0.844466	1.0000	4.7875	0.9259	91.21%
DMU5	1	0.131739	0.416069	1.0000	4.7875	0.9259	44.94%
DMU6	1	0.667096	0.376906	1.0000	4.7875	0.9259	40.71%
DMU7	1	2.542196	0.287517	1.0000	4.7875	0.9259	53.10%
DMU8	1	1.351179	0.476039	1.0000	4.7875	0.9259	51.41%
DMU9	1	-1.78282	0.386048	1.0000	4.7875	0.9259	41.70%
DMU10	1	4.78745	0.925884	1.0000	4.7875	0.9259	100.00%

18. Radial Supper-efficiency Model (RSEM) I-CRS

DMU	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Efficiency**
DMU1	1	4.486161	0	0.689124	74.43%
DMU2	1	0.430017	0	0.373543	40.34%
DMU3	1	0	2.026055	0.246631	42.32%
DMU4	1	2.737628	0	0.844466	91.21%
DMU5	1	0	0.131739	0.416069	44.94%
DMU6	1	0	0.667096	0.376906	40.71%
DMU7	1	0	2.542196	0.287517	53.10%
DMU8	1	0	1.351179	0.476039	51.41%
DMU9	1	1.782823	0	0.386048	41.70%
DMU10	1	0	4.78745	0.925884	244.04%

19. RSEM O-CRS

DMU	Input 1	Input 2	Output 1	Output 2	Efficiency
DMU1	1	4.486161	0	0.689124	74.43%
DMU2	1	0.430017	0	0.373543	40.34%
DMU3	1	0	2.026055	0.246631	42.32%
DMU4	1	2.737628	0	0.844466	91.21%
DMU5	1	0	0.131739	0.416069	44.94%
DMU6	1	0	0.667096	0.376906	40.71%
DMU7	1	0	2.542196	0.287517	53.10%
DMU8	1	0	1.351179	0.476039	51.41%
DMU9	1	1.782823	0	0.386048	41.70%
DMU10	1	0	4.78745	0.925884	244.04%

20. RSEM I-VRS

The efficiency levels of DMUs cannot be estimated as these methods are estimating zero values for DMUs.

21. RSEM O-VRS

DMU	Input 1	Input 2	Output 1	Output 2	Efficiency
DMU1	1	4.486161	0	0.689124	74.43%
DMU2	1	0.430017	0	0.373543	40.34%
DMU3	1	0	2.026055	0.246631	42.32%
DMU4	1	2.737628	0	0.844466	91.21%
DMU5	1	0	0.131739	0.416069	44.94%
DMU6	1	0	0.667096	0.376906	40.71%
DMU7	1	0	2.542196	0.287517	53.10%
DMU8	1	0	1.351179	0.476039	51.41%
DMU9	1	1.782823	0	0.386048	41.70%
DMU10	1	0	4.78745	0.925884	244.04%

22. Scale Efficiency Measure (SEM) I-VRS

DMU	Input 1	Input 2	Output 1	Output 2	Efficiency
DMU1	1	4.486161	0	0.689124	74.43%
DMU2	1	0.430017	0	0.373543	40.34%
DMU3	1	0	2.026055	0.246631	42.32%
DMU4	1	2.737628	0	0.844466	91.21%
DMU5	1	0	0.131739	0.416069	44.94%
DMU6	1	0	0.667096	0.376906	40.71%
DMU7	1	0	2.542196	0.287517	53.10%
DMU8	1	0	1.351179	0.476039	51.41%
DMU9	1	1.782823	0	0.386048	41.70%
DMU10	1	0	4.78745	0.925884	100.00%

23. SEM O-VRS

DMU	Input 1	Input 2	Output 1	Output 2	Efficiency
DMU1	1	4.486161	0	0.689124	100.00%
DMU2	1	0.430017	0	0.373543	100.00%
DMU3	1	0	2.026055	0.246631	100.00%
DMU4	1	2.737628	0	0.844466	100.00%
DMU5	1	0	0.131739	0.416069	100.00%
DMU6	1	0	0.667096	0.376906	100.00%
DMU7	1	0	2.542196	0.287517	100.00%
DMU8	1	0	1.351179	0.476039	100.00%
DMU9	1	1.782823	0	0.386048	100.00%
DMU10	1	0	4.78745	0.925884	100.00%

24. Radial Models with Value Judgements (RMVJ) I-CRS

					Weights				**Improvements**				
DMU	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Efficiency**
DMU1	1	4.486161	0	0.689124	1.0000	0.0000	0.0000	1.0800	0.7443	0.0000	3.5632	0.6891	74.43%
DMU2	1	0.430017	0	0.373543	1.0000	0.0000	0.0000	1.0800	0.4034	0.0000	1.9315	0.3735	40.34%
DMU3	1	0	2.026055	0.246631	1.0000	0.0000	0.2089	0.0000	0.4232	0.0000	2.0261	0.3918	42.32%
DMU4	1	2.737628	0	0.844466	1.0000	0.0000	0.0000	1.0800	0.9121	0.0000	4.3665	0.8445	91.21%
DMU5	1	0	0.131739	0.416069	1.0000	0.0000	0.0000	1.0800	0.4494	0.0000	2.1514	0.4161	44.94%
DMU6	1	0	0.667096	0.376906	1.0000	0.0000	0.0000	1.0800	0.4071	0.0000	1.9489	0.3769	40.71%
DMU7	1	0	2.542196	0.287517	1.0000	0.0000	0.2089	0.0000	0.5310	0.0000	2.5422	0.4917	53.10%
DMU8	1	0	1.351179	0.476039	1.0000	0.0000	0.0000	1.0800	0.5141	0.0000	2.4614	0.4760	51.41%
DMU9	1	1.782823	0	0.386048	1.0000	0.0000	0.0000	1.0800	0.4170	0.0000	1.9961	0.3860	41.70%
DMU10	1	0	4.78745	0.925884	1.0000	0.0000	0.2089	0.0000	1.0000	0.0000	4.7874	0.9259	100.00%

25. RMVJ O-CRS

					Weights				Improvements				
DMU	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Efficiency**
DMU1	1	4.486161	0	0.689124	1.3436	0.0000	0.0000	1.4511	1.0000	0.0000	4.7874	0.9259	74.43%
DMU2	1	0.430017	0	0.373543	2.4787	0.0000	0.0000	2.6771	1.0000	0.0000	4.7874	0.9259	40.34%
DMU3	1	0	2.026055	0.246631	2.3629	0.0000	0.4936	0.0000	1.0000	0.0000	4.7874	0.9259	42.32%
DMU4	1	2.737628	0	0.844466	1.0964	0.0000	0.0000	1.1842	1.0000	0.0000	4.7874	0.9259	91.21%
DMU5	1	0	0.131739	0.416069	2.2253	0.0000	0.0000	2.4034	1.0000	0.0000	4.7874	0.9259	44.94%
DMU6	1	0	0.667096	0.376906	2.4565	0.0000	0.0000	2.6532	1.0000	0.0000	4.7874	0.9259	40.71%
DMU7	1	0	2.542196	0.287517	1.8832	0.0000	0.3934	0.0000	1.0000	0.0000	4.7874	0.9259	53.10%
DMU8	1	0	1.351179	0.476039	1.9450	0.0000	0.0000	2.1007	1.0000	0.0000	4.7874	0.9259	51.41%
DMU9	1	1.782823	0	0.386048	2.3984	0.0000	0.0000	2.5904	1.0000	0.0000	4.7874	0.9259	41.70%
DMU10	1	0	4.78745	0.925884	1.0000	0.0000	0.2089	0.0000	1.0000	0.0000	4.7874	0.9259	100.00%

26. RMVJ I-VRS

					Weights				Improvements				
DMU	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Efficiency**
DMU1	1	4.486161	0	0.689124	1.0000	0.0000	0.0000	0.0000	1.0000	2.7376	0.0000	0.8445	100.00%
DMU2	1	0.430017	0	0.373543	1.0000	0.0000	0.0000	0.0000	1.0000	0.4300	0.1110	0.4834	100.00%
DMU3	1	0	2.026055	0.246631	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	2.0261	0.2466	100.00%
DMU4	1	2.737628	0	0.844466	1.0000	0.0000	0.0000	0.0000	1.0000	2.7376	0.0000	0.8445	100.00%
DMU5	1	0	0.131739	0.416069	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.1317	0.4161	100.00%
DMU6	1	0	0.667096	0.376906	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.6671	0.3769	100.00%
DMU7	1	0	2.542196	0.287517	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	2.5422	0.3736	100.00%
DMU8	1	0	1.351179	0.476039	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	1.3512	0.4760	100.00%
DMU9	1	1.782823	0	0.386048	1.0000	0.0000	0.0000	0.0000	1.0000	1.7828	0.0459	0.6951	100.00%
DMU10	1	0	4.78745	0.925884	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	4.7874	0.9259	100.00%

27. RMVJ O-VRS

					Weights				Improvements				
DMU	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Efficiency**
DMU1	1	4.486161	0	0.689124	1.3436	0.0000	0.0000	1.4511	1.0000	0.0000	4.7874	0.9259	74.43%
DMU2	1	0.430017	0	0.373543	2.4787	0.0000	0.0000	2.6771	1.0000	1.0000	4.7874	0.9259	40.34%
DMU3	1	0	2.026055	0.246631	2.3629	0.0000	0.4936	0.0000	1.0000	2.0000	4.7874	0.9259	42.32%
DMU4	1	2.737628	0	0.844466	1.0964	0.0000	0.0000	1.1842	1.0000	3.0000	4.7874	0.9259	91.21%
DMU5	1	0	0.131739	0.416069	2.2253	0.0000	0.0000	2.4034	1.0000	4.0000	4.7874	0.9259	44.94%
DMU6	1	0	0.667096	0.376906	2.4565	0.0000	0.0000	2.6532	1.0000	5.0000	4.7874	0.9259	40.71%
DMU7	1	0	2.542196	0.287517	1.8832	0.0000	0.3934	0.0000	1.0000	6.0000	4.7874	0.9259	53.10%
DMU8	1	0	1.351179	0.476039	1.9450	0.0000	0.0000	2.1007	1.0000	7.0000	4.7874	0.9259	51.41%
DMU9	1	1.782823	0	0.386048	2.3984	0.0000	0.0000	2.5904	1.0000	8.0000	4.7874	0.9259	41.70%
DMU10	1	0	4.78745	0.925884	1.0000	0.0000	0.2089	0.0000	1.0000	9.0000	4.7874	0.9259	100.00%

28. Additive Model (AM) I-CRS

					Weights				
DMU	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Objective**
DMU1	1	4.486161	0	0.689124	5.7133	1.0000	1.0000	1.0000	9.5104
DMU2	1	0.430017	0	0.373543	5.7133	1.0000	1.0000	1.0000	5.7698
DMU3	1	0	2.026055	0.246631	5.7133	1.0000	1.0000	1.0000	3.4406
DMU4	1	2.737628	0	0.844466	5.7133	1.0000	1.0000	1.0000	7.6065
DMU5	1	0	0.131739	0.416069	5.7133	1.0000	1.0000	1.0000	5.1655
DMU6	1	0	0.667096	0.376906	5.7133	1.0000	1.0000	1.0000	4.6693
DMU7	1	0	2.542196	0.287517	5.7133	1.0000	1.0000	1.0000	2.8836
DMU8	1	0	1.351179	0.476039	5.7133	1.0000	1.0000	1.0000	3.8861
DMU9	1	1.782823	0	0.386048	5.7133	1.0000	1.0000	1.0000	7.1101
DMU10	1	0	4.78745	0.925884	5.7133	1.0000	1.0000	1.0000	0.0000

29. AM I-VRS

					Weights				
DMU	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Objective**
DMU1	1	4.486161	0	0.689124	5.7133	1.0000	1.0000	1.0000	9.5104
DMU2	1	0.430017	0	0.373543	1.0000	1.0000	1.0000	1.0000	5.7698
DMU3	1	0	2.026055	0.246631	1.0000	1.0000	1.0000	1.0000	3.4406
DMU4	1	2.737628	0	0.844466	1.0000	1.0000	1.0000	1.0000	7.6065
DMU5	1	0	0.131739	0.416069	1.0000	1.0000	1.0000	1.0000	5.1655
DMU6	1	0	0.667096	0.376906	1.0000	1.0000	1.0000	1.0000	4.6693
DMU7	1	0	2.542196	0.287517	1.0000	1.0000	1.0000	1.0000	2.8836
DMU8	1	0	1.351179	0.476039	1.0000	1.0000	1.0000	1.0000	3.8861
DMU9	1	1.782823	0	0.386048	5.7133	1.0000	1.0000	1.0000	7.1101
DMU10	1	0	4.78745	0.925884	5.7133	1.0000	1.0000	1.0000	0.0000

30. Free Disposal Hull Models (FDHM) I-CRS

DMU	**Input 1**	**Input 2**	**Output 1**	**Output 2**	**Efficiency**
DMU1	1	4.486161	0	0.689124	74.43%
DMU2	1	0.430017	0	0.373543	40.34%
DMU3	1	0	2.026055	0.246631	42.32%
DMU4	1	2.737628	0	0.844466	91.21%
DMU5	1	0	0.131739	0.416069	44.94%
DMU6	1	0	0.667096	0.376906	40.71%
DMU7	1	0	2.542196	0.287517	53.10%
DMU8	1	0	1.351179	0.476039	51.41%
DMU9	1	1.782823	0	0.386048	41.70%
DMU10	1	0	4.78745	0.925884	100.00%

31. FDHM I-VRS

	Input 1	Input 2	Output 1	Output 2	Efficiency
DMU1	1	4.486161	0	0.689124	100.00%
DMU2	1	0.430017	0	0.373543	100.00%
DMU3	1	0	2.026055	0.246631	100.00%
DMU4	1	2.737628	0	0.844466	100.00%
DMU5	1	0	0.131739	0.416069	100.00%
DMU6	1	0	0.667096	0.376906	100.00%
DMU7	1	0	2.542196	0.287517	100.00%
DMU8	1	0	1.351179	0.476039	100.00%
DMU9	1	1.782823	0	0.386048	100.00%
DMU10	1	0	4.78745	0.925884	100.00%

32. Cost Efficiency Models (CEM) O-CRS Cost Efficiency

DMU	Input 1	Input 2	Output 1	Output 2	Cost Efficiency
DMU1	1	4.486161	0	0.689124	0.0352
DMU2	1	0.430017	0	0.373543	0.1377
DMU3	1	0	2.026055	0.246631	0.4232
DMU4	1	2.737628	0	0.844466	0.0687
DMU5	1	0	0.131739	0.416069	0.4494
DMU6	1	0	0.667096	0.376906	0.4071
DMU7	1	0	2.542196	0.287517	0.5310
DMU8	1	0	1.351179	0.476039	0.5141
DMU9	1	1.782823	0	0.386048	0.0463
DMU10	1	0	4.78745	0.925884	1.0000

33. CEM O-CRS Technical Efficiency

DMU	Input 1	Input 2	Output 1	Output 2	Technical Efficiency
DMU1	1	4.486161	0	0.689124	0.7443
DMU2	1	0.430017	0	0.373543	0.4034
DMU3	1	0	2.026055	0.246631	0.4232
DMU4	1	2.737628	0	0.844466	0.9121
DMU5	1	0	0.131739	0.416069	0.4494
DMU6	1	0	0.667096	0.376906	0.4071
DMU7	1	0	2.542196	0.287517	0.5310
DMU8	1	0	1.351179	0.476039	0.5141
DMU9	1	1.782823	0	0.386048	0.4170
DMU10	1	0	4.78745	0.925884	1.0000

34. CEM O-CRS Allocative Efficiency

DMU	Input 1	Input 2	Output 1	Output 2	Allocative Efficiency
DMU1	1	4.486161	0	0.689124	0.0473
DMU2	1	0.430017	0	0.373543	0.3414
DMU3	1	0	2.026055	0.246631	1.0000
DMU4	1	2.737628	0	0.844466	0.0753
DMU5	1	0	0.131739	0.416069	1.0000
DMU6	1	0	0.667096	0.376906	1.0000
DMU7	1	0	2.542196	0.287517	1.0000
DMU8	1	0	1.351179	0.476039	1.0000
DMU9	1	1.782823	0	0.386048	0.1111
DMU10	1	0	4.78745	0.925884	1.0000

35. CEM O-CRS Profit Efficiency

DMU	Input 1	Input 2	Output 1	Output 2	Profit Efficiency
DMU1	1	4.486161	0	0.689124	76.6556
DMU2	1	0.430017	0	0.373543	18.2959
DMU3	1	0	2.026055	0.246631	5.4188
DMU4	1	2.737628	0	0.844466	38.4689
DMU5	1	0	0.131739	0.416069	4.3853
DMU6	1	0	0.667096	0.376906	5.0241
DMU7	1	0	2.542196	0.287517	4.1720
DMU8	1	0	1.351179	0.476039	3.6108
DMU9	1	1.782823	0	0.386048	57.8599
DMU10	1	0	4.78745	0.925884	1.0000

36. CEM O-CRS Revenue Efficiency

DMU	Input 1	Input 2	Output 1	Output 2	Revenue Efficiency
DMU1	1	4.486161	0	0.689124	0.7443
DMU2	1	0.430017	0	0.373543	0.4034
DMU3	1	0	2.026055	0.246631	0.2664
DMU4	1	2.737628	0	0.844466	0.9121
DMU5	1	0	0.131739	0.416069	0.4494
DMU6	1	0	0.667096	0.376906	0.4071
DMU7	1	0	2.542196	0.287517	0.3105
DMU8	1	0	1.351179	0.476039	0.5141
DMU9	1	1.782823	0	0.386048	0.4170
DMU10	1	0	4.78745	0.925884	1.0000

37. CEM O-VRS Cost Efficiency

DMU	Input 1	Input 2	Output 1	Output 2	Cost Efficiency
DMU1	1	4.486161	0	0.689124	0.0473
DMU2	1	0.430017	0	0.373543	0.3414
DMU3	1	0	2.026055	0.246631	1.0000
DMU4	1	2.737628	0	0.844466	0.0753
DMU5	1	0	0.131739	0.416069	1.0000
DMU6	1	0	0.667096	0.376906	1.0000
DMU7	1	0	2.542196	0.287517	1.0000
DMU8	1	0	1.351179	0.476039	1.0000
DMU9	1	1.782823	0	0.386048	0.1111
DMU10	1	0	4.78745	0.925884	1.0000

38. CEM O-VRS Technical Efficiency

DMU	Input 1	Input 2	Output 1	Output 2	Technical Efficiency
DMU1	1	4.486161	0	0.689124	1.0000
DMU2	1	0.430017	0	0.373543	1.0000
DMU3	1	0	2.026055	0.246631	1.0000
DMU4	1	2.737628	0	0.844466	1.0000
DMU5	1	0	0.131739	0.416069	1.0000
DMU6	1	0	0.667096	0.376906	1.0000
DMU7	1	0	2.542196	0.287517	1.0000
DMU8	1	0	1.351179	0.476039	1.0000
DMU9	1	1.782823	0	0.386048	1.0000
DMU10	1	0	4.78745	0.925884	1.0000

39. CEM O-VRS Allocative Efficiency

DMU	Input 1	Input 2	Output 1	Output 2	Allocative Efficiency
DMU1	1	4.486161	0	0.689124	0.0473
DMU2	1	0.430017	0	0.373543	0.3414
DMU3	1	0	2.026055	0.246631	1.0000
DMU4	1	2.737628	0	0.844466	0.0753
DMU5	1	0	0.131739	0.416069	1.0000
DMU6	1	0	0.667096	0.376906	1.0000
DMU7	1	0	2.542196	0.287517	1.0000
DMU8	1	0	1.351179	0.476039	1.0000
DMU9	1	1.782823	0	0.386048	0.1111
DMU10	1	0	4.78745	0.925884	1.0000

40. CEM O-VRS Profit Efficiency

DMU	Input 1	Input 2	Output 1	Output 2	Profit Efficiency
DMU1	1	4.486161	0	0.689124	57.0538
DMU2	1	0.430017	0	0.373543	7.3814
DMU3	1	0	2.026055	0.246631	2.2932
DMU4	1	2.737628	0	0.844466	35.0861
DMU5	1	0	0.131739	0.416069	1.9706
DMU6	1	0	0.667096	0.376906	2.0452
DMU7	1	0	2.542196	0.287517	2.2154
DMU8	1	0	1.351179	0.476039	1.8565
DMU9	1	1.782823	0	0.386048	24.1247
DMU10	1	0	4.78745	0.925884	1.0000

41. CEM O-VRS Revenue Efficiency

DMU	Input 1	Input 2	Output 1	Output 2	Revenue Efficiency
DMU1	1	4.486161	0	0.689124	0.7443
DMU2	1	0.430017	0	0.373543	0.4034
DMU3	1	0	2.026055	0.246631	0.2664
DMU4	1	2.737628	0	0.844466	0.9121
DMU5	1	0	0.131739	0.416069	0.4494
DMU6	1	0	0.667096	0.376906	0.4071
DMU7	1	0	2.542196	0.287517	0.3105
DMU8	1	0	1.351179	0.476039	0.5141
DMU9	1	1.782823	0	0.386048	0.4170
DMU10	1	0	4.78745	0.925884	1.0000

42. Standard DEA/AHP Linear Programming (LP)

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10	Total	Efficiency	Efficiency (%)	Rank
DMU1	1.0000	1.0000	1.0000	0.8160	1.0000	1.0000	1.0000	1.0000	1.0000	0.7443	9.5603	0.0907	9.07%	***5***
DMU2	1.0000	1.0000	1.0000	1.0000	0.8978	0.9911	1.0000	0.7847	1.0000	0.4034	9.0770	0.0861	8.61%	***9***
DMU3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.8578	1.0000	1.0000	0.4232	9.2810	0.0881	8.81%	***7***
DMU4	1.2254	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.4245	0.9121	10.5620	0.1002	10.02%	***2***
DMU5	1.0000	1.1138	1.0000	1.0000	1.0000	1.0000	1.0000	0.8740	1.0778	0.4494	9.5150	0.0903	9.03%	***6***
DMU6	1.0000	1.0090	1.0000	1.0000	1.0000	1.0000	1.0000	0.7918	1.0000	0.4071	9.2078	0.0874	8.74%	***8***
DMU7	1.0000	1.0000	1.1658	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.5310	9.6968	0.0920	9.20%	***4***
DMU8	1.0000	1.2744	1.0000	1.0000	1.1441	1.2630	1.0000	1.0000	1.2331	0.5141	10.4288	0.0990	9.90%	***3***
DMU9	1.0000	1.0000	1.0000	0.7020	0.9278	1.0000	1.0000	0.8110	1.0000	0.4170	8.8577	0.0841	8.41%	***10***
DMU10	1.3436	2.4787	2.3629	1.0964	2.2253	2.4565	1.8832	1.9450	2.3984	1.0000	19.1900	0.1821	18.21%	***1***
Total	**10.5690**	**11.8759**	**11.5287**	**9.6144**	**11.1951**	**11.7106**	**10.7410**	**10.2064**	**12.1338**	**5.8016**	**105.3765**	**1.0000**	**100.00%**	

43. Standard DEA/AHP Average Efficiency (Avg.)

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10	Efficiency (%)	Rank
DMU1	1.0000	1.0000	1.0000	0.8160	1.0000	1.0000	1.0000	1.0000	1.0000	0.7443	1.0569	***7***
DMU2	1.0000	1.0000	1.0000	1.0000	0.8978	0.9911	1.0000	0.7847	1.0000	0.4034	1.1876	***2***
DMU3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.8578	1.0000	1.0000	0.4232	1.1529	***4***
DMU4	1.2254	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.4245	0.9121	0.9614	***9***
DMU5	1.0000	1.1138	1.0000	1.0000	1.0000	1.0000	1.0000	0.8740	1.0778	0.4494	1.1195	***5***
DMU6	1.0000	1.0090	1.0000	1.0000	1.0000	1.0000	1.0000	0.7918	1.0000	0.4071	1.1711	***3***
DMU7	1.0000	1.0000	1.1658	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.5310	1.0741	***6***
DMU8	1.0000	1.2744	1.0000	1.0000	1.1441	1.2630	1.0000	1.0000	1.2331	0.5141	1.0206	***8***
DMU9	1.0000	1.0000	1.0000	0.7020	0.9278	1.0000	1.0000	0.8110	1.0000	0.4170	1.2134	***1***
DMU10	1.3436	2.4787	2.3629	1.0964	2.2253	2.4565	1.8832	1.9450	2.3984	1.0000	0.5802	***10***
Average	**1.0569**	**1.1876**	**1.1529**	**0.9614**	**1.1195**	**1.1711**	**1.0741**	**1.0206**	**1.2134**	**0.5802**		

44. Standard DEA/AHP Total

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10	Total	Efficiency	Efficiency (%)	Rank
DMU1	0.0946	0.0842	0.0867	0.0849	0.0893	0.0854	0.0931	0.0980	0.0824	0.1283	0.9269	0.0927	9.27%	***4***
DMU2	0.0946	0.0842	0.0867	0.1040	0.0802	0.0846	0.0931	0.0769	0.0824	0.0695	0.8563	0.0856	8.56%	***9***
DMU3	0.0946	0.0842	0.0867	0.1040	0.0893	0.0854	0.0799	0.0980	0.0824	0.0729	0.8775	0.0877	8.77%	***7***
DMU4	0.1159	0.0842	0.0867	0.1040	0.0893	0.0854	0.0931	0.0980	0.1174	0.1572	1.0313	0.1031	10.31%	***2***
DMU5	0.0946	0.0938	0.0867	0.1040	0.0893	0.0854	0.0931	0.0856	0.0888	0.0775	0.8989	0.0899	8.99%	***6***
DMU6	0.0946	0.0850	0.0867	0.1040	0.0893	0.0854	0.0931	0.0776	0.0824	0.0702	0.8683	0.0868	8.68%	***8***
DMU7	0.0946	0.0842	0.1011	0.1040	0.0893	0.0854	0.0931	0.0980	0.0824	0.0915	0.9237	0.0924	9.24%	***5***
DMU8	0.0946	0.1073	0.0867	0.1040	0.1022	0.1079	0.0931	0.0980	0.1016	0.0886	0.9841	0.0984	9.84%	***3***
DMU9	0.0946	0.0842	0.0867	0.0730	0.0829	0.0854	0.0931	0.0795	0.0824	0.0719	0.8337	0.0834	8.34%	***10***
DMU10	0.1271	0.2087	0.2050	0.1140	0.1988	0.2098	0.1753	0.1906	0.1977	0.1724	1.7993	0.1799	17.99%	***1***
Total	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**10.0000**	**1.0000**	**100.00%**	

45. Proposed DEA CE/AHP Model Avg. with 2 Criteria

DMU	Input1	Output1
DMU1	0.6891	-4.4862
DMU2	0.3735	-0.4300
DMU3	0.2466	2.0261
DMU4	0.8445	-2.7376
DMU5	0.4161	0.1317
DMU6	0.3769	0.6671
DMU7	0.2875	2.5422
DMU8	0.4760	1.3512
DMU9	0.3860	-1.7828
DMU10	0.9259	4.7874

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10	Total
DMU1	1.0000	5.6550	-0.7925	2.0081	-20.5602	-3.6781	-0.7363	-2.2935	1.4096	-1.2590	-19.2468
DMU2	0.1768	1.0000	-0.1401	0.3551	-3.6357	-0.6504	-0.1302	-0.4056	0.2493	-0.2226	-3.4035
DMU3	-1.2619	-7.1361	1.0000	-2.5340	25.9450	4.6414	0.9291	2.8942	-1.7788	1.5888	24.2876
DMU4	0.4980	2.8161	-0.3946	1.0000	-10.2386	-1.8316	-0.3666	-1.1421	0.7020	-0.6270	-9.5846
DMU5	-0.0486	-0.2750	0.0385	-0.0977	1.0000	0.1789	0.0358	0.1116	-0.0686	0.0612	0.9361
DMU6	-0.2719	-1.5375	0.2155	-0.5460	5.5899	1.0000	0.2002	0.6236	-0.3833	0.3423	5.2328
DMU7	-1.3582	-7.6807	1.0763	-2.7274	27.9251	4.9956	1.0000	3.1151	-1.9146	1.7100	26.1412
DMU8	-0.4360	-2.4656	0.3455	-0.8755	8.9644	1.6037	0.3210	1.0000	-0.6146	0.5489	8.3917
DMU9	0.7094	4.0117	-0.5622	1.4245	-14.5854	-2.6092	-0.5223	-1.6270	1.0000	-0.8931	-13.6536
DMU10	-0.7943	-4.4916	0.6294	-1.5950	16.3304	2.9214	0.5848	1.8217	-1.1196	1.0000	15.2872
Total	**-1.7867**	**-10.1038**	**1.4159**	**-3.5879**	**36.7348**	**6.5716**	**1.3155**	**4.0979**	**-2.5186**	**2.2495**	**34.3882**
Average	**-0.1787**	**-1.0104**	**0.1416**	**-0.3588**	**3.6735**	**0.6572**	**0.1315**	**0.4098**	**-0.2519**	**0.2249**	

Efficiency	Rank
-0.1787	7
-1.0104	10
0.1416	5
-0.3588	9
3.6735	1
0.6572	2
0.1315	6
0.4098	3
-0.2519	8
0.2249	4

46. Proposed DEA CE/AHP Total with 2 Criteria

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10	Total	Efficiency	Rank
DMU1	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597	-5.5969	-0.5597	***10***
DMU2	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990	-0.9897	-0.0990	***7***
DMU3	0.7063	0.7063	0.7063	0.7063	0.7063	0.7063	0.7063	0.7063	0.7063	0.7063	7.0628	0.7063	***2***
DMU4	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787	-2.7872	-0.2787	***8***
DMU5	0.0272	0.0272	0.0272	0.0272	0.0272	0.0272	0.0272	0.0272	0.0272	0.0272	0.2722	0.0272	***6***
DMU6	0.1522	0.1522	0.1522	0.1522	0.1522	0.1522	0.1522	0.1522	0.1522	0.1522	1.5217	0.1522	***5***
DMU7	0.7602	0.7602	0.7602	0.7602	0.7602	0.7602	0.7602	0.7602	0.7602	0.7602	7.6018	0.7602	***1***
DMU8	0.2440	0.2440	0.2440	0.2440	0.2440	0.2440	0.2440	0.2440	0.2440	0.2440	2.4403	0.2440	***4***
DMU9	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970	-3.9704	-0.3970	***9***
DMU10	0.4445	0.4445	0.4445	0.4445	0.4445	0.4445	0.4445	0.4445	0.4445	0.4445	4.4455	0.4445	***3***
Total	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**10.0000**		

47. Proposed DEA CE/AHP LP with 3 Criteria

DMU	Input1	Output1	Output2
DMU1	1	-4.48616	0.689124
DMU2	1	-0.43002	0.373543
DMU3	1	2.026055	0.246631
DMU4	1	-2.73763	0.844466
DMU5	1	0.131739	0.416069
DMU6	1	0.667096	0.376906
DMU7	1	2.542196	0.287517
DMU8	1	1.351179	0.476039
DMU9	1	-1.78282	0.386048
DMU10	1	4.78745	0.925884

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10	Total	Efficiency	Rank
DMU1	1.0000	10.4325	2.7941	1.6387	1.6563	1.8284	2.3968	1.4476	2.5163	0.7443	26.4551	0.1138	***3***
DMU2	0.5421	1.0000	1.5146	0.4423	0.8978	0.9911	1.2992	0.7847	0.9676	0.4034	8.8428	0.0380	***10***
DMU3	0.3579	0.6602	1.0000	0.2921	15.3793	3.0371	0.8578	1.4995	0.6389	0.4232	24.1459	0.1039	***4***
DMU4	1.2254	6.3663	3.4240	1.0000	2.0296	2.2405	2.9371	1.7739	2.1875	0.9121	24.0965	0.1037	***5***
DMU5	0.6038	1.1138	1.6870	0.4927	1.0000	1.1039	1.4471	0.8740	1.0778	0.4494	9.8495	0.0424	***9***
DMU6	0.5469	1.0090	1.5282	0.4463	5.0638	1.0000	1.3109	0.7918	0.9763	0.4071	13.0803	0.0563	***7***
DMU7	0.4172	0.7697	1.2548	0.3405	19.2972	3.8108	1.0000	1.8815	0.7448	0.5310	30.0474	0.1293	***2***
DMU8	0.6908	1.2744	1.9302	0.5637	10.2565	2.0255	1.6557	1.0000	1.2331	0.5141	21.1439	0.0910	***6***
DMU9	0.5602	4.1459	1.5653	0.6512	0.9278	1.0243	1.3427	0.8110	1.0000	0.4170	12.4454	0.0535	***8***
DMU10	1.3436	2.4787	3.7541	1.0964	36.3403	7.1766	3.2203	3.5432	2.3984	1.0000	62.3514	0.2682	***1***
Total	**7.2878**	**29.2506**	**20.4523**	**6.9640**	**92.8485**	**24.2381**	**17.4676**	**14.4071**	**13.7406**	**5.8016**	**232.4582**		

48. Proposed DEA CE/AHP Avg. with 3 Criteria

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10	Efficiency	Rank
DMU1	1.0000	10.4325	2.7941	1.6387	1.6563	1.8284	2.3968	1.4476	2.5163	0.7443	0.7288	***8***
DMU2	0.5421	1.0000	1.5146	0.4423	0.8978	0.9911	1.2992	0.7847	0.9676	0.4034	2.9251	***2***
DMU3	0.3579	0.6602	1.0000	0.2921	15.3793	3.0371	0.8578	1.4995	0.6389	0.4232	2.0452	***4***
DMU4	1.2254	6.3663	3.4240	1.0000	2.0296	2.2405	2.9371	1.7739	2.1875	0.9121	0.6964	***9***
DMU5	0.6038	1.1138	1.6870	0.4927	1.0000	1.1039	1.4471	0.8740	1.0778	0.4494	9.2849	***1***
DMU6	0.5469	1.0090	1.5282	0.4463	5.0638	1.0000	1.3109	0.7918	0.9763	0.4071	2.4238	***3***
DMU7	0.4172	0.7697	1.2548	0.3405	19.2972	3.8108	1.0000	1.8815	0.7448	0.5310	1.7468	***5***
DMU8	0.6908	1.2744	1.9302	0.5637	10.2565	2.0255	1.6557	1.0000	1.2331	0.5141	1.4407	***6***
DMU9	0.5602	4.1459	1.5653	0.6512	0.9278	1.0243	1.3427	0.8110	1.0000	0.4170	1.3741	***7***
DMU10	1.3436	2.4787	3.7541	1.0964	36.3403	7.1766	3.2203	3.5432	2.3984	1.0000	0.5802	***10***
Average	**0.7288**	**2.9251**	**2.0452**	**0.6964**	**9.2849**	**2.4238**	**1.7468**	**1.4407**	**1.3741**	**0.5802**		

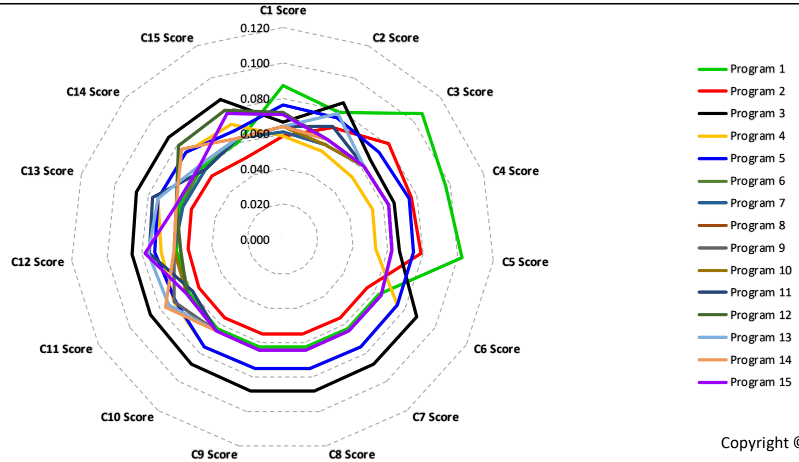
49. Proposed DEA CE/AHP Total with 3 Criteria

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10	Total	Efficiency	Rank
DMU1	0.1372	0.3567	0.1366	0.2353	0.0178	0.0754	0.1372	0.1005	0.1831	0.1283	1.5082	0.1508	***2***
DMU2	0.0744	0.0342	0.0741	0.0635	0.0097	0.0409	0.0744	0.0545	0.0704	0.0695	0.5655	0.0566	***10***
DMU3	0.0491	0.0226	0.0489	0.0419	0.1656	0.1253	0.0491	0.1041	0.0465	0.0729	0.7261	0.0726	***6***
DMU4	0.1681	0.2176	0.1674	0.1436	0.0219	0.0924	0.1681	0.1231	0.1592	0.1572	1.4188	0.1419	***3***
DMU5	0.0828	0.0381	0.0825	0.0708	0.0108	0.0455	0.0828	0.0607	0.0784	0.0775	0.6299	0.0630	***8***
DMU6	0.0750	0.0345	0.0747	0.0641	0.0545	0.0413	0.0750	0.0550	0.0711	0.0702	0.6154	0.0615	***9***
DMU7	0.0572	0.0263	0.0614	0.0489	0.2078	0.1572	0.0572	0.1306	0.0542	0.0915	0.8924	0.0892	***4***
DMU8	0.0948	0.0436	0.0944	0.0809	0.1105	0.0836	0.0948	0.0694	0.0897	0.0886	0.8503	0.0850	***5***
DMU9	0.0769	0.1417	0.0765	0.0935	0.0100	0.0423	0.0769	0.0563	0.0728	0.0719	0.7187	0.0719	***7***
DMU10	0.1844	0.0847	0.1836	0.1574	0.3914	0.2961	0.1844	0.2459	0.1745	0.1724	2.0748	0.2075	***1***
Total	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**10.0000**		

ANNEX G - SPMT SNAPSHOT (AHP EXAMPLE)

Portfolio Summary

Number of Programs	15
Number of Critera (n)	15



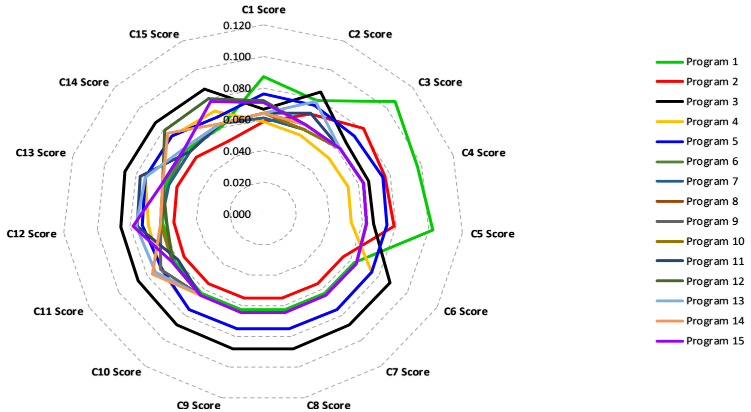
	%	Rank
Program 1	7.35%	3
Program 2	6.08%	15
Program 3	8.10%	1
Program 4	6.73%	4
Program 5	7.41%	2
Program 6	6.30%	13
Program 7	6.24%	14
Program 8	6.30%	12
Program 9	6.38%	10
Program 10	6.31%	11
Program 11	6.51%	8
Program 12	6.56%	7
Program 13	6.64%	5
Program 14	6.49%	9
Program 15	6.58%	6

n =	15

Random Index (RI)	
n	**RI**
1	0
2	0
3	0.58
4	0.9
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.51
11	1.52
12	1.54
13	1.56
14	1.58
15	1.59

Programs	15

Random Index (RI)	
n	**RI**
1	0
2	0
3	0.58
4	0.9
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.51
11	1.52
12	1.54
13	1.56
14	1.58
15	1.59



	Rank
Program 1	3
Program 2	15
Program 3	1
Program 4	4
Program 5	2
Program 6	13
Program 7	14
Program 8	12
Program 9	10
Program 10	11
Program 11	8
Program 12	7
Program 13	5
Program 14	9
Program 15	6

	Intensity Scale	
Less important than	Extremely less important	1/9
		1/8
	Very strongly less important	1/7
		1/6
	Strongly less important	1/5
		1/4
	Moderately less important	1/3
		1/2
	Equal Importance	1
More important than		2
	Moderately more important	3
		4
	Strongly more important	5
		6
	Very strongly more important	7
		8
	Extremely more important	9

Portfolio Summary

Summary	C1		C2		C3		C4		C5		C6		C7		C8		C9		C10		C11		C12		C13		C14		C15		Final Score	%	Rank
	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score			
Program 1	0.074	0.087	0.042	0.079	0.064	0.107	0.067	0.097	0.091	0.102	0.060	0.063	0.069	0.063	0.083	0.063	0.056	0.063	0.082	0.063	0.060	0.061	0.064	0.061	0.072	0.062	0.056	0.061	0.060	0.061	0.0735	7.35%	3
Program 2	0.074	0.058	0.042	0.070	0.064	0.081	0.067	0.077	0.091	0.079	0.060	0.055	0.069	0.055	0.083	0.055	0.056	0.055	0.082	0.055	0.060	0.055	0.064	0.054	0.072	0.054	0.056	0.054	0.060	0.051	0.0608	6.08%	15
Program 3	0.074	0.067	0.042	0.085	0.064	0.067	0.067	0.066	0.091	0.067	0.060	0.088	0.069	0.088	0.083	0.088	0.056	0.088	0.082	0.088	0.060	0.086	0.064	0.086	0.072	0.087	0.056	0.086	0.060	0.087	0.0810	8.10%	1
Program 4	0.074	0.058	0.042	0.055	0.064	0.053	0.067	0.054	0.091	0.053	0.060	0.075	0.069	0.075	0.083	0.075	0.056	0.075	0.082	0.075	0.060	0.071	0.064	0.069	0.072	0.074	0.056	0.074	0.060	0.072	0.0673	6.73%	4
Program 5	0.074	0.076	0.042	0.076	0.064	0.073	0.067	0.075	0.091	0.074	0.060	0.075	0.069	0.075	0.083	0.075	0.056	0.075	0.082	0.075	0.060	0.070	0.064	0.073	0.072	0.074	0.056	0.074	0.060	0.068	0.0741	7.41%	2
Program 6	0.074	0.064	0.042	0.062	0.064	0.062	0.067	0.063	0.091	0.062	0.060	0.064	0.069	0.064	0.083	0.064	0.056	0.064	0.082	0.064	0.060	0.063	0.064	0.062	0.072	0.060	0.056	0.063	0.060	0.063	0.0630	6.30%	13
Program 7	0.074	0.061	0.042	0.059	0.064	0.062	0.067	0.063	0.091	0.062	0.060	0.064	0.069	0.064	0.083	0.064	0.056	0.064	0.082	0.064	0.060	0.063	0.064	0.062	0.072	0.059	0.056	0.059	0.060	0.063	0.0624	6.24%	14
Program 8	0.074	0.064	0.042	0.062	0.064	0.062	0.067	0.063	0.091	0.062	0.060	0.064	0.069	0.064	0.083	0.064	0.056	0.064	0.082	0.064	0.060	0.063	0.064	0.058	0.072	0.063	0.056	0.063	0.060	0.063	0.0630	6.30%	12
Program 9	0.074	0.064	0.042	0.062	0.064	0.062	0.067	0.063	0.091	0.062	0.060	0.064	0.069	0.064	0.083	0.064	0.056	0.064	0.082	0.064	0.060	0.071	0.064	0.062	0.072	0.063	0.056	0.063	0.060	0.063	0.0638	6.38%	10
Program 10	0.074	0.064	0.042	0.059	0.064	0.062	0.067	0.063	0.091	0.062	0.060	0.064	0.069	0.064	0.083	0.064	0.056	0.064	0.082	0.064	0.060	0.063	0.064	0.062	0.072	0.063	0.056	0.063	0.060	0.063	0.0631	6.31%	11
Program 11	0.074	0.064	0.042	0.070	0.064	0.062	0.067	0.063	0.091	0.062	0.060	0.064	0.069	0.064	0.083	0.064	0.056	0.064	0.082	0.064	0.060	0.059	0.064	0.076	0.072	0.077	0.056	0.059	0.060	0.063	0.0651	6.51%	8
Program 12	0.074	0.072	0.042	0.062	0.064	0.062	0.067	0.063	0.091	0.062	0.060	0.064	0.069	0.064	0.083	0.064	0.056	0.064	0.082	0.064	0.060	0.063	0.064	0.058	0.072	0.063	0.056	0.079	0.060	0.080	0.0656	6.56%	7
Program 13	0.074	0.064	0.042	0.078	0.064	0.062	0.067	0.063	0.091	0.062	0.060	0.064	0.069	0.064	0.083	0.064	0.056	0.064	0.082	0.064	0.060	0.074	0.064	0.077	0.072	0.074	0.056	0.063	0.060	0.063	0.0664	6.64%	5
Program 14	0.074	0.064	0.042	0.062	0.064	0.062	0.067	0.063	0.091	0.062	0.060	0.064	0.069	0.064	0.083	0.064	0.056	0.064	0.082	0.064	0.060	0.077	0.064	0.062	0.072	0.063	0.056	0.077	0.060	0.063	0.0649	6.49%	9
Program 15	0.074	0.071	0.042	0.062	0.064	0.062	0.067	0.063	0.091	0.062	0.060	0.064	0.069	0.064	0.083	0.064	0.056	0.064	0.082	0.064	0.060	0.063	0.064	0.079	0.072	0.063	0.056	0.063	0.060	0.078	0.0658	6.58%	6

Step 1: Pairwise Comparison

Factor	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
C1	1	7	3	1	1	1	1	1	1	1	1	1	1/4	1	1
C2	1/7	1	1/7	1/5	1/5	1	1	1	1	1/6	1	1	1	1	1
C3	1/3	7	1	1	1	1	1/4	1	1	1	1	1	1	1	1
C4	1	5	1	1	1	1	1	1	1	1	1	1	1	1	1
C5	1	5	1	1	1	1	1	1	1	1	1	9	1	1	1
C6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C7	1	1	4	1	1	1	1	1	1	1	1	1/3	1	1	1
C8	1	1	1	1	1	1	1	1	1	1	1	1	1	9	1
C9	1	1	1	1	1	1	1	1	1	1/5	1	1	1	1	1
C10	1	6	1	1	1	1	1	1	5	1	1	1	1	1	1
C11	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C12	1	1	1	1	1/9	1	3	1	1	1	1	1	1	1	1
C13	4	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C14	1	1	1	1	1	1	1	1/9	1	1	1	1	1	1	1
C15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Total	16.476	40.000	19.143	14.200	13.311	15.000	16.250	14.111	19.000	13.367	15.000	22.333	14.250	23.000	15.000

Step 2: Normalisation

Factor	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	Total	Avg Total/n	%
C1	**0.061**	0.175	0.157	0.070	0.075	0.067	0.062	0.071	0.053	0.075	0.067	0.045	0.018	0.043	0.067	1.104	0.074	7.36%
C2	0.009	**0.025**	0.007	0.014	0.015	0.067	0.062	0.071	0.053	0.012	0.067	0.045	0.070	0.043	0.067	0.626	0.042	4.17%
C3	0.020	0.175	**0.052**	0.070	0.075	0.067	0.015	0.071	0.053	0.075	0.067	0.045	0.070	0.043	0.067	0.965	0.064	6.43%
C4	0.061	0.125	0.052	**0.070**	0.075	0.067	0.062	0.071	0.053	0.075	0.067	0.045	0.070	0.043	0.067	1.002	0.067	6.68%
C5	0.061	0.125	0.052	0.070	**0.075**	0.067	0.062	0.071	0.053	0.075	0.067	0.403	0.070	0.043	0.067	1.360	0.091	9.07%
C6	0.061	0.025	0.052	0.070	0.075	**0.067**	0.062	0.071	0.053	0.075	0.067	0.045	0.070	0.043	0.067	0.902	0.060	6.01%
C7	0.061	0.025	0.209	0.070	0.075	0.067	**0.062**	0.071	0.053	0.075	0.067	0.015	0.070	0.043	0.067	1.029	0.069	6.86%
C8	0.061	0.025	0.052	0.070	0.075	0.067	0.062	**0.071**	0.053	0.075	0.067	0.045	0.070	0.391	0.067	1.250	0.083	8.33%
C9	0.061	0.025	0.052	0.070	0.075	0.067	0.062	0.071	**0.053**	0.015	0.067	0.045	0.070	0.043	0.067	0.842	0.056	5.61%
C10	0.061	0.150	0.052	0.070	0.075	0.067	0.062	0.071	0.263	**0.075**	0.067	0.045	0.070	0.043	0.067	1.237	0.082	8.25%
C11	0.061	0.025	0.052	0.070	0.075	0.067	0.062	0.071	0.053	0.075	**0.067**	0.045	0.070	0.043	0.067	0.902	0.060	6.01%
C12	0.061	0.025	0.052	0.070	0.008	0.067	0.185	0.071	0.053	0.075	0.067	**0.045**	0.070	0.043	0.067	0.958	0.064	6.39%
C13	0.243	0.025	0.052	0.070	0.075	0.067	0.062	0.071	0.053	0.075	0.067	0.045	**0.070**	0.043	0.067	1.084	0.072	7.23%
C14	0.061	0.025	0.052	0.070	0.075	0.067	0.062	0.008	0.053	0.075	0.067	0.045	0.070	**0.043**	0.067	0.839	0.056	5.59%
C15	0.061	0.025	0.052	0.070	0.075	0.067	0.062	0.071	0.053	0.075	0.067	0.045	0.070	0.043	**0.067**	0.902	0.060	6.01%
Total	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000			

Step 3: Consistency Analysis

Consistency Measure	
C1	18.009
C2	16.459
C3	17.873
C4	17.474
C5	18.507
C6	16.634
C7	16.776
C8	17.374
C9	16.641
C10	17.376
C11	16.634
C12	16.542
C13	16.894
C14	16.559
C15	16.634
λ_{max}	**17.092**

λ_{max} = **17.092**

$$\mathrm{CI} = \mu = \frac{\lambda_{max} - n}{n-1} = \frac{17.092 - 15}{15 - 1} = \mathbf{0.149}$$

RI = 1.59

$$CR = \frac{\lambda_{max} - N}{(N-1)RI} = \frac{17.092 - 15}{14 \times 1.59} = \mathbf{0.094}$$

CR = **9%** **Consistency OK**

C1:

C1	Program 1	Program 2	Program 3	Program 4	Program 5	Program 6	Program 7	Program 8	Program 9	Program 10	Program 11	Program 12	Program 13	Program 14	Program 15
Program 1	1	3	5	2	1	1	1	1	1	1	1	1	1	1	1
Program 2	1/3	1	1/3	2	1/5	1	1	1	1	1	1	1	1	1	1
Program 3	1/5	3	1	2	1	1	1	1	1	1	1	1	1	1	1/3
Program 4	1/2	1/2	1/2	1	1	1	1	1	1	1	1	1	1	1	1
Program 5	1	5	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 7	1	1	1	1	1	1	1	1	1	1	1	1/3	1	1	1
Program 8	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 10	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 11	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 12	1	1	1	1	1	1	3	1	1	1	1	1	1	1	1
Program 13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 15	1	1	3	1	1	1	1	1	1	1	1	1	1	1	1
Total	**13.033**	**22.500**	**19.833**	**18.000**	**14.200**	**15.000**	**17.000**	**15.000**	**15.000**	**15.000**	**15.000**	**14.333**	**15.000**	**15.000**	**14.333**

C1	Program 1	Program 2	Program 3	Program 4	Program 5	Program 6	Program 7	Program 8	Program 9	Program 10	Program 11	Program 12	Program 13	Program 14	Program 15
Program 1	**0.077**	0.133	0.252	0.111	0.070	0.067	0.059	0.067	0.067	0.067	0.067	0.070	0.067	0.067	0.070
Program 2	0.026	**0.044**	0.017	0.111	0.014	0.067	0.059	0.067	0.067	0.067	0.067	0.070	0.067	0.067	0.070
Program 3	0.015	0.133	**0.050**	0.111	0.070	0.067	0.059	0.067	0.067	0.067	0.067	0.070	0.067	0.067	0.023
Program 4	0.038	0.022	0.025	**0.056**	0.070	0.067	0.059	0.067	0.067	0.067	0.067	0.070	0.067	0.067	0.070
Program 5	0.077	0.222	0.050	0.056	**0.070**	0.067	0.059	0.067	0.067	0.067	0.067	0.070	0.067	0.067	0.070
Program 6	0.077	0.044	0.050	0.056	0.070	**0.067**	0.059	0.067	0.067	0.067	0.067	0.070	0.067	0.067	0.070
Program 7	0.077	0.044	0.050	0.056	0.070	0.067	**0.059**	0.067	0.067	0.067	0.067	0.023	0.067	0.067	0.070
Program 8	0.077	0.044	0.050	0.056	0.070	0.067	0.059	**0.067**	0.067	0.067	0.067	0.070	0.067	0.067	0.070
Program 9	0.077	0.044	0.050	0.056	0.070	0.067	0.059	0.067	**0.067**	0.067	0.067	0.070	0.067	0.067	0.070
Program 10	0.077	0.044	0.050	0.056	0.070	0.067	0.059	0.067	0.067	**0.067**	0.067	0.070	0.067	0.067	0.070
Program 11	0.077	0.044	0.050	0.056	0.070	0.067	0.059	0.067	0.067	0.067	**0.067**	0.070	0.067	0.067	0.070
Program 12	0.077	0.044	0.050	0.056	0.070	0.067	0.176	0.067	0.067	0.067	0.067	**0.070**	0.067	0.067	0.070
Program 13	0.077	0.044	0.050	0.056	0.070	0.067	0.059	0.067	0.067	0.067	0.067	0.070	**0.067**	0.067	0.070
Program 14	0.077	0.044	0.050	0.056	0.070	0.067	0.059	0.067	0.067	0.067	0.067	0.070	0.067	**0.067**	0.070
Program 15	0.077	0.044	0.151	0.056	0.070	0.067	0.059	0.067	0.067	0.067	0.067	0.070	0.067	0.067	**0.070**
Total	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

Total	Avg Total/n	%
1.309	0.087	**8.72%**
0.877	0.058	**5.85%**
0.999	0.067	**6.66%**
0.877	0.058	**5.85%**
1.140	0.076	**7.60%**
0.963	0.064	**6.42%**
0.916	0.061	**6.11%**
0.963	0.064	**6.42%**
0.963	0.064	**6.42%**
0.963	0.064	**6.42%**
0.963	0.064	**6.42%**
1.080	0.072	**7.20%**
0.963	0.064	**6.42%**
0.963	0.064	**6.42%**
1.063	0.071	**7.09%**

Consistency Measure	
Program 1	16.526
Program 2	15.308
Program 3	15.889
Program 4	15.291
Program 5	16.230
Program 6	15.583
Program 7	15.588
Program 8	15.583
Program 9	15.583
Program 10	15.583
Program 11	15.583
Program 12	15.582
Program 13	15.583
Program 14	15.583
Program 15	15.984
$\lambda_{\max}$	**15.699**

$\lambda_{\max}$ = **15.699**

$$\mathrm{CI} = \mu = \frac{\lambda_{\max} - n}{n-1} = \frac{15.699 - 15}{15 - 1} = \mathbf{0.050}$$

RI = 1.59

$$CR = \frac{\lambda_{\max} - N}{(N-1)RI} = \frac{15.699 - 15}{14 \times 1.59} = \mathbf{0.031}$$

CR = **3%** **Consistency OK**

C2:

C2	Program 1	Program 2	Program 3	Program 4	Program 5	Program 6	Program 7	Program 8	Program 9	Program 10	Program 11	Program 12	Program 13	Program 14	Program 15
Program 1	1	3	3	3	1	1	1	1	1	1	1	1	1/5	1	1
Program 2	1/3	1	3	3	1/5	1	1	1	1	1	1	1	1	1	1
Program 3	1/3	1/3	1	3	1	1	1	1	1	8	1	1	1	1	1
Program 4	1/3	1/3	1/3	1	1	1	1	1	1	1	1	1	1	1	1
Program 5	1	5	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 7	1	1	1	1	1	1	1	1	1	1	1/3	1	1	1	1
Program 8	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 10	1	1	1/8	1	1	1	1	1	1	1	1	1	1	1	1
Program 11	1	1	1	1	1	1	3	1	1	1	1	1	1	1	1
Program 12	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 13	5	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Total	**17.000**	**19.667**	**17.458**	**21.000**	**14.200**	**15.000**	**17.000**	**15.000**	**15.000**	**22.000**	**14.333**	**15.000**	**14.200**	**15.000**	**15.000**

C2	Program 1	Program 2	Program 3	Program 4	Program 5	Program 6	Program 7	Program 8	Program 9	Program 10	Program 11	Program 12	Program 13	Program 14	Program 15	Total	Avg Total/n	%
Program 1	**0.059**	0.153	0.172	0.143	0.070	0.067	0.059	0.067	0.067	0.045	0.070	0.067	0.014	0.067	0.067	1.185	0.079	**7.90%**
Program 2	0.020	**0.051**	0.172	0.143	0.014	0.067	0.059	0.067	0.067	0.045	0.070	0.067	0.070	0.067	0.067	1.044	0.070	**6.96%**
Program 3	0.020	0.017	**0.057**	0.143	0.070	0.067	0.059	0.067	0.067	0.364	0.070	0.067	0.070	0.067	0.067	1.270	0.085	**8.47%**
Program 4	0.020	0.017	0.019	**0.048**	0.070	0.067	0.059	0.067	0.067	0.045	0.070	0.067	0.070	0.067	0.067	0.818	0.055	**5.45%**
Program 5	0.059	0.254	0.057	0.048	**0.070**	0.067	0.059	0.067	0.067	0.045	0.070	0.067	0.070	0.067	0.067	1.133	0.076	**7.55%**
Program 6	0.059	0.051	0.057	0.048	0.070	**0.067**	0.059	0.067	0.067	0.045	0.070	0.067	0.070	0.067	0.067	0.929	0.062	**6.20%**
Program 7	0.059	0.051	0.057	0.048	0.070	0.067	**0.059**	0.067	0.067	0.045	0.023	0.067	0.070	0.067	0.067	0.883	0.059	**5.89%**
Program 8	0.059	0.051	0.057	0.048	0.070	0.067	0.059	**0.067**	0.067	0.045	0.070	0.067	0.070	0.067	0.067	0.929	0.062	**6.20%**
Program 9	0.059	0.051	0.057	0.048	0.070	0.067	0.059	0.067	**0.067**	0.045	0.070	0.067	0.070	0.067	0.067	0.929	0.062	**6.20%**
Program 10	0.059	0.051	0.007	0.048	0.070	0.067	0.059	0.067	0.067	**0.045**	0.070	0.067	0.070	0.067	0.067	0.879	0.059	**5.86%**
Program 11	0.059	0.051	0.057	0.048	0.070	0.067	0.176	0.067	0.067	0.045	**0.070**	0.067	0.070	0.067	0.067	1.047	0.070	**6.98%**
Program 12	0.059	0.051	0.057	0.048	0.070	0.067	0.059	0.067	0.067	0.045	0.070	**0.067**	0.070	0.067	0.067	0.929	0.062	**6.20%**
Program 13	0.294	0.051	0.057	0.048	0.070	0.067	0.059	0.067	0.067	0.045	0.070	0.067	**0.070**	0.067	0.070	1.168	0.078	**7.79%**
Program 14	0.059	0.051	0.057	0.048	0.070	0.067	0.059	0.067	0.067	0.045	0.070	0.067	0.070	**0.067**	0.070	0.933	0.062	**6.22%**
Program 15	0.059	0.051	0.057	0.048	0.070	0.067	0.059	0.067	0.067	0.045	0.070	0.067	0.070	0.067	**0.067**	0.929	0.062	**6.20%**
Total	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.006**			

Consistency Measure	
Program 1	17.166
Program 2	16.754
Program 3	16.784
Program 4	15.491
Program 5	16.932
Program 6	16.145
Program 7	16.205
Program 8	16.145
Program 9	16.145
Program 10	15.802
Program 11	16.018
Program 12	16.145
Program 13	16.907
Program 14	16.091
Program 15	16.145
λ_{max}	**16.325**

λ_{max} = **16.325**

$$\text{CI} = \mu = \frac{\lambda_{\max} - n}{n-1} = \frac{16.325 - 15}{15 - 1} = \mathbf{0.095}$$

RI = 1.59

$$CR = \frac{\lambda_{\max} - N}{(N-1)RI} = \frac{16.325 - 15}{14 \times 1.59} = \mathbf{0.060}$$

CR = **6%** **Consistency OK**

……..C15:

C15	Program 1	Program 2	Program 3	Program 4	Program 5	Program 6	Program 7	Program 8	Program 9	Program 10	Program 11	Program 12	Program 13	Program 14	Program 15
Program 1	1	2	1/9	1	1	1	1	1	1	1	1	1	1	1	1
Program 2	1/2	1	1	1/5	1/5	1	1	1	1	1	1	1	1	1	1/8
Program 3	9	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 4	1	5	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 5	1	5	1	1	1	1	1	1	1	1	1	1/6	1	1	1
Program 6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 7	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 8	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 10	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 11	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 12	1	1	1	1	6	1	1	1	1	1	1	1	1	1	1
Program 13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Program 15	1	8	1	1	1	1	1	1	1	1	1	1	1	1	1
Total	**22.500**	**31.000**	**14.111**	**14.200**	**19.200**	**15.000**	**15.000**	**15.000**	**15.000**	**15.000**	**15.000**	**14.167**	**15.000**	**15.000**	**14.125**

C15	Program 1	Program 2	Program 3	Program 4	Program 5	Program 6	Program 7	Program 8	Program 9	Program 10	Program 11	Program 12	Program 13	Program 14	Program 15	Total	Avg Total/n	%
Program 1	**0.044**	0.065	0.008	0.070	0.052	0.067	0.067	0.067	0.067	0.067	0.067	0.071	0.067	0.067	0.071	0.914	0.061	6.09%
Program 2	0.022	**0.032**	0.071	0.014	0.010	0.067	0.067	0.067	0.067	0.067	0.067	0.071	0.067	0.067	0.009	0.763	0.051	5.08%
Program 3	0.400	0.032	**0.071**	0.070	0.052	0.067	0.067	0.067	0.067	0.067	0.067	0.071	0.067	0.067	0.071	1.300	0.087	8.67%
Program 4	0.044	0.161	0.071	**0.070**	0.052	0.067	0.067	0.067	0.067	0.067	0.067	0.071	0.067	0.067	0.071	1.074	0.072	7.16%
Program 5	0.044	0.161	0.071	0.070	**0.052**	0.067	0.067	0.067	0.067	0.067	0.067	0.012	0.067	0.067	0.071	1.015	0.068	6.77%
Program 6	0.044	0.032	0.071	0.070	0.052	**0.067**	0.067	0.067	0.067	0.067	0.067	0.071	0.067	0.067	0.071	0.945	0.063	6.30%
Program 7	0.044	0.032	0.071	0.070	0.052	0.067	**0.067**	0.067	0.067	0.067	0.067	0.071	0.067	0.067	0.071	0.945	0.063	6.30%
Program 8	0.044	0.032	0.071	0.070	0.052	0.067	0.067	**0.067**	0.067	0.067	0.067	0.071	0.067	0.067	0.071	0.945	0.063	6.30%
Program 9	0.044	0.032	0.071	0.070	0.052	0.067	0.067	0.067	**0.067**	0.067	0.067	0.071	0.067	0.067	0.071	0.945	0.063	6.30%
Program 10	0.044	0.032	0.071	0.070	0.052	0.067	0.067	0.067	0.067	**0.067**	0.067	0.071	0.067	0.067	0.071	0.945	0.063	6.30%
Program 11	0.044	0.032	0.071	0.070	0.052	0.067	0.067	0.067	0.067	0.067	**0.067**	0.071	0.067	0.067	0.071	0.945	0.063	6.30%
Program 12	0.044	0.032	0.071	0.070	0.313	0.067	0.067	0.067	0.067	0.067	0.067	**0.071**	0.067	0.067	0.071	1.205	0.080	8.03%
Program 13	0.044	0.032	0.071	0.070	0.052	0.067	0.067	0.067	0.067	0.067	0.067	0.071	**0.067**	0.067	0.071	0.945	0.063	6.30%
Program 14	0.044	0.032	0.071	0.070	0.052	0.067	0.067	0.067	0.067	0.067	0.067	0.071	0.067	**0.067**	0.071	0.945	0.063	6.30%
Program 15	0.044	0.258	0.071	0.070	0.052	0.067	0.067	0.067	0.067	0.067	0.067	0.071	0.067	0.067	**0.071**	1.171	0.078	7.80%
Total	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**			

Consistency Measure	
Program 1	15.980
Program 2	15.535
Program 3	17.159
Program 4	16.810
Program 5	16.794
Program 6	15.877
Program 7	15.877
Program 8	15.877
Program 9	15.877
Program 10	15.877
Program 11	15.877
Program 12	16.657
Program 13	15.877
Program 14	15.877
Program 15	17.374
λ_{max}	**16.221**

λ_{max} = **16.221**

$$CI = \mu = \frac{\lambda_{max} - n}{n - 1} = \frac{16.221 - 15}{15 - 1} = \mathbf{0.087}$$

RI = 1.59

$$CR = \frac{\lambda_{max} - N}{(N-1)RI} = \frac{16.221 - 15}{14 \times 1.59} = \mathbf{0.055}$$

CR = 5% Consistency OK

ANNEX H - SPMT SNAPSHOT (DEA EXAMPLE)

Portfolio Efficiency Assessment Using The Standard Data Envelopment Analysis (DEA) Method

Selected unit **1**

	Inputs Used			Outputs produced		STEP 1 Constraints that max efficiency = 1			
DMUs	**Input 1**	**Input 2**	**Input 3**	**Output 1**	**Output 2**	**Weighted inputs**		**Weighted outputs**	**Constraints**
1	128	6	7	8	195	1	>=	0.714285714	-0.285714286
2	112	16	8	7	239	1.142857143	>=	0.625	-0.517857143
3	151	7	4	6	118	0.571428571	>=	0.535714286	-0.035714286
4	30	8	8	6	201	1.142857143	>=	0.535714286	-0.607142857
5	72	3	7	9	280	1	>=	0.803571429	-0.196428571
6	138	10	2	1	104	0.285714286	>=	0.089285714	-0.196428571
7	32	5	6	5	230	0.857142857	>=	0.446428571	-0.410714286
8	191	8	8	9	499	1.142857143	>=	0.803571429	-0.339285714
9	68	5	2	3	139	0.285714286	>=	0.267857143	-0.017857143
10	29	8	4	2	141	0.571428571	>=	0.178571429	-0.392857143
11	89	2	5	8	373	0.714285714	>=	0.714285714	0
12	193	7	2	2	246	0.285714286	>=	0.178571429	-0.107142857
13	18	4	10	3	383	1.428571429	>=	0.267857143	-1.160714286
14	116	9	10	4	189	1.428571429	>=	0.357142857	-1.071428571
15	13	6	5	5	308	0.714285714	>=	0.446428571	-0.267857143
									1
Weights	**0**	**0**	**0.142857**	**0.089286**	**0**				

STEP 2

Constraints that the selected units has weighted inputs = 1 (one unit at a time)

Selected unit =	**1**		
Weighted inputs	1	=	1

STEP 3

Maximize the weighted outputs for the selected units (one unit at a time)

Selected unit =	**1**
Weighted outputs	**0.71429**

DEA Solver

STEP 4

Portfolio Efficiency Scores

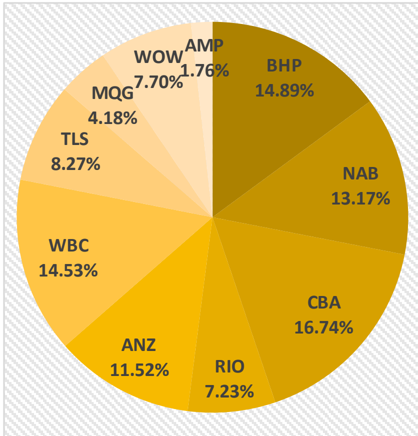
Efficiency	**%**	**Rank**
0.714285714	71.43%	5
0.546875	54.69%	9
0.9375	93.75%	2
0.46875	46.88%	11
0.803571429	80.36%	4
0.3125	31.25%	12
0.520833333	52.08%	10
0.703125	70.31%	6
0.9375	93.75%	2
0.3125	31.25%	12
1	100.00%	1
0.625	62.50%	7
0.1875	18.75%	15
0.25	25.00%	14
0.625	62.50%	7

ANNEX I - SPMT SNAPSHOT (PROPOSED MODEL – PT DEA CE/AHP)

STRATEGIC PORTFOLIO MANAGEMENT TOOL (SPMT)

Step 1 - Developing a Portfolio

Company	Synonym	Last price $ (end of 2014)	Shares No.	Position $	Share in portfolio
BHP Billiton	BHP	27.44	45.619	1,252	14.89%
National Australia Bank	NAB	31.96	34.638	1,107	13.17%
Commonwealth Bank	CBA	85.19	16.517	1,407	16.74%
Rio Tinto	RIO	58.00	10.483	608	7.23%
ANZ Banking Group	ANZ	32.09	30.19	969	11.52%
Westpac Banking Corp	WBC	32.94	37.095	1,222	14.53%
Telstra Corp Ltd	TLS	5.97	116.451	695	8.27%
Macquarie Group	MQG	58.29	6.031	352	4.18%
Woolworths	WOW	30.68	21.107	648	7.70%
AMP	AMP	5.50	26.862	148	1.76%
Total				**8,407**	**100.0%**



Step 2 - Calculating Portfolio Parameters

Company	Share in portfolio	Expected return (Re)	Risk (σ)	Variance (σ^2)
BHP Billiton	14.89%	-0.45%	2.63%	0.07%
National Australia Bank	13.17%	-0.04%	1.93%	0.04%
Commonwealth Bank	16.74%	0.20%	1.57%	0.02%
Rio Tinto	7.23%	-0.27%	2.91%	0.08%
ANZ Banking Group	11.52%	0.01%	2.04%	0.04%
Westpac Banking Corp	14.53%	0.07%	1.94%	0.04%
Telstra Corp Ltd	8.27%	0.25%	1.70%	0.03%
Macquarie Group	4.18%	0.14%	2.18%	0.05%
Woolworths	7.70%	-0.18%	1.96%	0.04%
AMP	1.76%	0.48%	3.04%	0.09%
S&P		**0.03%**	**1.42%**	**0.02%**

Step 3 - Collecting Input and Output Data for DMUs

DMUs	Input (σ^2)	Output (Re)
1	0.689124	-4.486161
2	0.373543	-0.430017
3	0.246631	2.026055
4	0.844466	-2.737628
5	0.416069	0.131739
6	0.376906	0.667096
7	0.287517	2.542196
8	0.476039	1.351179
9	0.386048	-1.782823
10	0.925884	4.787450

Step 4 - Proposed Integrated DEA Cross-Efficiency/AHP Model

COMPARISON MATRIX

DMUs	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10
DMU1	1.0000	5.6550	-0.7925	2.0081	-20.5602	-3.6781	-0.7363	-2.2935	1.4096	-1.2590
DMU2	0.1768	1.0000	-0.1401	0.3551	-3.6357	-0.6504	-0.1302	-0.4056	0.2493	-0.2226
DMU3	-1.2619	-7.1361	1.0000	-2.5340	25.9450	4.6414	0.9291	2.8942	-1.7788	1.5888
DMU4	0.4980	2.8161	-0.3946	1.0000	-10.2386	-1.8316	-0.3666	-1.1421	0.7020	-0.6270
DMU5	-0.0486	-0.2750	0.0385	-0.0977	1.0000	0.1789	0.0358	0.1116	-0.0686	0.0612
DMU6	-0.2719	-1.5375	0.2155	-0.5460	5.5899	1.0000	0.2002	0.6236	-0.3833	0.3423
DMU7	-1.3582	-7.6807	1.0763	-2.7274	27.9251	4.9956	1.0000	3.1151	-1.9146	1.7100
DMU8	-0.4360	-2.4656	0.3455	-0.8755	8.9644	1.6037	0.3210	1.0000	-0.6146	0.5489
DMU9	0.7094	4.0117	-0.5622	1.4245	-14.5854	-2.6092	-0.5223	-1.6270	1.0000	-0.8931
DMU10	-0.7943	-4.4916	0.6294	-1.5950	16.3304	2.9214	0.5848	1.8217	-1.1196	1.0000
Total	***-1.7867***	***-10.1038***	***1.4159***	***-3.5879***	***36.7348***	***6.5716***	***1.3155***	***4.0979***	***-2.5186***	***2.2495***
Average	***-0.1787***	***-1.0104***	***0.1416***	***-0.3588***	***3.6735***	***0.6572***	***0.1315***	***0.4098***	***-0.2519***	***0.2249***

AHP MEAN NORMALISATION MATRIX

DMUs	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10
DMU1	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597	-0.5597
DMU2	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990	-0.0990
DMU3	0.7063	0.7063	0.7063	0.7063	0.7063	0.7063	0.7063	0.7063	0.7063	0.7063
DMU4	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787	-0.2787
DMU5	0.0272	0.0272	0.0272	0.0272	0.0272	0.0272	0.0272	0.0272	0.0272	0.0272
DMU6	0.1522	0.1522	0.1522	0.1522	0.1522	0.1522	0.1522	0.1522	0.1522	0.1522
DMU7	0.7602	0.7602	0.7602	0.7602	0.7602	0.7602	0.7602	0.7602	0.7602	0.7602
DMU8	0.2440	0.2440	0.2440	0.2440	0.2440	0.2440	0.2440	0.2440	0.2440	0.2440
DMU9	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970	-0.3970
DMU10	0.4445	0.4445	0.4445	0.4445	0.4445	0.4445	0.4445	0.4445	0.4445	0.4445
Total	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*

DMUs	Total	Efficiency	Rank	Consistency
DMU1	-5.5969	-0.5597	10	10
DMU2	-0.9897	-0.0990	7	10
DMU3	7.0628	0.7063	2	10
DMU4	-2.7872	-0.2787	8	10
DMU5	0.2722	0.0272	6	10
DMU6	1.5217	0.1522	5	10
DMU7	7.6018	0.7602	1	10
DMU8	2.4403	0.2440	4	10
DMU9	-3.9704	-0.3970	9	10
DMU10	4.4455	0.4445	3	10
Total	*10*			10

$$CI = \frac{\lambda_{max} - n}{n - 1}$$

$$CR = \frac{CI}{RI\ (n)}$$

RI=	1.49		
CR=	0	<=	0.1
	0.0%	<=	10%

Step 5 - Testing the Portfolio Efficiency Results

Phase 1 - Portfolio actual risk and return

$$R_p = \sum_{i=1}^{N} X_i R_i = \quad -0.03\%$$

Correlation matrix

Company	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	1.000	0.433	0.369	0.749	0.455	0.497	0.520	0.334	0.445	0.480
NAB	0.433	1.000	0.603	0.319	0.689	0.729	0.392	0.360	0.534	0.385
CBA	0.369	0.603	1.000	0.215	0.656	0.730	0.663	0.444	0.342	0.349
RIO	0.749	0.319	0.215	1.000	0.327	0.316	0.447	0.168	0.352	0.375
ANZ	0.455	0.689	0.656	0.327	1.000	0.752	0.517	0.369	0.435	0.505
WBC	0.497	0.729	0.730	0.316	0.752	1.000	0.507	0.520	0.576	0.560
TLS	0.520	0.392	0.663	0.447	0.517	0.507	1.000	0.219	0.455	0.439
MQG	0.334	0.360	0.444	0.168	0.369	0.520	0.219	1.000	0.246	0.339
WOW	0.445	0.534	0.342	0.352	0.435	0.576	0.455	0.246	1.000	0.450
AMP	0.480	0.385	0.349	0.375	0.505	0.560	0.439	0.339	0.450	1.000

Share Matrix

BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%

Weights Multiplication Matrix

Company	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	0.022	0.020	0.025	0.011	0.017	0.022	0.012	0.006	0.011	0.003
NAB	0.020	0.017	0.022	0.010	0.015	0.019	0.011	0.006	0.010	0.002
CBA	0.025	0.022	0.028	0.012	0.019	0.024	0.014	0.007	0.013	0.003
RIO	0.011	0.010	0.012	0.005	0.008	0.011	0.006	0.003	0.006	0.001
ANZ	0.017	0.015	0.019	0.008	0.013	0.017	0.010	0.005	0.009	0.002
WBC	0.022	0.019	0.024	0.011	0.017	0.021	0.012	0.006	0.011	0.003
TLS	0.012	0.011	0.014	0.006	0.010	0.012	0.007	0.003	0.006	0.001
MQG	0.006	0.006	0.007	0.003	0.005	0.006	0.003	0.002	0.003	0.001
WOW	0.011	0.010	0.013	0.006	0.009	0.011	0.006	0.003	0.006	0.001
AMP	0.003	0.002	0.003	0.001	0.002	0.003	0.001	0.001	0.001	0.000

Risk matrix

BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%

Risk Multiplication Matrix

Company	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	0.001	0.001	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.001
NAB	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
CBA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RIO	0.001	0.001	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.001
ANZ	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
WBC	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
TLS	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
MQG	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
WOW	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
AMP	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Final Multiplication Matrix

Company	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	0.00002	0.00000	0.00000	0.00001	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
NAB	0.00000	0.00001	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
CBA	0.00000	0.00000	0.00001	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
RIO	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
ANZ	0.00000	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000
WBC	0.00001	0.00001	0.00001	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
TLS	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
MQG	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
WOW	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
AMP	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

σ^2 = 0.00024 $\sigma = \sqrt{\sigma^2} =$ 1.5%

Now we see that the risk of our portfolio is higher than for S&P index 1.42%

Phase 2 - Checking Sharpe-Ratio (SR)

$$SR = \frac{E(R_p) - R_f}{\sigma}$$

Rf = 1.98% / 53 = 0.03736%

PORTFOLIO COEFFICIENT

Company	Expected return (Re)	Risk (σ)	Risk-free rate (Rf)	Sharpe ratio (SR)
BHP Billiton	-0.449%	2.625%	0.037%	-18.512%
National Australia Bank	-0.043%	1.933%	0.037%	-4.158%
Commonwealth Bank	0.203%	1.570%	0.037%	10.522%
Rio Tinto	-0.274%	2.906%	0.037%	-10.706%
ANZ Banking Group	0.013%	2.040%	0.037%	-1.186%
Westpac Banking Corp	0.067%	1.941%	0.037%	1.512%
Telstra Corp Ltd	0.254%	1.696%	0.037%	12.789%
Macquarie Group	0.135%	2.182%	0.037%	4.481%
Woolworths	-0.178%	1.965%	0.037%	-10.975%
AMP	0.479%	3.043%	0.037%	14.506%
Portfolio	**-0.026%**	**1.542%**	**0.037%**	**-4.095%**
S&P index	**0.032%**	**1.418%**	**0.037%**	**-0.405%**

Phase 3 - Checking Beta (β)

$$\beta_a = \frac{Cov(r_a, r_p)}{Var(r_p)}$$

Beta (β) Calculation

Company	Covariance	Variance	Beta
BHP Billiton	0.00027	0.00020	1.34
National Australia Bank	0.00019	0.00020	0.96
Commonwealth Bank	0.00016	0.00020	0.82
Rio Tinto	0.00022	0.00020	1.11
ANZ Banking Group	0.00022	0.00020	1.10
Westpac Banking Corp	0.00023	0.00020	1.13
Telstra Corp Ltd	0.00018	0.00020	0.87
Macquarie Group	0.00015	0.00020	0.77
Woolworths	0.00017	0.00020	0.86
AMP	0.00029	0.00020	1.45
Portfolio	**0.00021**	**0.00020**	**1.04**

Phase 4 - Decision Making

CALCULATED PARAMETERS

Company	Share in portfolio	Expected return (Re)	Risk (σ)	Sharpe ratio	Beta
BHP Billiton	14.9%	-0.4%	2.6%	-0.19	1.34
National Australia Bank	13.2%	0.0%	1.9%	-0.04	0.96
Commonwealth Bank	16.7%	0.2%	1.6%	0.11	0.82
Rio Tinto	7.2%	-0.3%	2.9%	-0.11	1.11
ANZ Banking Group	11.5%	0.0%	2.0%	-0.01	1.10
Westpac Banking Corp	14.5%	0.1%	1.9%	0.02	1.13
Telstra Corp Ltd	8.3%	0.3%	1.7%	0.13	0.87
Macquarie Group	4.2%	0.1%	2.2%	0.04	0.77
Woolworths	7.7%	-0.2%	2.0%	-0.11	0.86
AMP	1.8%	0.5%	3.0%	0.15	1.45
Portfolio		**-0.03%**	**1.54%**	**-0.041**	**1.040**
S&P index		**0.03%**	**1.42%**	**-0.004**	

Lowest Sharpe Ratio =	-0.19	Reduce the value of shares in	**BHP Billiton**
Largest Sharpe Ratio =	0.15	Increase the value of shares in	**AMP**
Lowest Beta =	0.77	Reduce the value of shares in	**Macquarie Group**
Largest Beta =	1.45	Increase the value of shares in	**AMP**

NEW PORTFOLIO WITH MODIFIED SHARE VALUES

Company	Synonym	Last price $ (end of 2014)	Shares No.	Position $	Share in portfolio
BHP Billiton	BHP	$27.44	6	$164.67	2.0%
National Australia Bank	NAB	$31.96	34.638	$1,107.14	13.2%
Commonwealth Bank	CBA	$85.19	16.517	$1,407.06	16.7%
Rio Tinto	RIO	$58.00	10.483	$608.01	7.2%
ANZ Banking Group	ANZ	$32.09	30.19	$968.80	11.5%
Westpac Banking Corp	WBC	$32.94	37.095	$1,221.75	14.5%
Telstra Corp Ltd	TLS	$5.97	116.451	$695.21	8.3%
Macquarie Group	MQG	$58.29	4	$233.16	2.8%
Woolworths	WOW	$30.68	21.107	$647.56	7.7%
AMP	AMP	$5.50	246.2	$1,354.10	16.1%
Portfolio				**8,407**	**100%**

AVERAGE WEEKLY RETURN

	OLD	NEW	S&P index
2015 average weekly return	-0.157%	-0.062%	-0.026%

AVERAGE WEEKLY PERFORMANCE IN 2014

Company	Change - 2014
BHP Billiton	-0.45%
National Australia Bank	-0.04%
Commonwealth Bank	0.20%
Rio Tinto	-0.27%
ANZ Banking Group	0.01%
Westpac Banking Corp	0.07%
Telstra Corp Ltd	0.25%
Macquarie Group	0.14%
Woolworths	-0.18%
AMP	0.48%

RESULTS COMPARISON TABLE

Company	Expected return (Re)	Risk (σ)	Sharpe ratio	Efficiency
BHP Billiton	-0.45%	2.63%	-0.19	-0.5597
National Australia Bank	-0.04%	1.93%	-0.04	-0.0990
Commonwealth Bank	0.20%	1.57%	0.11	0.7063
Rio Tinto	-0.27%	2.91%	-0.11	-0.2787
ANZ Banking Group	0.01%	2.04%	-0.01	0.0272
Westpac Banking Corp	0.07%	1.94%	0.02	0.1522
Telstra Corp Ltd	0.25%	1.70%	0.13	0.7602
Macquarie Group	0.14%	2.18%	0.04	0.2440
Woolworths	-0.18%	1.96%	-0.11	-0.3970
AMP	0.48%	3.04%	0.15	0.4445

RANKING SCORES

Company	Expected return (Re)	Risk (σ)	Sharpe ratio	Efficiency
BHP Billiton	10	8	10	10
National Australia Bank	7	3	7	7
Commonwealth Bank	3	1	3	2
Rio Tinto	9	9	8	8
ANZ Banking Group	6	6	6	6
Westpac Banking Corp	5	4	5	5
Telstra Corp Ltd	2	2	2	1
Macquarie Group	4	7	4	4
Woolworths	8	5	9	9
AMP	1	10	1	3

ANNEX J – PUBLICATION I

Multi-criteria Decision-making Methods for Project Portfolio Management: A Literature Review

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ABSTRACT

Project Portfolio Management (PPM) has become a key element of large organisations' service delivery due to the close attention inherently paid to numerous issues in the discipline of project management. Its success is closely associated with the degree of understanding of its issues and the quality of decisions made at the portfolio level which can be addressed using Multi-criteria Decision-making (MCDM) methods. Although several of these MCDM methods have been introduced to support decision-making functions as part of PPM, there has been little assessment of their performances, particularly when combining some of them. This paper identifies the key challenges of PPM, proposes a new framework for classifying PPM MCDM-related methods and presents a literature review of applications of MCDM methods to PPM.

Keywords: Strategic Decision Making, Project Portfolio Management (PPM), Multi-criteria Decision Making (MCDM), MCDM Classification, PPM Challenges, Decision Problem.

1. INTRODUCTION

Management activities, such as improving public services, implementing new policies, and introducing new management systems, are conducted through projects and portfolios, with their poor performances and, in particular, their failures to deliver targeted benefits, having a negative effect on national growth, not to mention the waste of public assets and taxpayers' money (Chih & Zwikael, 2013). There are many decision-making techniques that can support Project Portfolio Management (PPM), with organisations which use structured ones to manage and implement their portfolios more successful due to their capability to reduce the gap between PPM and Multi-criteria Decision Making (MCDM) (Müller, Martinsuo, & Blomquist, 2008). However, in order to use appropriate decision- making methods, it is necessary to understand the challenges of PPM decision making.

Although a few studies discuss PPM challenges (e.g., Cooper, Edgett, & Kleinschmidt, 2001b; Elonen & Artto, 2003) and relevant decision-making issues (e.g., Manos, Papathanasiou, Bournaris, & Voudouris, 2010), there is no frameworks for properly linking them, in particular, using MCDM in PPM decision making.

Properly understanding PPM and its decision-making challenges also helps to correctly identify the factors required to develop a structured framework for selecting the ideal MCDM method(s) as a tool(s) in PPM decision making.

Based on the observed knowledge gaps, the primary concerns of this study are: "What is PPM?"; "What are the key challenges of PPM?"; "What are the failure factors of PPM?"; "What is a MCDM?"; "What kinds of MCDM methods are available?"; and "How can MCDM methods be classified?". In this study, a comprehensive review of the literature is conducted to analyse the challenges of PPM decision making. Then, MCDM techniques are classified to improve knowledge of their assessment and decision-making approaches, with their strengths and weaknesses in relation to PPM decision making analysed to determine any constraints and limitations on applying them. Accordingly, a solid structure of MCDM techniques that improves knowledge of the assessment and selection techniques for projects in complex organisations are presented.

The selection of publications considered is restricted based on the following factors. The review covers the literature on decision making, and organisational and portfolio management published between 1860 and 2016, with Google Scholar used to retrieve the relevant articles accessed using the following search phrases: ["Project Portfolio Management" OR "Portfolio Management" OR "Project and Program Management"] AND ["Multi-criteria Decision Making" OR "Complex Decision Making"] which produces more than 1400 extracted publications.

The work in this study extends the sensitivity analysis frameworks introduced by Barron and Schmidt (1988), Insua and French (1991), Wolters and Mareschal (1995), and Ringuest (1997). The difficulties of PPM decision making can be identified in different project situations, such as the selection of projects, prioritisation and balancing of resources (e.g., cost and time) or financial management. Since selecting and prioritising of projects in PPM are our areas of interest, this research is undertaken from a management decision-making rather than mathematical point of view.

2. PROJECT PORTFOLIO MANAGEMENT (PPM)

2.1. PPM OVERVIEW

Portfolio management seems to have been first employed in the 1950s to determine inventory portfolios (Markowitz, 1952). Most studies acknowledge that PPM is generally considered as an active decision-making procedure whereby a set of projects is modified (Martinsuo & Lehtonen, 2007). Project and program management are focused on 'performing the project/program right' while portfolio management refers to 'carrying out the right project' (Cooke-Davies, 2002; PMI, 2006). In this study, we focus on the following.

"Project Portfolio management is a dynamic decision process, whereby a business's list of active new products (and R&D) projects are constantly up-dated and revised. In this process, new projects are evaluated, selected and prioritized; existing projects may be accelerated, killed or de-prioritized; and resources are allocated and reallocated to the active projects. The portfolio decision process is characterized by uncertain and changing information, dynamic opportunities, multiple goals and strategic considerations, interdependence among projects, and multiple decision-makers and locations" (Cooper, Edgett, & Kleinschmidt, 2001a).

The systematic control of a portfolio's outcomes has enhanced benefits for businesses (Platje, Seidel, & Wadman, 1994). As PPM can handle several projects as a single program, it is more popular with practitioners (Artto, Dietrich, & Nurminen, 2004). Many studies emphasise the significance of PPM for assessing, prioritising and choosing the right projects and programs according to organisational policies (e.g., Cooper et al., 2001a). Also, as the main critical studies of PPM concentrate on its practices of project selection and prioritisation (Artto et al., 2004; Elonen & Artto, 2003; PMI, 2006), choosing the most appropriate project is a significant aspect of organisational management. The goals of PPM are maximising a portfolio's value, developing its strategic arrangement and balancing its assignments (Cooper, Edgett, & Kleinschmidt, 2002) which this research uses to determine whether a PPM is successful.

Various analyses have suggested that PPM and its performance results need to be assessed at the project, portfolio and organisational levels (Müller et al., 2008), with an effective PPM required to promote an organisation's overall goals. Therefore, an organisation's short- and long-term success factors are taken into account in the work of Shenhar, Dvir, Levy, and Maltz (2001) and applies the measurements of Maylor, Brady, Cooke-Davies, and Hodgson (2006) on Cooper's three PPM goals (i.e., maximising a portfolio's value, developing its strategic arrangement and balancing its assignments) (Cooper et al., 2002) to discover their relationships. MCDM methods can fulfil these requirements; for example, their scoring techniques are used for large portfolios while pair-wise comparison methods are more suitable for smaller projects. However, finding the most suitable method(s) for PPM is a challenging task that requires a constructive review and comparison of MCDM methods to identify the most suitable one(s) for PPM decision making for determining which projects in a portfolio add most value to the organisational objectives.

2.2. PPM Decision Making Challenges

While several studies describe various PPM issues, such as obtaining executive-level support and commitment (Kendall & Rollins, 2003), gaining a perception of a portfolio across projects (McDonough III & Spital, 2003; Wheelwright & Clark, 1992), and having proper information (Martino, 1995; Wideman, 2004) and sufficient time to perform PPM (Lawson, Longhurst, & Ivey, 2006; Vähäniitty, 2006), a major concern is ascertaining the key challenges of PPM.

Most organisations encounter difficulties when selecting specific projects (De Reyck et al., 2005; Meskendahl, 2010) using an adaptable decision-making practice (Bessant, Von Stamm, & Moeslein, 2011; Blichfeldt & Eskerod, 2008). While several PPM studies indicate the significance of selecting a specific group of projects, they do not properly examine the issues faced during the selection process (Bessant et al., 2011). PPM studies have not presented a comprehensive idea of exactly how processes for selection and project prioritisation are actually stated in PPM. Therefore, further investigation is required to determine exactly the types of methods employed for the examination and selection of projects (Geraldi, 2008).

The challenges of assessing and selecting options and projects are discussed below through an examination of PPM studies as well as observations based on decision-making principles.

2.2.1. Sensitivity Analysis/Uncertainty Treatment. Organisations deal with several uncertainties, including insufficient data, inaccurate cost information, the completion period and availability of resources and benefits (Cooper et al., 2001a). A sensitivity analysis is an essential aspect of quantitative decision models (Dantzig, 1998; Insua, 1990) and an effective process because it demonstrates the advantages and disadvantages of a/the particular examination (Commission, 1992) while efficient uncertainty management is the most critical challenge in the decision-making process (Felli & Hazen, 1998; Steffens, Martinsuo, & Artto, 2007). A comprehensive decision assessment demands an in depth sensitivity examination (Belton & Hodgkin, 1999) which can be very challenging (Larichev, 2000). The selection process consists of numerical inputs which might not be fully accurate (French et al., 1998). Every step in the MCDM procedure consists of some kind of uncertainty, such as selecting the technique (Bouyssou, 1990) and factors, examining the factors' values and choosing weights (Janssen, Nijkamp, & Rietveld, 1990). Consequently, a Decision Maker (DM) usually has to first estimate the effect of change on the relevant portfolio and then calculate the essential information with considerably higher degrees of accuracy and reliability. For these reasons, a sensitivity analysis of MCDM challenges must be conducted. Insua (1990) emphasises the need for this as difficult decisions can be extremely sensitive to certain changes in the issues; for example, assessing and selecting an entirely new system which is being created is an extremely unknown/uncertain situation (Wheelwright & Clark, 1992).

2.2.2. Dependencies. Dealing with a portfolio of projects with uncertainty is a difficult task exacerbated by the existence of interdependencies (Collyer & Warren, 2009; Perminova, Gustafsson, & Wikström, 2008) which is among the reasons for a PPM failure (Elonen & Artto, 2003). PPM procedures are used to determine dependencies among the projects in a portfolio so that decisions can be made knowing the potential impacts of these projects on each other (Shenhar et al., 2001). Although the interdependencies in portfolios with several projects need to be known to facilitate good judgments (Blau, Pekny, Varma, & Bunch, 2004), communications among the various procedures/methods available are extremely complicated (Dawidson, 2006). Choices or unforeseen situations occurring in a single task impact on other functions (e.g., re- prioritisations of programs or evaluations of strategies). Most scientific studies of PPM manage each project as an individual process while recognising the value of considering projects' interdependencies (Collyer & Warren, 2009; Dahlgren & Söderlund, 2010; Söderlund, 2004). To indicate the additional characteristic of

PPM compared with individual project management, Cooper and Edgett (2003) employ the analogy that a project procedure addresses the 'fingers' while PPM focuses on the 'fist'.

2.2.3. Decision Traceability. To deal with PPM complexities, such as uncertainty or dependencies among projects, it is essential to keep track of data and ensure that critical data is not eliminated or unnecessary data incorporated. This process has to be traceable (backwards and forwards throughout the decision cycle and from the strategic to operational levels) (Danilovic & Browning, 2007).

2.2.4. Simplicity. Although there are more than 100 different methods which can be used to calculate, examine and select decision options, most are seldom employed because: they are complicated and involve an excessive amount of input information; provide insufficient management of risk and uncertainty; are incapable of identifying interrelationships and related requirements; might simply be too difficult to understand or apply; and might not be considered from the perspective of a structured method and practice (Cooper, 2001; Cooper, Edgett, & Kleinschmidt, 1997a). Although several earlier decision-making techniques tried to improve formulaic options via mathematical models and optimisation methods, generally, they are not often applied because of their complex structures (Coldrick, Longhurst, Ivey, & Hannis, 2005). Costa (1988) states that, although there are various MCDM techniques which might be useful (in theory), they are subject to failure due to their lack of simplicity, with their complexities being the main reason for DMs preferring simple weight-rating methods. Despite the fact that there is no shortage of decision-making methods with individual positive aspects, there is certainly a lack of an overall framework for rationally arranging them in an adaptable procedure which could sustain the practice of portfolio decision making, partly because of the complexities involved in using some of them. DMs are unlikely to apply a technique/method/tool that is not both effective and simple to operate (Moore & Benbasat, 1991). To attempt to overcome these issues, suitable techniques need to provide the best features of some current techniques with fewer complexities. Therefore, simple decision-support tools/techniques are key elements for multiple decision making (Bender & Simonovic, 2000).

2.2.5. Quantitative and Qualitative Measures. The strategic arrangement of projects in a portfolio, which is critical, requires both quantitative and qualitative techniques (Kester, Hultink, & Lauche, 2009). It is also in line with analysing specifications that assist the selection of project options and decisions (Bergman & Mark, 2002). A project's related risk level is a qualitative factor, its estimated profit a quantitative one, and its involvement in organisational strategy both qualitative and quantitative ones (Ohr & McFarthing, 2013). Although quantitative data, such as costs and time, is readily available for most projects, qualitative analysis is more often used for complex ones. In current PPM, most portfolio decisions are subjective based on assessments of various project options.

2.2.6. Number of Projects. The number of programs/projects planned for a given portfolio can be quite significant (Cooper et al., 1997a) and confusion regarding portfolio decisions arises as the number of projects to be taken into consideration increases (Levine, 2005). Cooper and Edgett (2003) justify the significance of excellent decision making and the need to acquire top-quality information for that purpose. Selecting and delivering a number of projects beyond an organisations' capacity are among the main reasons for projects' failures to achieve organisational objectives (Almendra & Christiaans, 2009; Yelin, 2005). As the possibility of reaching sound organisational decisions can be diminished if many programs/projects must be considered, verification processes must be conducted before the commencement of portfolio selection to justify the inclusion of specific programs/projects in this process.

2.2.7. Trade-offs/Conflict. MCDM enhances a DM's ability to examine trade-offs between options and assess their influences on different stakeholders (Mysiak, Giupponi, & Rosato, 2005). There are several, usually inconsistent, targets linked to the selection of programs/projects for inclusion in a portfolio; for instance, are financial targets more important than political ones, and if so, to exactly what degree? In a MCDM's closing stage, the ideal option is that which offers an appropriate cross-section of trade-offs among variables (Simonovic, Burn, & Lence, 1997).

2.2.8. Group Decision Making. As DMs usually work in groups, which make formal and informal choices at different levels (Gutiérrez, Janhager, Ritzén, & Sandström, 2008), their decision-making processes are a great deal more complicated than that of an individual or, arguably, even inefficient

(Proctor, 2001). The members of a decision group may vary from an organisation's senior executives with similar targets to its mid-level managers with entirely opposite ones (Davey & Olson, 1998). A key factor behind the complexities of group decision making is the lack of a strategy in which all DMs are able to present their opinions (Georgopoulou, Lalas, & Papagiannakis, 1997), but there are few methods which can adequately overcome this difficulty (Leyva-Lopez & Fernandez-Gonzalez, 2003). It is necessary that DMs ensure that their perspectives are considered in a decision-making process (Miettinen & Salminen, 1999). Souder (1975) seeks to achieve consensus on portfolios by discovering mixtures of integrated comparisons, group discussions and participant connections in decision making.

2.2.9. Hierarchical Structure (Mutual Links between Projects and Strategic Levels). A PPM procedure starts from, and reports to, the strategic level and manages a link between that and the operational level (Poskela, Dietrich, Berg, Artto, & Lehtonen, 2005). As previously stated, PPM decision-making methods can be very complicated, difficult to use and normally require large amounts of input information (Cooper et al., 2001b). To minimise these types of issues, a portfolio is structured hierarchically, with each phase beginning from a top-down (i.e., strategic level) or bottom-up (i.e., project/operational level) perspective. Moreover, PPM is generally set up at several levels within an organisation, including departmental, divisional, branch or unit ones, while some techniques, e.g., top-down and bottom-up ones, can line operations up at only an organisation's strategic level (Cooper & Edgett, 2008). The capability of PPM to use top-down strategic objectives with bottom-up strategic processes are examined in various investigations (e.g., Crawford, 2001), with many studies (e.g., Meskendahl, 2010) suggesting the need for a mutual connection between the operational and strategic levels of an organisation. Killen, Hunt, and Kleinschmidt (2008) believe that the association of new system achievements with portfolio performance is a key factor for organisational growth.

2.2.10. Other Criteria. Other challenges and requirements in accordance with operational assumptions (e.g., workforce management, financial availability, honesty, and politics and policy variations) are not considered in this assessment because they rely more on managing capabilities than on the techniques themselves. Nevertheless, this does not imply that these factors are less important during a PPM MCDM assessment process but that they are more in line with the operational stage following the selection of the preferred MCDM method(s).

A summary of the key PPM challenges in this study are presented in Table 1.

Table 1. Summary of Key PPM Challenges

Challenging factors	Description
Sensitivity Analysis/Uncertainty Treatment	A decision assessment involves different inputs which may not be entirely specific (e.g., insufficient data, inaccurate cost information, an undetermined completion period, and little knowledge of the resources and benefits).
Dependencies	For effective decision making, the interdependencies in portfolios with several projects need to be known. Every program depends on the others and may be linked by many different dependencies. Often, as projects in portfolios are very interdependent in nature, all of them must be considered in every step of a decision-making process.
Decision Traceability	To deal with PPM complexities (e.g., uncertainty and dependencies), it is essential to keep track of data and ensure that critical data is not eliminated and/or unnecessary data incorporated.
Simplicity	While most decision-making methods are very difficult to understand and/or apply, DMs are unlikely to use one that is not effective and simple. Also, as there is an overall lack of a framework for arranging these methods, choosing simple ones is one of the key elements for multiple decision making.

Quantitative and Qualitative Techniques	The strategic arrangement of projects in a portfolio, which is extremely critical, requires both quantitative and qualitative techniques.
Number of Projects	As the number of possible projects in a portfolio can be enormous, the method used to solve decision challenges cannot be restricted to dealing with a certain number of items or options which is the case in some techniques.
Trade-offs/Conflict	There are several, usually inconsistent, targets linked to the selection of programs, with prioritising them a challenging task. As non-compensatory methods fail to permit trade-offs between elements, only compensatory ones are selected for detailed analysis in this study.
Group Decision Making	Large and difficult decisions, especially at executive senior management levels, often require several DMs operating in groups.
Mutual link between Projects and Strategic Levels (Hierarchical Structure)	PPM is generally set up at several levels, with its decision-making methods very complicated and usually requiring large amounts of input information. To minimise these types of issues, a portfolio needs to be structured in a hierarchical way so that each phase can begin from a top-down (strategic level) or bottom-up (project/operational level) perspective and examine the maturity of all levels in a PPM process (e.g., project, program and portfolio management/strategic ones).

3. Classification of PPM Decision-making Techniques

An appropriate harmonic combination of projects must be selected to increase the benefit of a portfolio and its organisational strategy (PMI, 2006). Given that each project performs a unique function and presents an individual input to PPM, organisations have to determine, choose, prioritise and allocate options to different kinds of projects (Geraldi, 2008).

Techniques for eliminating and resolving multi-criteria issues are continually being developed while the number of MCDM-related articles is gradually increasing (Wallenius et al., 2008). As there is no single MCDM method or tool that can support strategic PPM decision making, different ones are used to suit different PPM situations (Killen et al., 2008; Verbano & Nosella, 2010).

Despite the fact that earlier investigations examined and evaluated decision making, the work of Neumann and Morgenstern (1947) and Savage Leonard (1954) can be regarded as the beginning of multi-criteria studies.

3.1. Proposed Classification Framework

On the basis of an extensive literature review of various decision-making methods (e.g., Hwang and Yoon, 1981; Hobbs, 1986; Hwang & Yoon, 1981; MacCrimmon, 1973; Ozernoy, 1992), this study proposes a mixture of all those taxonomies in three categories which also incorporate those which may not have been presented in other publications: MCDM (also called Multi-criteria Decision Analysis (MCDA)), Artificial Intelligence (AI) and others (Figure 1).

This research concentrates primarily on the application of decision-making methods for PPM. As, in the literature, PPM issues are related to MCDM methods, several of which are used in problem-solving procedures (e.g., Gürbüz, Alptekin, & Alptekin, 2012; Jozi, Shoshtary, & Zadeh, 2015). Therefore, non-PPM issues or methods not included in the MCDM category are not considered for further investigation in this study. Figure 1 presents a framework for classifying decision-making methods.

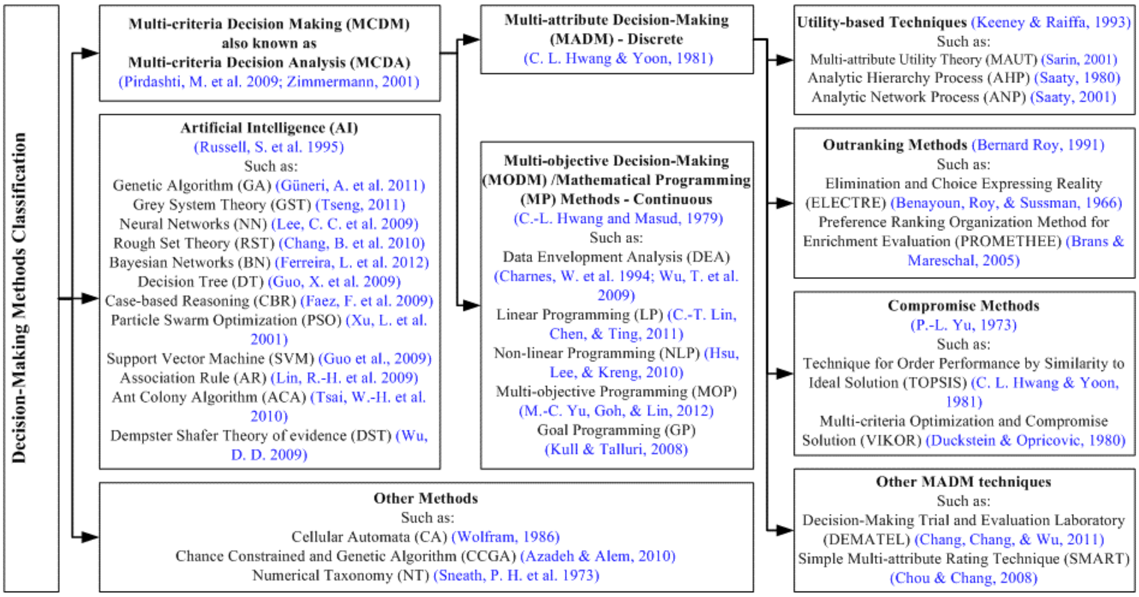

Figure 1. Classification of Decision-Making Techniques

3.2. Multi-criteria Decision Making (MCDM)

MCDM methods for minimising the challenges and complexities involved in dealing with large amounts of data during decision-making operations appear to have been used for the first time in the financial industry in the 1960s (Figueira, Greco, & Ehrgott, 2005), with a significant number of MCDM assessments based on a more recent investigation by MacCrimmon (1973). MCDM also incorporates several methods that enable estimations of various requirements to assist DMs to select, rank and evaluate various options (Belton & Stewart, 2002), and examine decision problems specified by various difficult goals (Nijkamp, Rietveld, & Voogd, 2013). Many MCDM methods require determination of the most suitable techniques for managing the issues associated with decision making (Brunner & Starkl, 2004). Although several researchers explain these issues in a basic manner by outlining their individual components and patterns, only a few (e.g., Goicoechea, Hansen, & Duckstein, 1982; and Milan, 1982) clarify the steps in their algorithms.

Some researchers discuss processes for classifying and selecting a suitable MCDM technique based on its input specifications (e.g., Hwang and Yoon, 1981; Hobbs, 1986; Hwang & Yoon, 1981; and Ozernoy, 1992). Also, Jelassi and Ozernoy (1989) recommend using a professional framework to select MCDM techniques, with Jacquet-Lagreze and Siskos (2001) suggesting measurable, ordinal, probabilistic and fuzzy requirements. Bouyssou (1990), Georgopoulou et al. (1997) and Al-Kloub, Al-Shemmeri, and Pearman (1997) all agree on the requirements for selecting MCDM methods, that is, they need to be simple and easy to understand, operational, complete, non- redundant and essential. Furthermore, Kheireldin and Fahmy (2001) categorise MCDM methods as cardinal, frequency, scale-modelling and mixed information. MCDM methods are also grouped according to their allocated weights (Harboe, 1992). Hajkowicz (2000) proposes classifying MCDM methods as 'continuous' and 'discrete' techniques but excludes outranking ones.

This study classifies MCDM into Multi-objective Decision Making (MODM) (or continuous) and Multi-attribute Decision Making (MADM) (or discrete) techniques. The former can be used for an unlimited (infinite) number of options implicitly identified by their difficulties whereas the latter consider a limited (finite) number of options and criteria (Hajkowicz, Young, & MacDonald, 2000) which enables them to be sub-divided into ranking techniques (Nijkamp et al., 2013). Therefore, MODM techniques handle design/search problems and seek an optimal quantity which may change considerably in a decision challenge whereas MADM ones are effective for selection/evaluation problems (Hwang & Lin, 2012).

3.2.1. Multi-attribute Decision Making (MADM)/Discrete Methods

According to Yoon and Hwang (1995), MADM techniques share the following features: they screen, prioritise, select and rank a limited (finite) number of options; have various elements per issue and a variety of units of measurement among the elements; usually require data regarding the relative advantages of each element; generally, are available based on ordinal or cardinal data; and their difficulties can be stated in a matrix structure.

Research conducted during the past three decades shows an increasing number of new and combined MADM techniques with different classifications (e.g., Nijkamp et al., 2013), most of which belong to the categories of Multi- attribute Utility (utility-based); Outranking; and Mixed (compromise) methods. Greco, Matarazzo, and Słowiński (2004) classify these methods in the three categories of utility features, outranking relationships and models of decision principles. while Kangas, Kangas, and Pykäläinen (2001), and Guitouni and Martel (1998) categorise them as: (i) the Value and Utility Theory (known as 'American School' techniques); (ii) Outranking (a.k.a. 'European School' techniques); and (iii) Interactive approaches. Based on the theories behind them, this study groups MADM methods as follows.

3.2.1.1. Utility-based Techniques (UBT) (a.k.a. Multi-attribute Utility Techniques, Compensatory Methods or Performance Aggregation-based Methods)

Neumann and Morgenstern (1947) and Savage Leonard (1954) were the first to present effective observations of how multi-criteria decisions are made. However, their experiments do not clearly assist DMs in making decisions involving complex multi-criteria tasks. In order to overcome these challenges, Keeney and Raiffa (1993) present UBTs that basically aim to allocate a utility amount to every alternative, for example the Analytic Hierarchy Process (AHP) or Analytic Network Process (ANP). What might make their recommendations useful is that their model considers uncertainty and provides options for the alternatives to communicate with each another. Using a UBT, DMs can obtain accurate responses and solutions to a variety of choices (Belton & Stewart, 2002). UBTs are also referred to as Compensatory Methods because of their inadequate performances for some criteria (Linkov et al., 2006). A UBT does not consider choices to be mutually independent and tends to be more user-friendly and straightforward than other MCDM methods. However, its use of additive utility features is only applicable when the criteria are independent.

3.2.1.2. Outranking Methods (a.k.a. Partially Compensatory or Preference Aggregation-based Methods)

Outranking methods assess sets of preferences to determine whether option 'A' is at least as effective as option 'B' (Roy, 1991), that is, they rely on the philosophy that, as one option can attain a level of control over other available ones (Kangas et al., 2001), all the options need to be ranked (Rogers & Bruen, 1998). Two methods in this category are: Elimination and Choice Expressing Reality (ELECTRE); and Preference Ranking Organisation Method for Enrichment Evaluation (PROMETHEE). As Outranking methods do not assume that only one best option is available; for instance, they do not consider the relative levels of importance of under-and over-performances, they are also referred to as Partially Compensatory Methods. Usually, they are used when the factor metrics are difficult to aggregate or there are broad ranges of different units and unique dimensions for each factor (Seager & Theis, 2004). The major issue regarding the use of an Outranking method is the different definitions of what represents outranking and how its threshold variables are arranged and later adopted by a DM.

3.2.1.3. Compromise Methods

The Compromise model (Milan, 1982; Yu, 1973) can assist DMs to arrive at a final decision for a problem with mixed factors and offer the best possible practical option by sharing ideas. Sometimes, the selection process draws on political factors whereby a DM can define the essential elements of compromise options (Yu, 1973). Compromise methods, such as the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), are driven by an aggregating feature that provides bonding to the ideal (Chatterjee, Athawale, & Chakraborty, 2009) and a foundation for discussions concerning a DM's choice based on the factors' weights (Sayadi, Heydari, & Shahanaghi, 2009).

3.2.2. Multi-objective Decision Making (MODM)/Continuous methods

It is quite normal to simultaneously deal with various targets without having a clear direction as to which refer to performances and which to issues. These difficulties of ‘many multiple decision criteria’, ‘depending on limitations’ and ‘several targets’ are generally known as MODM problems. It is most likely that Kuhn and Tucker (1951) were the first to identify these issues which are also called ‘vector-maximum’ ones. The challenges of MODM (in a mathematical programming framework) are broken into different groups. The first does not require obtaining any data from DMs throughout the process of selecting an alternative as its techniques depend on pre-assumptions about the DMs’ choices (Milan, 1982; Zeleny, 2012). The second involves collecting cardinal or ordinal selected data prior to the solving process. A few of these approaches collect only cardinal priorities while others, such as Goal Programming (GP), use a combination of the capabilities of both cardinal and ordinal data. The third delivers a number of alternative options from which DMs are able to select the ideal one, for example, Data Envelopment Analysis (DEA) which offers options and results consistently connected to a DM’s opinion (Wu & Blackhurst, 2009).

MODM methods are much better at describing reality and verifying a large number of options than MADM ones (Cohon, 2013).

More detailed information on MODM and MADM methods and applications can be found in Hwang and Masud (1979) and Hwang and Yoon (1981).

4. CONCLUSION

PPM has become an essential part of an organisation’s capability to successfully direct its projects (Cooper, Edgett, & Kleinschmidt, 1997b). It is a decision-making practice that examines and selects options, prioritises them and directs them between activities (Cooper et al., 2001b). However, few studies have addressed using MCDM in PPM decision making.

PPM aims to present a logical structure by which to determine the projects that need to be performed by a corporation (Tidd et al. 1997; Jonas, 2010; Killen & Hunt, 2010), with those associated with organisational policies required to be compared. Therefore, it is essential to identify the most suitable projects in PPM for selection and prioritisation procedures (Archibald, 2004; Englund & Graham, 1999; Wheelwright, 1992). Different projects may possess unique functions, with their types indicating various difficulties for final decisions and choosing PPM practices (Blomquist & Müller, 2006). Nevertheless, PPM studies have not yet properly highlighted the difficulties that DMs and organisations might encounter when integrating various methods (Geraldi, 2008) for identifying different options and projects (Bessant et al., 2011).

In this study, the PPM challenges are described and the problems associated with them are discussed in detail. Moreover, PPM MCDM techniques are broadly reviewed in light of other studies (e.g., Cooper et al., 2001b; Danilovic & Sandkull, 2005; Dawidson, 2006; Dye & Pennypacker, 1999; Verbano & Nosella, 2010).

There is a considerable degree of uncertainty related to the scoring of projects based on particular measures while decision assessments have different inputs which may not be entirely specific (French et al., 1998). According to Zimmermann (2000), a shortage of data might be the most common reason for uncertainty. Different studies that recommend procedures for modelling uncertainty are primarily concerned with examining criteria weights (CWs) (Wolters & Mareschal, 1995). This is certainly insufficient since many other areas of multi- criteria elements (i.e., CW and assessment techniques) can have an impact on the review and rating of options.

It would be an advantage for applications to put their techniques into practice, execute and control their data, and present their outcomes from both specific and multi-perspective viewpoints. This study identifies that practical functionality acts as a significant factor in the selection of a suitable technique (Miettinen, 2001). Another key element identified as important for selecting a technique for portfolio management decision making is the number of panel members responsible. A portfolio decision is normally arrived at by a committee which combines both the goal and weighted factors concerning organisational requirements defined by a program decision committee.

There are two main issues linked to MCDM which are hard to resolve. Firstly, some targets are qualitative (e.g., they have political targets) and, secondly, the targets usually conflict with each other. Hwang and Yoon (1981) propose two techniques (i.e., compensatory and non-compensatory) for solving such problems and identify that compensatory methods (e.g., scoring ones) allow trade-offs, that is, a minor decrease in one element is appropriate when it is supported by improvements in others. On the other hand, non-compensatory methods tend not to allow trade-offs, that is, a negative value in one element cannot be mitigated by positive values in any other. Therefore, as every element/aspect must be considered individually, evaluations are produced on an attribute-by-attribute basis. Although non-compensatory methods can remove dominant solutions/options, as they can suggest several alternatives which may not be effective for making decisions, they are excluded from this study.

As a result of this investigation, the key challenges of PPM include a sensitivity analysis of its interdependencies, traceability, simplicity, supporting quantitative and qualitative data, project quantity, trade-offs, group decision making and the mutual links between portfolio levels.

The major difficulty of this practice is classifying different MCDM techniques. An examination of the literature available on MCDM during the past three decades demonstrates that the complexity and diversity levels of this area of study have increased significantly, resulted in more new and mixed techniques and led to many classifications being proposed (e.g., Figueira et al., 2005). However, this study discovers that those classifications are generally not independent of the authors' intentions in undertaking their examinations. Another issue is that some classifications are confusing or even conflicting, with identical inaccuracies related to several methods identified; for example, AHP is regarded as a qualitative method by some researchers (e.g., Alphonce, 1997) and a quantitative one by others (e.g., Moffett & Sarkar, 2006).

This study identifies that MCDM methods are the most suitable for dealing with PPM issues and classifies them in two groups, MODM and MADM techniques. Then, MADM ones are grouped in the three sets of: UBTs; Outranking; and Compromise methods. It seems that MADM techniques, in particular UBTs, are more suitable for PPM than MODM ones due to their simplicity and capability to handle uncertainty. However, their major drawback is probably that, in many difficult circumstances, they require many specifications to indicate an appropriate condition for decision making which makes them complicated and problematic (Ma, 2006).

Several researchers identify project prioritisation as a key factor in PPM (Elonen & Artto, 2003; Fricke & Shenbar, 2000). To date, there has been no comprehensive study focusing on managing the entire process from strategic planning using PPM to organisational achievements; for example, there is no ideal approach for adopting PPM, identifying the appropriate method for organising activities or techniques for use with organisational factors (Dawidson, 2006). Businesses prefer methodologies that fit their own cultures and enable them to examine the program aspects they think are the most critical (Cooper, 2012; Hall & Nauda, 1990). Also, the most suitable methodologies for developing a portfolio for one program might not be the best for another. Therefore, finding the most suitable PPM MCDM technique(s) is a challenging task which requires further investigation.

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ANNEX K – PUBLICATION II

A Systematic Comparison of Multi-criteria Decision Making Methods for the Improvement of Project Portfolio Management in Complex Organisations

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ABSTRACT:

The successful delivery of organisational objectives is significantly linked to the effective collection of project portfolios. There are many different Multi-criteria Decision Making (MCDM) methods available which can be used to calculate, examine and select Project Portfolio Management (PPM) decision options. However, finding the most suitable one is a challenging task which requires a constructive review and comparison of existing PPM MCDM approaches. This study identifies the strengths and weaknesses of MCDM methods for assisting in PPM decision making. Of more than 100 methods identified in more than 1400 publications, eight (Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Data Envelopment Analysis (DEA), Dominance-based Rough Set Approach (DRSA), ELimination and Choice Expressing the Reality (ELECTRE), Preference-ranking Organisation Method for Enrichment Evaluations (PROMETHEE), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)) that best suit PPM are down-selected and compared. Although none is ideally suited for application to portfolio management, two standard ones (AHP and DEA) are shown to be the most suitable and are recommended for further investigation and validation.

Keywords: Strategic Decision Making, Project Portfolio Management (PPM), Multi-criteria Decision Making (MCDM), PPM MCDM Techniques Comparison, Decision Making Tool.

JEL Codes: *C44, D7, D81, G11, O22.*

1. INTRODUCTION

Comprehensive and effective Project Portfolio Management (PPM) is a key element of an organisation's strategic concepts (Dietrich & Lehtonen, 2005; Grundy, 2000) for selecting and maintaining proper portfolio choices. Since the achievement of organisational strategic goals often depends on the outcomes of projects (Aubry, Hobbs, & Thuillier, 2007), it is essential to identify the projects or portfolio of projects (and/or programs) which align well with these goals without exceeding the limitations of the available resources (Blichfeldt & Eskerod, 2008). To analyse a portfolio's performance, it is important to aggregate the overall performances of its projects in a mathematically meaningful way that implies their strategic impacts at different levels of abstraction.

These challenges can be addressed using various Multi-criteria Decision Making (MCDM) methods which aim to maintain decisions (Roy, 1996) with often conflicting criteria by rating the options; categorising the decisions into a number of classifications; and/or identifying a preferred option (Gomes, 1989). The evaluation of a portfolio's performance requires selecting an appropriate portfolio assessment method(s). Several studies have highlighted that using unsuitable and poor assessment methods could result in the selection of particular sorts of projects in a portfolio and the rejection of the rest (Brun, Sætre, & Gjelsvik, 2008; Kester, Hultink, & Lauche, 2009) with, consequently, certain projects possibly being rejected if they just fail to match the relevant model (Corso & Pellegrini, 2007; Sandstrom & Bjork, 2010).

While many experts considered ways of selecting appropriate techniques for analysing decision problems (Cooper, Edgett, & Kleinschmidt, 2001a), most selection factors were based on technical assumptions without considering the specificities of a PPM assessment and the reasons for a PPM's failure. Most studies did not provide clear reasons for choosing any single technique and often only a few were compared. Moreover, each assessment was confined mainly to a specific industry which resulted in the elimination of some useful PPM-related MCDM methods.

This study conducted a comprehensive review of the literature on MCDM techniques to analyse the strengths and weaknesses of each MCDM approach in PPM decision-making, to determine any constraints and limitation on applying them, and identify how PPM challenges can be overcome using a preferred MCDM method(s). Accordingly, a systematic comparison of MCDM techniques and development of a solid structure that improves knowledge of the assessment and selection techniques for projects in complex organisations are presented.

Based on the observed knowledge gaps, the primary concerns of this study are: "Could MCDM methods be used for PPM decision making?"; "Which MCDM methods are the most suitable for PPM decision making?"; and "How can MCDM methods be selected?".

This study is focused on key reasons behind the failures of PPM and aims to apply those factors to develop a comparison model for analysing and comparing several MCDM techniques. An extensive examination of the literature on more than 100 MCDM techniques is conducted to identify the most suitable for PPM, in which all methods identified in ANNEX A. This is probably the first research study to benchmark PPM MCDM methods on this scale. MCDM techniques from various groups are classified according to their specifications. Then, an examination of them in terms of their different classifications as well as differences among those belonging to the same group is carried out. After they are analysed, those preferred for overcoming the challenges of PPM selection, which this study aims to resolve, are specified. Detailed specifications of the positive and negative examination points of the techniques in terms of the comparison criteria is presented in ANNEX B and the software packages available for the MCDM methods under consideration is presented in ANNEX C.

2. Reviewing Suitability of MCDM Techniques for PPM

There are more than 100 MCDM methods and techniques available in the literature to assist decision making. Many of them are not usually applied since they are very complicated and require large amounts of input information. They are neither capable of sufficiently managing risk and uncertainty nor understanding the interdependencies among factors. Also, their calculation processes are very complicated or do not have an organised structure (Cooper, 1988). Without undertaking a systematic review of MCDM methods in the literature, a decision maker has the challenge of choosing a suitable one for supporting PPM decision making. None is the most suitable in all circumstances and the selection of a particular one is restricted by uncertainty (Mysiak, Giupponi, & Rosato, 2005). Since different techniques usually generate different outcomes, even when applied to a similar issue and information, the most critical question is probably "which method is the most practical?" (Triantaphyllou, 2001).

Based on an extensive literature review carried out as part of this study, it is clear that, despite the fact that there are several techniques which can be applied for PPM, no single one can deal with all its previously discussed challenges. In existing PPM studies, there is little consideration of adopting a mixed structure that could also: examine various factors to identify the best option; include the complete engagement of a decision maker; and obtain the full benefit of the features of a technique by dividing its procedure into a flexible and practical number of actions and implementing the best method in each step. As previously described, because this is due mainly to the challenges associated with PPM, selecting a particular MCDM technique is usually based primarily on familiarity with it (Guitouni & Martel, 1998). Accordingly, instead of seeking the best technique, the decision situation is modified to ensure that the chosen one matches the decision makers preferred option rather than its suitability for the problem considered. The selection of an appropriate MCDM technique could be considered a multi-criteria challenge (Abrishamchi, Ebrahimian, Tajrishi, & Mariño, 2005). As MCDM techniques possess unique positive and negative values, it is very difficult to claim that any one is more suitable. However, certain ones tend to be more appropriate if uncertainty is the main issue and others if trade-offs are a more critical factor (Von Winterfeldt & Edwards, 1993). Also, as using different techniques will most likely provide different suggestions, selecting MCDM ones for PPM needs to be fully investigated which is the primary objective of this study.

Studies in the literature present several different criteria for these comparisons. However, although various models have been introduced, there has been little analysis of their applicability, particularly for PPM decision making. Brief outlines of a number of the research papers published in the literature which discuss such comparisons are provided below.

Belton and Stewart (2002) introduce an in-depth examination of MCDM techniques while several articles (e.g., Sun, 2005) examine existing PPM decision-making methods. Despite this, there are basically two main issues involved in conducting these assessments: the number of MCDM techniques is rapidly increasing (Bouyssou, Marchant, Pirlot, Tsoukiàs, & Vincke, 2006); and researchers almost never provide good reasons for selecting a particular one. Furthermore, researchers identify that a set of MCDM techniques needs to be employed as there is no single one that can fully support PPM decision making (Verbano & Nosella, 2010).

Eckenrode (1965) states that ranking techniques are less complicated and likely to be more beneficial than those involving suitable decisions being indicated by ratios of criteria weights. MacCrimmon (1973) identified the demand for evaluating MCDM methods along with the significance of the decision difficulty and recommended a classification of MCDM techniques. MacCrimmon (1973) identifies the demand for evaluating MCDM methods as well as the significance of a decision's difficulty and recommends a classification of MCDM techniques. Hwang and Yoon (1981) present a comparison model of a few Multi-objective Decision Making (MODM) and Multi-attribute Decision Making (MADM) techniques. Duckstein, Gershon, and McAniff (1982) compare three MCDM techniques (i.e., ELECTRE, Compromise Programming (CP) and Multi-attribute Utility Theory (MAUT) with regard to several criteria: "(1) the type of information (qualitative or quantitative); (2) consistency of the outcomes between methodologies; (3) stability of the outcomes in relation to variations in the parameters' principles; (4) simplicity of computation; and (5) level of activity necessary between the decision making and with decision analyst". Hobbs, Chankong, Hamadeh, and Stakhiv (1992) reveal that knowing a technique's aspects influences a user's opinion of how they function. Munda, Nijkamp, and Rietveld (1994) and Munda, Nijkamp, and Rietveld (1995) consider different factors, such as the differences between qualitative and quantitative data as well as the level of uncertainty. Accessibility, flexibility, facilitation, learning, interaction and simplicity are presented as critical features of a Decision Support System (DSS) in a study conducted by Simonovic and Bender (1996). Also, Weistroffer and Narula (1997) present a number of criteria for method selection, that is, a technique should: be practical and simple to operate; record and represent ideas; assist decision makers to structure circumstances according to the primary steps in decision making; handle different types and numbers of decision tasks; and be possible to use while obtaining knowledge of the relevant DSS's functions. The compensation level among factors is presented by Hayashi (2000) and the regulatory, descriptive, practical and normative characteristics of decision-making introduced as the main criteria by Bouyssou et al. (2006). As Kangas and Kangas (2005) consider that selecting the most effective technique means understanding each one, simple and straightforward MCDM methods are preferable. Taylor (2006) outlines that a good comparison model needs to be practical, capable, flexible, simple, cost-effective and easy to calculate, with Souder (1973) proposing on the first five requirements and Meredith and Mantel Jr (2011) the last. The Standard for Portfolio Management (PMI, 2013) recommends different strategies for optimising a portfolio (e.g., developing a list of portfolio elements to be considered for prioritisation), such as applying scoring methods like multi-criteria analysis to set aside those projects not fulfilling threshold requirements. This guideline recommends using single-criterion prioritisation, multi-criteria weighting ranking and multi-criteria scoring techniques for weighting and ranking portfolio elements.

Despite the fact that many researchers have attempted to identify the best technique for a decision situation and different MCDM ones have been compared with each other, there is no commonly agreed structure or procedures that enable the most suitable one(s) to be selected for a particular decision scenario; for example, although Denpontin (1983) establishes an extensive catalogue of various techniques, he claims that it is challenging to group them because decision-making experiments vary in their numbers, values and accuracy of data.

Gershon and Duckstein (1983) compare four MADM classification techniques (ELECTRE, CP, Cooperative Game Theory (CGT) and MAUT) and suggest that the main differences between them are the ways in which they behave. Brans, Vincke, and Mareschal (1986) assess two well-known MADM outranking methods, i.e., PROMETHEE and ELECTRE, and determine that the former is more reliable than the latter. Tecle, Fogel, and Duckstein (1988) implement three MCDM methods, CP and CGT to select the most suitable option and ELECTRE to down-select options. A comparison of ELECTRE, AHP, Simple Additive Weighting (SAW) and the Weighted Linear Assignment Method (WLAM) undertaken by Karni, Sanchez, and Tummala (1990) indicates that the ranking results obtained from ELECTRE, AHP and SAW in each case study do not differ greatly but the WLAM presents a different outcome. In a comparison study of six methods (i.e., AHP, SAW, ELECTRE, Goal Programming (GP), additive utility functions and multiplicative utility functions) carried out by Hobbs et al. (1992), no method is considered more suitable than or preferred over others. Duckstein, Treichel, and Magnouni (1994) compare CP, ELECTRE, MAUT and Utility Theory Additive (UTA) techniques and concluded that all produce the same outcomes. Hobbs and Meier (1994) examine holistic, Additive Value Function (AVF) and GP methods, and suggest that, as none can be considered the best, multiple techniques should be applied.

A comparison study of AHP, MAUT and ZAPROS methods conducted by Olson, Moshkovich, Schellenberger, and Mechitov (1995) who concludes that, once the option values are equal, each method produces different solutions for the same option. Moreover, Bella, Duckstein, and Szidarovszky (1996) uses ELECTRE and CP to rank options while Özelkan and Duckstein (1996) compare PROMETHEE, GAIA, Multicriterion Q-analysis (MCQA), CP and CGT, and reveal that they are not significantly different. Salminen, Hokkanen, and Lahdelma (1998) apply ELECTRE, PROMETHEE and Simple Multi-attribute Rating Technique (SMART) methods to four real environmental problems in Finland using ELECTRE both alone and in combination with different techniques. Bell, Hobbs, Elliott, Ellis, and Robinson (2001) compare eight different methods (i.e., ELECTRE, Min Max Regret and stochastic dominance, additive non-linear value functions, goal programming, fuzzy sets, non-linear utility functions, linear utility functions and additive linear value functions) and conclude that no individual technique can determine the ideal option. Kangas, Kangas, Leskinen, and Pykäläinen (2001) draw a similar conclusion when comparing Multi-attribute Value Theory (MAVT), ELECTRE and PROMETHEE methods, finding that each generates different outcomes for the same issue and, moreover, the propose mixed MCDM techniques as a possible direction for future study. In planning for sustainable energy, Pohekar and Ramachandran (2004) identify that the AHP is the most widely used method and is often accompanied by outranking methods such as PROMETHEE and ELECTRE. Various later studies assess a number of MCDM techniques for dealing with real-world challenges (e.g., Antucheviciene, Zakarevicius, & Zavadskas, 2011; Estrella Maldonado, Delabastita, Wijffels, Cattrysse, & Van Orshoven, 2014; Ginevičius & Podvezko, 2009; Ho, Xu, & Dey, 2010; Holt, 1998; Kadziński & Słowiński, 2015; Killen & Kjaer, 2012; Li, Wu, & Lai, 2013; Tahriri, Osman, Ali, & Yusuff, 2008).

A common issue between the majority of these studies was the fact that most of them failed to present a clear reason for selecting a method. The selection process was mostly based on random choices; selecting those methods that had been used more widely; choosing a technique created by themselves or a technique that they had experience with. Some just reference other people's work, or in some cases, the number of published articles in the area was the base for selecting a specific model. Topcu and Ulengin (2004) identify that it is almost impossible for experts to develop a suitable selection model for identifying the best MCDM technique because they are unable to validate their reasons for selecting one over another. The results of these studies also differed: some studies presented that the ranking results from all methods did not differ a lot; others believed that no method was more suitable or preferred. In a majority of the comparison studies, each method produced different solutions for the same option, suggesting the combination of techniques to better select and manage projects. However, some concluded that no individual technique was able to determine the ideal option or some even left the final decision with the readers to decide which method was the most suitable. The comparison process was conducted based on a limited number of methods which were most preferred by the authors themselves without any explanation as to why these methods had been selected for comparison. Some of these methods were only presented in the authors' publications, were never presented elsewhere and included no practical case studies to justify these techniques.

3. Proposed Model for Comparison of PPM MCDM Methods

Having a PPM structure is essential for the processes of comparing MCDM methods and balancing a project portfolio. Based on studies conducted by Cooper, Edgett, and Kleinschmidt (2001b) and Crawford, Hobbs, and Turner (2006), this study suggests that project proposals should be broken down into sub-sets of projects with similar strategies and the same features which would assist decision makers to compare them using the same criteria or methods.

This research reviews various studies that introduce different criteria for selecting the most suitable technique(s). However, there is an absence of a framework which organises them practically and specifically for PPM decisions. Therefore, it is essential to modify a structure or develop a suitable one for assessing the criteria for comparing appropriate decision-making methods for PPM (which consider a variety of criteria) and finally selecting the most suitable one(s).

The success of PPM is directly related to the level of understanding of PPM issues. The challenges of executing and delivering PPM are related to the uncertainties created by turbulences in the relevant industry, sudden technological variations and uncommon resources being shared among the many areas of an organisation (Eisenhardt & Brown, 1997; Elsenhardt & Martin, 2000).

The issues regarding project, program and portfolio management highlighted in a number of studies (Artto, 2001a, 2001b; Rintala, Poskela, Artto, & Korpi-Filppula, 2004; Staw & Ross, 1987). Cooper et al. (2001b) describe a number of issues and concerns regarding achieving successful PPM, with the key ones resource management, project prioritisation, decision making without reliable data and there being too many small projects in a portfolio. Prioritisation is challenging because selection techniques are incapable of comparing different projects, some of which are tangible and others intangible (Archer & Ghasemzadeh, 1996). Also, as some projects are unique, they cannot be compared with others although grouping them with the others makes comparisons easier; for example, some projects could refer to work procedure improvements and others to the delivery of IT devices (Blichfeldt & Eskerod, 2008). There are uncertainties related to project variables (e.g., cost and risk) (Radulescu & Radulescu, 2001). The level of a project's complexity depends on its degree of uncertainty regarding the direction in which to go and the way to achieve its goals (Marmgren & Ragnarsson, 2001). A simple analysis of formerly well-known products entails a lower level of risk than that of projects attempting to develop a completely new technology (Verbano & Nosella, 2010). Decision makers may experience conflicting understandings of a project's concept and organisational requirements (Brun et al., 2008; Brun, Steinar Saetre, & Gjelsvik, 2009) or even be unable to fully identify an entirely new product concept (Engwall & Jerbrant, 2003). Another key organisational issue is the lack of connection between strategic and project selection levels (Elonen & Artto, 2003).

Decision makers need to incorporate different types of decision-making tools that integrate various methods and judgements, such as formal and informal (Blichfeldt & Eskerod, 2008; Olausson & Berggren, 2010), as well as well-ordered and not well-organised (Steffens, Martinsuo, & Artto, 2007). However, PPM studies have not yet properly highlighted the difficulties decision makers might have to deal with when integrating various methods (Geraldi, 2008) those of organisations incorporating different methods for identifying options and projects (Bessant, Von Stamm, & Moeslein, 2011). Moreover, there are studies that describe PPM issues, such as obtaining executive-level support and commitment (Kendall & Rollins, 2003), gaining a perception of a portfolio across projects (McDonough III & Spital, 2003; Wheelwright & Clark, 1992), and having proper information (Martino, 1995; Wideman, 2004) and sufficient time to perform PPM (Lawson, Longhurst, & Ivey, 2006; Vähäniitty, 2006). The challenges of assessing and selecting options and projects are reviewed through an examination of PPM studies as well as observations based on decision-making principles.

Based on an extensive literature review carried out, this study identifies the difficulties associated with PPM decision making, that is, sensitivity/uncertainty, interdependencies in projects, decision traceability, simplicity, both quantitative and qualitative requirements, number of projects, trade-offs and conflict issues, group decision-making challenges and the lack of a mutual link between projects and strategic levels. To overcome them, this study analyses the literature and establishes a variety of conditions that must exist in cases in which a technique is to be successful in practice. It also considers the selection paradigm of Deason and White (1984), choice algorithm of Gershon (1981), selection model of Tecle (1988) and hierarchical process for portfolio selection of Cooper (2005) to present a model for comparing MCDM methods for PPM decision making according to their suitability in terms of their handling of PPM challenges, comprehensiveness and relatively simple delivery. For the purpose of this study, several MCDM techniques are analysed to determine which fulfils as many criteria/specifications as possible and categorised based on the set of seven comparison criteria (factors/groups) listed in Table 1 suggested as essential by several authors (e.g., Antunes, 2012; Buchholz, Rametsteiner, Volk, & Luzadis, 2009; Munda, 2005, 2008; Polatidis, Haralambopoulos, Munda, & Vreeker, 2006; Rowley, Peters, Lundie, & Moore, 2012; Sadok et al., 2009; Sala, Farioli, & Zamagni, 2013; Teghem, Delhaye, & Kunsch, 1989). Also, the comparisons in Figure 1, ANNEX B and Table 1 are evaluated according to the literature review as well as examinations of Cohon and Marks (1977) and Khairullah and Zionts (1979).

The criteria proposed for comparing PPM MCDM techniques and reducing their number to a smaller sub-set are described in Table 1.

Table 1 - Proposed Selection Criteria for Comparison of PPM MCDM Techniques

Stage 1 - Mandatory Selection Criteria		
Criteria		**Description**
1	Sensitivity Analysis/Uncertainty Treatment	Does the method deal with unknown or missing data?
2	Dependencies	Does the method take into account the interdependencies of the criteria based on the weight of each criterion during the evaluation process? Does the method consider the interdependencies of the alternatives based on their weights during the evaluation process?
3	Decision Traceability	Is the method traceable (i.e., judgements and choices are required to be mutually traceable during the decision process from the strategic to operational level)?
4	Simplicity	Is the method user-friendly and easy to use (e.g., software available)?
Stage 2 - Beneficial Selection Criteria		
5	**Criteria**	**Description**
5.1	Quantitative and Qualitative	Does the method support both quantitative and qualitative information?
5.2	Number of projects	Is the method restricted to a specified number of criteria or options?
5.3	Trade-offs/Conflict	Does the method support compensatory methods?
5.4	Group Decision Making	Does the method support group decision making?
5.5	Hierarchical Structure (mutual link between projects and strategic levels)	Does the method support a hierarchical structure and different levels of attributes? Does the method support maturity on all PPM process levels?
6	**Beneficial Sub-criteria**	**Description**
Note: *these sub-criteria are part of the main beneficial ones described above, with the following showing exactly which elements are considered during the group down-selection process.*		
6.1	Thresholds/Setting Parameters	Does the method manage indifference and options once two options are compared?
6.2	Allowing criteria and alternative weighting	Can the criteria be weighted within the criteria hierarchy and the alternatives weighted within the alternatives hierarchy?
6.3	Supporting rank reversal	Does the method suffer from the rank reversal issue (i.e., the ranking might be changed whenever another option is presented)?
6.4	Supporting sub-criteria	Does the method organise the considerations into a multi-level hierarchy (particularly when many factors are required)?
7	**Additional considerations during selection process**	
7.1	Type of Problem	Does this method support both ranking and classification processes/methods?
7.2	Advantages	What are this method's benefits?
7.3	Disadvantages	What are this method's limitations?
7.4	Area of Applications	In which industry or area of expertise has this method been used?
7.5	Integrated methods	Does this method integrate with others?
7.6	Learning dimension	Is this method difficult to learn?

These criteria are separated into the two categories of 'Mandatory Selection Criteria' (criteria 1 to 4), which eliminate methods from further evaluation when they are incapable of meeting requirements, and 'Beneficial Selection Criteria' (criteria 5 to 7) which do not necessarily eliminate methods from further examination. The Beneficial Sub-criteria (criteria 6) and Additional Consideration (criteria 7) are part of the main beneficial ones, with these criteria showing exactly which elements are considered during the group down-selection process in stage 2. Considering these sub-criteria in conjunction with criteria 5 will increase the accuracy of the selection process by capturing a variety of conditions that could be existed in cases in which a technique is to be successful in practice. Figure 1. presents a flowchart for executing the model which includes the requirements of both groups.

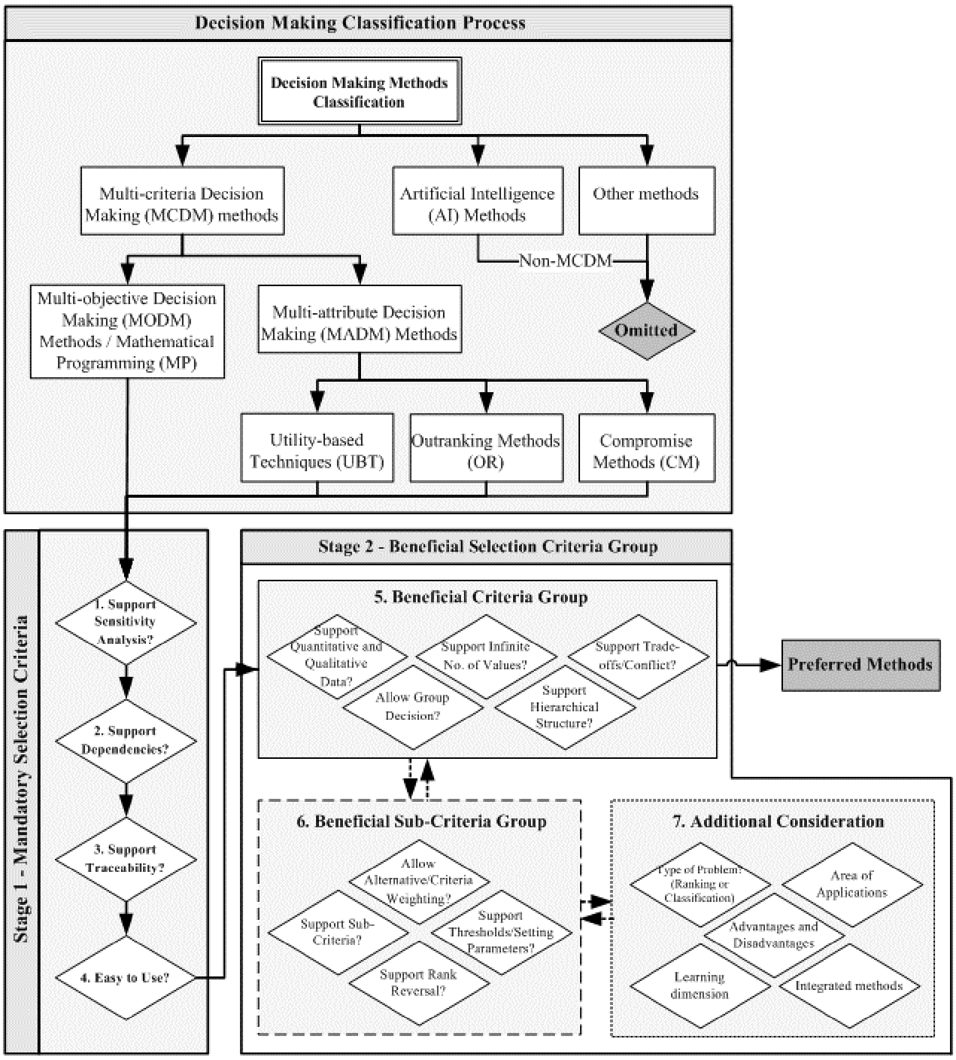

Figure 1. FLOWCHART FOR SELECTION OF PPM DECISION-MAKING TECHNIQUES

4. RESULTS FROM COMPARISON OF PPM MCDM METHODS

4.1. Down-selection process

The framework proposed in this study is focused on improving and managing procedures for the selection of methods for PPM decision making. It identifies factors that are essential to decision makers who have to make decisions regarding portfolio selection. All these methods are analysed through implementing the proposed selection model in Table 1 for decision-making techniques and the seven proposed comparison criteria in Figure 1.

In order to shortlist the appropriate PPM-related MCDM methods, of more than the 100 identified in the literature, a pre-selection stage (Classification of Decision-making Methods) is conducted to eliminate those designed for a specific industry/situation and unsuitable for PPM decision making or not included in the MCDM categories in Figure 1 (i.e., MADM and MODM) which are classified according to their types of data input. All Artificial Intelligence (AI) techniques are omitted from this study since they are normally employed to provide approximate answers and options for difficult optimisation conditions; for example, a genetic algorithm (GA) method is incapable of ensuring a truly ideal solution to a complex optimisation problem (Xu & Ding, 2011). Others, such as the Chance Constrained and GA (CCGA) (Azadeh & Alem, 2010) and Numerical Taxonomy (NT) (Sokal & Sneath, 1963), are designed for a specific industry or situation and may not be suitable for many real-life challenges, including general PPM decision making; for example, CCGA is a genetic model and NT a classification method in biological systematics which involves grouping numerical types of taxonomic units according to their characteristics. The characteristics and differences in behaviour associated with these techniques are examined and the techniques that comply with this study's essential requirements defined in Stage 2 identified for further investigation. The consecutive use of the associated requirements results in eliminating many of the MCDM methods.

Uncertainty management, which is regarded as the most critical challenge in decision making (e.g., Felli & Hazen, 1998), also requires an understanding of portfolios' interdependencies (e.g., Verma & Sinha, 2002). To deal with PPM's uncertainties and dependencies, it is essential to keep track of data (Danilovic & Browning, 2007). Moreover, decision makers are unlikely to apply methods that are neither effective nor simple to operate (Moore & Benbasat, 1991). Therefore, as a first priority, any preferred method needs to be capable of dealing with 'sensitivity issues', 'support dependencies between projects', 'be traceable' and 'be simple' (as specified as mandatory selection criteria in our framework).

As the strategic arrangement of projects in a portfolio is extremely critical, both quantitative and qualitative techniques are required to estimate a project's related risk level (as a qualitative factor), profit (as a quantitative factor) and involvement in the organisational strategy (both qualitative and quantitative factors simultaneously) (e.g., Kester et al., 2009). Furthermore, the techniques that allow criteria to be defined by both objectives and attributes defined implicitly or explicitly in the best scenarios are selected, with those that have the capability to implement infinite numbers of alternatives also collected. Similarly, the mathematical approaches that cannot use qualitative values are eliminated. In addition, it is beneficial to have a process-/outcome-oriented decision-modelling paradigm as the preferred MCDM techniques need to allow decision makers to choose and prioritise options and decisions in line with various requirements.

For MADM, utility-based methods have difficulties producing adequate performance values for some criteria and are incapable of considering degrees of under-performance. As arranging the threshold variables in these methods is very difficult, they are often not employed for the selection of real options (Greening & Bernow, 2004) as they consider more than one best solution. In general, a key disadvantage of MADM methods is that they are very complicated and problematic when dealing with many decision specifications in complex situations. Most of them are subjective, facilitate only quantitative values and are incapable of dealing with qualitative data. However, it seems that 'Utility-based Techniques' are suitable for PPM as most of them support uncertainty and are very easy to use.

MODM methods such as DEA are selected for further investigation as they can provide a number of options from alternatives which assist decision makers to select the ideal one. They are much better for describing reality and are capable of verifying more options than MADM methods (Cohon, 2013). While, at this stage, MODM techniques for PPM are not omitted because the capability to support qualitative data and unlimited (infinite) numbers of options are critical elements of this study, many methods are not involved in this assessment, with several omitted due to issues regarding analysing 'sensitivity' and 'dependency', and the 'capability to track a discrete set of solutions'.

Of more than 100 MCDM methods presented in ANNEX A, over 40 found to be irrelevant or unsuitable for this study's direction are eliminated while only 46 of the others can adequately manage 'uncertainty'. Many methods are identified as being very complicated and requiring large amounts of input information, with the number of those for consideration significantly decreasing once the 'dependency' factor is included. Therefore, only 28 are assessed as being capable of supporting interdependencies among projects or not needing to support them while only 11 of the remaining 28 support the 'traceability' function, with three of the remainder very complicated or not following an organised structure.

A total of eight MCDM methods (AHP, ANP, DEA, DRSA, ELECTRE, VIKOR, PROMETHEE and TOPSIS) are selected for a final investigation to identify a preferred one. They are more appropriate for decision making for PPM due to their capabilities for dealing with any kind of judgement considerations, their simple outcomes, low complexity for managing criteria and the decisions they contain. Furthermore, all have been employed to address various real-life challenges (Herva & Roca, 2013), are simple in concept and computation and are applicable to multi-level hierarchies. The challenge now is to identify which of these techniques is considered the most suitable for applying to solve the challenges on which this study is focused.

The following sub-sections present short outlines of the aspects of each MCDM technique analysed as well as brief discussions of their advantages and disadvantages, concentrating on the unique functions essential for the evaluation stage. Detailed specifications of the positive and negative examination points of the techniques in terms of the comparison criteria are presented in ANNEX B, respectively.

4.1.1. Analytic Hierarchy Process (AHP)

The AHP, which was developed in the 1980s (Saaty, 1980a), is very popular in the literature investigated for this study, with the majority of authors comparing it with other MCDM techniques (Lai, 1995). It has proven to be significant for application performance issues, business policy and strategy, resource management, and political planning and strategy. Also, several studies apply it for industrial development, project delivery, DSSs, risk and uncertainty assessments, measurements of project complexity, determinations of water resources (decision making in an urban water supply) (Benítez, Delgado-Galván, Izquierdo, & Pérez-García, 2012) and development of Enterprise Resource Planning (ERP) systems.

An in-depth literature review and examination of the AHP method including its advantages and disadvantages is presented in Danesh, Ryan, and Abbasi (2015).

4.1.2. Analytic Network Process (ANP)

Technically, ANP is regarded as the general form of AHP (Saaty, 2006) but in relation to positive aspects, it is more focused on a network framework. ANP enables project interdependency and it is able to prioritise groups or even clusters of components; “which will help a complicated networked decision-making with different intangible criteria” (Tsai, Leu, Liu, Lin, & Shaw, 2010). A hierarchy is not essential in the ANP technique, whereas clusters of components exchange levels and every single group includes nodes or elements. In ANP nodes are likely to be arranged in groups. ANP replicates the way humans make choices in which the importance of requirements can transform with the available options.

The downside of employing the ANP technique could be a restricted number of criteria and alternatives. As a result of feedback loops and interconnections it might be hard to develop ANP in a general tool such as an Excel spreadsheet. ANP’s efficiency scores might be changed whenever another option is presented. However, its biggest weakness is that it undermines the outcomes of weighing the clusters (Wang, 2012). AHP utilises a basic weighted total for aggregation, while ANP needs the super matrix to be squared frequently. Therefore, ANP is not recommended when no dependency is available. Given that the ANP draws on setting up choices between requirements and options employing pair-wise evaluations, it only facilitates quantitative values—it cannot deal with qualitative data.

Designed in 1996, the method continues to be employed for activities in assessment investigation (Jinyuan, Kaihu, Lin, Rui, & Xiaoli, 2012), performance evaluation (Chen & Lee, 2007), information system (Liang & Li, 2008), university-industry and supply chain virtual enterprises partner selection processes (Ning & Xue-wei, 2006; Xiao-bo & Ting-ting, 2009), R&D projects (Jung & Seo, 2010), environmental risk assessment (ERA) (Chen, Li, Ren, Xu, & Hong, 2011), inter-enterprise performance (Verdecho, Alfaro-Saiz, & Rodriguez-Rodriguez, 2012), ERP (Gürbüz, Alptekin, & Alptekin, 2012), organisational performance (Boj, Rodriguez-Rodriguez, & Alfaro-Saiz, 2014) and measuring the complexity of mega construction projects (He, Luo, Hu, & Chan, 2015) as well as for project preference and supply-chain management.

4.1.3. Data Envelopment Analysis (DEA)

Suggested by Charnes, Cooper, and Rhodes (1978), DEA is a mathematical programming technique that presents related performance assessments for decision-making units (DMUs) with several inputs and outputs (Adler, Friedman, & Sinuany-Stern, 2002). To enable its application to a broad number of activities, a DMU refers to anything examined in the model which it considers to be *n* DMUs. DEA employs a linear programming approach to determine appropriate selections of options/choices (Thanassoulis, Kortelainen, & Allen, 2012) which it compares, with the best obtaining a score of one and the others less than one.

A significant benefit of DEA is that, it is a non-parametric method with no requirement to apply past assumptions or connect inputs and outputs (Seiford & Thrall, 1990). Consequently, it eliminates subjective elements, minimises errors and makes the estimation process easier (Qiang Chen, Lu, Lu, & Zhang, 2010). However, an issue handled by DEA could be dealt with equally well using multi-criteria examinations (Belton & Vickers, 1993). Although it might not be obvious compared with other techniques, DEA can establish connections between inputs and outputs based on which it calculates the performances of DMUs. Therefore, in order to present every DMU in the most effective light, it optimises the weightings of all variables with those of the inputs and outputs not allocated by decision makers (Giannoulis & Ishizaka, 2010). Instead, it sets target values and identifies all benchmarks to assist decision makers in estimating DMUs' efficiencies.

A major disadvantage of DEA is the fact that it will "not handle imprecise information and considers that all input and output information are accurately identified but this theory might not necessarily be true" (Wang, Greatbanks, & Yang, 2005). Its outcomes vary according to the inputs and outputs and, moreover, it cannot deal with variables with negative or zero values.

DEA is applied to compare project efficiencies (Hadad, Keren, & Laslo, 2013), Group Decision Support Systems (GDSSs) (Barkhi & Kao, 2010), safety performances (El-Mashaleh, Rababeh, & Hyari, 2010), project evaluation and selection strategies (Ghapanchi, Tavana, Khakbaz, & Low, 2012), R&D portfolio assessments (Vandaele & Decouttere, 2013), risk analyses (Shi, Zhou, Xiao, Chen, & Zuo, 2014) and ERPs (Sudhaman & Thangavel, 2015). Ramanathan (2003) provides excellent introductory material for DEA beginners, with a more detailed explanation provided in Cooper, Seiford, and Tone (2006).

4.1.4. Dominance-based Rough Set Approach (DRSA)

The DRSA is (Greco, 1997) capable of managing classification, selection and scoring difficulties. It draws on a data desk, the rows in which are referred to as options and the columns broken down into conditions, specifically, the requirements for examining the options and decision elements, to provide a general analysis of options which can easily be defined as a concept or professional decision (Slowinski, Greco, & Matarazzo, 2009). DRSA estimates the data according to the selection aspects by looking at the information in the requirements as well using "if... then..." decision specifications (Greco, Matarazzo, & Słowinński, 2005). These types of guidelines are straightforward primary links between condition and decision requirements (Roy & Słowiński, 2013).

Quantitative, qualitative, incomplete and inconsistent data can be accommodated by the DRSA. It requires a pair of examples from which to extract specifications but is limited by previous experiences and suffers from rank reversal problems.

4.1.5. ELimination Et Choix Traduisant la REalite—Elimination and Choice Expressing the Reality (ELECTRE)

The ELECTRE method was first presented in 1968 (Roy, 1968) to handle outranking connections by conducting a pair-wise analysis between options of each factor independently. It has a number of variants, such as ELECTRE I, II, III, IV and TRI (Balaji, Gurumurthy, & Kodali, 2009), each of which was developed to resolve various decision issues, such as selecting, scoring and explaining their concepts (Certa, Enea, & Lupo, 2013; Fernandez, Navarro, Duarte, & Ibarra, 2013; Figueira, Mousseau, & Roy, 2005; Figueira, Greco, Roy, & Słowiński, 2013; Roy, 1991). As ELECTRE focuses on a pair-wise analysis of options (Figueira, Mousseau, et al., 2005), it generally aims to determine whether option A is at least as effective as option B (Roy, 1996).

The key benefit of an ELECTRE technique is its capability to avoid compensation between requirements and any specific normalisation practice that distorts the initial information. It can prioritise options and remove those with less efficiency which is very useful when there are decision issues that have several requirements with many options.

However, an ELECTRE technique has the disadvantage that it requires a number of technical variables which means that it is often not simple to fully understand. It has not been proven to be a comprehensive solution for dealing with the variables and, as well as its results, its procedure might be difficult to clarify. Because of the way it integrates choices, factors with lower priorities or performance values are not presented. Its outranking technique has advantages as well as problems with options that are not perfectly recognised or outcomes that need to be checked (Konidari & Mavrakis, 2007). Also, it would not normally result in a single solution being differentiated from others as it identifies a sub-set of options to be chosen from the primary group of alternatives. Therefore, an ELECTRE technique is generally regarded as appropriate for decision issues identified by very few requirements and a number of options for helping to differentiate among a sub-group of more suitable alternatives. Developing and analysing quite a large number of retrofit options is costly. In such a situation, the decision maker is simply interested in determining which option is better for putting into practice rather than helping to reduce the primary group of options into a smaller set. Therefore, an ELECTRE technique might not be suitable for selecting the best option as it only generates the major ones.

4.1.6. Preference-ranking Organisation Method for Enrichment Evaluations (PROMETHEE)

The PROMETHEE created by Brans and Vincke in the 1980s (Brans & Vincke, 1985) is categorised under MADM techniques/outranking methods. It is an outranking model that proposes the most suitable option for a decision maker from existing alternatives. Basically, its approach consists of three steps: (1) defining a preferred option in line with the objectives; (2) defining a multi-criteria decision index and preference flows; and (3) achieving a complete or partial ranking of options in accordance with the specified decision framework.

The PROMETHEE is simple to employ and assumes that the requirements are proportionate. Given its framework, it can be performed directly on the factors used in the decision matrix without the need for any specific normalisation. It classifies options that are difficult to analyse due to its trading off assessment specifications as non-comparable options. It eliminates the need to carry out more pair-wise assessments while relative options are added or removed (Seo, Jeong, & Song, 2005).

This method cannot clearly allocate weights and does not provide an exact process for assigning values. Its efficiency scores are estimated from both negative and positive values and presented as different types of options. A traditional network representation of the PROMETHEE does not provide any visual details regarding variations in values. Finding out exactly how a rating is dependent on minor variations in the weighting of the requirements is another challenge of using this method which deals with only quantitative data and suffers from the rank reversal problem. It has been used in many fields, such as the automotive sector (Ignatius, Behzadian, Malekan, & Lalitha, 2012), web service selection (Karim, Ding, & Chi, 2011), exploration strategies for rescue robots (Taillandier & Stinckwich, 2011), evaluations of suppliers (Wang, Chen, & Chen, 2008) and DSS (Doumpos & Zopounidis, 2010).

4.1.7. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The TOPSIS, which was developed by Hwang and Yoon (1981), is used to rank alternatives with limited numbers of factors. It uses the basic prospect of minimising the negative ideal option and maximising the positive one (Hwang & Yoon, 1981; Yoon, 1980).

The TOPSIS facilitates quantitative values and is user-friendly, with its number of stages remaining the same regardless of the number of elements (İç, 2012). Its functionality and capability to retain the same number of stages irrespective of an issue's dimension enables it to be applied rapidly and stand by itself as a decision-making application. It allows just one alternative to be decided as the ideal one and can handle any types of factors and requirements. The TOPSIS approach requires a minimal variety of inputs from decision makers and its outcome is straightforward, with its only subjective variables the weights connected to the requirements. A variety of its applications is available in Behzadian, Otaghsara, Yazdani, and Ignatius (2012).

As the Euclidean Distance function in TOPSIS does not consider the relationship among elements, it is complicated to weight elements or maintain decision stability, particularly with added elements. Like the majority of MCDM techniques, it can experience the rank reversal issue.

The TOPSIS approach is applied in different domains. such as design, systems engineering, logistics and environmental management (Amiri, 2010; Bottani & Rizzi, 2006; Chen, Lin, & Huang, 2006; Tong, Wang, & Chen, 2005; Wu, Lin, & Lee, 2010).

4.1.8. VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)

VIKOR was developed by Duckstein and Opricovic (1980). It scores the options (A_i (i=1, 2, …, n)) based on the amounts of three values (S_i, R_i and Q_i) required to be estimated for all choices.

It is able to simultaneously assess many alternatives, even using many unrelated criteria, and score them all in a numerical order from worst to best. Moreover, it does not require a consistency test, and is simple to use but only capable of dealing with quantitative data.

According to Huang, Yan, and Ji (2008): the '*VIKOR algorithm can order directly without considering that the best solution is closer to the ideal point or more farther to the worst ideal point'*. Although this is why some decision makers may prefer VIKOR over other methods, such as TOPSIS, there is no tool available that is designed to execute it. Also, it finds it difficult to cope with incomplete and uncertain data, and also experiences the rank reversal issue. It is applied in different areas, such as networks (Bashiri, Geranmayeh, & Sherafati, 2012), MCDM problems in intuitionistic environments (Ying-yu & De-jian, 2011) and supplier selections (Jianxun, Zhiguang, & Feng, 2007).

4.2. Tools available for MCDM Methods

Dealing with a complex portfolio of projects with uncertainty is much more difficult than handling complexity in classical project management (Aritua, Smith, & Bower, 2009), especially controlling project interconnectivities (Collyer & Warren, 2009; Perminova, Gustafsson, & Wikström, 2008), which could be one of a PPM's shortcomings (Elonen & Artto, 2003).

Different systems, applications and methods are frequently presented and analysed in PPM research (Dawidson, 2006; Dickinson, Thornton, & Graves, 2001; Kester et al., 2009). Nevertheless, assessing the impact of a different application or technique is complicated since the nature of every organisation is unique and it might have different aspects that affect project efficiency. Despite several studies of organisational environments, a reliable one from which the results can be generalised is not yet available.

Although several studies indicate that strategic PPM decisions are considered in group sessions through applying graphical applications, these tools must be specially developed or modified according to an individual organisation's needs and desire for highly valuable decisions (Christensen, 1997; Cooper et al., 2001a; De Maio, Verganti, & Corso, 1994; Dickinson et al., 2001; Killen, Hunt, & Kleinschmidt, 2008; Mikkola, 2001; Phaal, Farrukh, & Probert, 2006; Rungi, 2007); for example, portfolio maps present projects and their options on two axes and are supported by extra information such as variations and risk (Cooper et al., 2001a; Mikkola, 2001; Phaal et al., 2006). Although these mapping tools offering a portfolio-level perspective, they generally look at projects independently. On the other hand, project interconnectivities might result in unexpected responses in their procedures (Aritua et al., 2009; Collyer & Warren, 2009; Perminova et al., 2008) that indicate the importance of projects' dependencies for making effective decisions (Blau, Pekny, Varma, & Bunch, 2004; Verma & Sinha, 2002). Using classical PPM tools is no longer acceptable because the complexity of a project portfolio is dramatically increasing and most projects are no longer considered independently or, if so, their independencies must be fully understood for successful decisions (Blau et al., 2004; Verma & Sinha, 2002). Although various organisations collect data related to projects' interconnectivities, their capabilities for using or applying this information or identifying multi-stage dependencies are limited (Danilovic & Browning, 2007; Dickinson et al., 2001). To meet these challenges, particularly as the complexities of decision-making systems increase, experts are participating in developing different ones (Aritua et al., 2009).

Only a few MCDM software tools are available in the market, most of which are commercial, with those for the eight MCDM techniques under consideration: the AHP (e.g., Expert Choice, Mind Decider, HIPRE 3+, MAkeItRational, Transparent Choice, Decision Analysis Module for Excel (DAME), ChoiceResults, 123AHP (Online), Decisions Lens and Super Decisions); ANP (e.g., ANP SOLVER, WEB ANP SOLVER, Decisions Lens and Super Decisions); DEA (e.g., Efficiency Measurement System, Win4DEAP and DEAFrontier); DSRA (e.g., 4eMka2 and jMAF); ELECTRE (e.g., ELECTRE III/IV and ELECTRE TRI); PROMETHEE (e.g., Visual PROMETHEE Academic and PROMETHEE); TOPSIS (e.g., Triptych); VIKOR (not applicable); and multi-software (e.g., SANA (ELECTRE I & 3, TOPSIS and PROMETHEE II), Decision Deck and DECERNS (AHP, PROMETHEE and TOPSIS)). Recently, Oxford University presented an application with a decision support system called OUTDO that examines the way variations in external variables influence complex or unknown selection procedures (Hunt, Bañares-Alcántara, & Hanbury, 2013). The software packages available for the MCDM methods under consideration is presented in ANNEX C.

4.3. Comparing Shortlisted/Down-selected Methods

The results from comparisons of the top eight MCDM methods against each criterion are discussed below with related references.

In PPM, the decision-making process often involves various options (alternatives) which require both ranking and classification processes and/or methods. However, if there are no alternatives available, only the classification process needs to be considered. Moreover, in the event that a portfolio consists of new as well as active components, both processes can be considered according to the individual elements. The DEA, DSRA and ELECTRE methods use classification processes and the others are based on ranking ones.

Uncertainty can be accounted for when the requirements are weighted together with examinations of the options' performances. Also, there is an important difference between managing unknown data in the input and output steps, and conducting a sensitivity examination (Buchholz et al., 2009), the examination highlights that all the methods perform well in this case and can deal with uncertainty. The PROMETHEE and ELECTRE techniques can manage uncertainty perfectly (Polatidis et al., 2006; Rowley et al., 2012) while the DEA, DSRA, ELECTRE and PROMETHEE are capable of managing unknown data better than the AHP, ANP and TOPSIS through their possibility distributions and threshold management. The DRSA deals with unknown data through allocating possibility ranks to the principles of which the requirements are capable (Greco, Matarazzo, & Slowinski, 2001a) or rating intervals instead of exact values in imprecise datasets (Dembczyński, Greco, & Słowiński, 2009). The interdependencies between the criteria and alternatives can be considered since all methods except the DRSA support them.

Although all eight methods are traceable, the publications on MCDM techniques fail to explain this fact and, in particular, that their frameworks do not restrict the amounts or natures of the factors which can be considered input criteria (Belton & Stewart, 2002; Figueira, Greco, & Ehrgott, 2005). Therefore, it is simply emphasised that every phase of an objective item is accounted for. As the AHP is backed up by several tools and its structure is simple, it is very easy to use and understandable (Linkov & Moberg, 2011). However, as a result of the large numbers of variables, assessment processes based on similarity and dissimilarity indices and de-selection processes, and outcomes reflected according to kernel graphs, ELECTRE techniques rank low (Munda, 2008; Polatidis et al., 2006). Although PROMETHEE is subject to the verification of time-intensive thresholds, it is easier to learn and apply than ELECTRE (Munda, 2008; Polatidis et al., 2006), is not difficult to use as a tool and has a variety of interfaces (Buchholz et al., 2009). The DRSA ranks perfectly in this case as it is presents various capabilities for organising the judgements and applying as well as explaining the outcomes (Roy & Słowiński, 2013; Slowinski et al., 2009). There is a lack of proper applications and tools for many techniques (e.g., VIKOR) while, as DECERNS, super decisions and ELECTRE, together with DRSA programs, fail to simultaneously analyse opinions in accordance with diverse inputs, it is necessary to re-run the software to obtain individual outcomes (Antunes, 2012; Buchholz et al., 2009; Linkov & Moberg, 2011).

While all methods except the DEA and DRSA are capable of dealing with quantitative data, the DSRA does not require the modification of information (Greco, Matarazzo, & Slowinski, 2001b). The most important step in decision-making techniques is to precisely evaluate the relevant information. This issue is particularly critical in approaches which should elicit qualitative data from a decision maker, which can be achieved by DEA and DRSA, while the others support quantitative values. However, as the AHP and

ANP can only support values that are quantified, they are clearly inferior to other MCDM methods in terms of their issues framework and cannot be used when there are certain/several requirements and options. The downside of employing the ANP and AHP techniques could be also a restricted number of criteria and alternatives. As it is crucial to perform a $n \times (n-1)/2$ analysis, it is recommended that no more than 10 criteria are used. For example, for an efficiency assessment of a portfolio with 100 projects and sub-projects, an examination of 4500 separate matrix (*100×(100–1)/2 =4500 matrix*) is required which can be a challenging task for a decision maker. As a result, it is not recommended that the AHP and ANP methods be applied individually given that PPM sometimes involves more than ten options and factors. On the other hand, the DEA can support an infinite number of values. Likewise, some applications, such as PROMETHEE ACADEMIC, restrict the quantity of options or criteria.

The rank reversal issue is a common problem of all the selected MCDM techniques, except the DEA, when another option is presented. Ratings are viewed as robust if the addition or removal of an option does not influence the classification or rating of any of the others, with the AHP criticised by Dyer (1990) as a flawed method because it results in arbitrary ratings. However, Saaty (1990) presents a separate aspect of this concern, declaring that this event can occur and, instead of becoming an issue, is a requirement. Experts have demonstrated that ELECTRE experiences rank reversal possibly as a result of the framework of its decision method which depends on a pair-wise analysis and is influenced by the total number of options, as is the AHP (Wang & Triantaphyllou, 2008). Generally, an ELECTRE technique does not result in the selection of only one answer/option from among the others and is one of the approaches that need to determine various criteria, most of which have no specific or realistic definitions. Moreover, its exploitation system is considered by several experts as unclear and difficult to understand (Brans & Vincke, 1985) while its graphical restriction makes its assessment a great deal more difficult. Also, it usually struggles to provide rankings of all the options and, instead, chooses a sub-set of alternatives regarded as being more suitable than others. Therefore, it might be better for decision issues with a few criteria and options for which it can identify more suitable choices (Lootsma, 1990). ELECTRE, PROMETHEE and VIKOR methods need considerable user interaction when dealing with a problem. Figueira and Roy (2009) emphasise that a turning point in the rankings is connected to variations in the input information which impact on the level of reliability of the value graphs and total scorings, suggesting the characteristics of this event are understandable and valid. PROMETHEE techniques are influenced by similar events since they also depend on pair-wise assessments. Mareschal, De Smet, and Nemery (2008) verify that rank reversal can be limited to a specific pair of circumstances, a concern recently further examined by Roland, De Smet, and Verly (2012). The robustness outcomes of the DRSA are affected by the appropriate assistance of specifications which means that the number of options that complies with the principle is in accordance with the total number of options on the data platform (Slowinski et al., 2009), factors that also apply to the PROMETHEE, ELECTRE and AHP techniques. There is a lack of published research concerning the rank reversal problem in the DRSA despite this method being likely to experience it because it relies on outranking comparisons.

Thresholds can be applied for two reasons: to help manage the difference between options if two options are compared (Mendoza & Martins, 2006); and to influence the level of compensation among the individual requirements (Buchholz et al., 2009). Several techniques, such as VIKOR, cannot set parameters values and there is no possibility of applying thresholds for the basic AHP and ANP methods (Antunes, 2012; Buchholz et al., 2009). In contrast, ELECTRE and PROMETHEE approaches deal with various thresholds given that they form frameworks on which techniques are based and both need the two categories of indifference and preference. However, PROMETHEE requires an additional category known as veto (Brans & Mareschal, 2005) and has to associate decisions and threshold values with every factor to help perceptions of the measurement scales of the factors. The DRSA enables thresholds to be determined from selection specifications (e.g., 'if' and 'then' situations) (Roy & Słowiński, 2013; Slowinski et al., 2009).

Group decisions can be only partially arrived at as, of the eight MCDM techniques considered, only the ANP and DEA methodologies are capable of grouping the criteria and alternatives. The AHP, ANP, DEA, PROMETHEE and VIKOR all allow the criteria to be organised into sub-criteria. The AHP and ANP methods support a hierarchical structure, with the former proven to be very useful if an elemental hierarchy has more than three levels (Yeh, 2002) which means that the goal needs to be placed on the top, factors which define options on the centre and options on the bottom levels. All the methods except ELECTRE and DRSA support the dependencies and weightings of criteria. Therefore, prioritising criteria is not possible when applying ELECTRE or DRSA while the ANP also undermines the outcomes of weighting clusters. The AHP, ANP and DEA are the only methods that support the weighting of alternatives. The

ANP has a scalability problem and, because of its specific drawbacks, the AHP has experienced higher useability, particularly when mixed with other MCDM techniques. Of all the methods, the AHP, ANP and DEA are the most integrated ones.

5. Conclusion and Future Works

What makes this study unique is the fact that it is probably the first of its kind to analyse PPM MCDM methods on this scale by comparing more than 100 MCDM techniques as well as proposing a solid framework for comparing and ranking them based on their advantages and disadvantages. The following conclusions can be drawn as a result of this investigation:

In order to analyse applications of MCDM techniques, as an initial objective, a literature review was conducted (covering more than 100 techniques in over 1400 articles) that addressed: (1) strategic PPM problems; and (2) decision-making methods and problems. From it, the most suitable MCDM methods for a portfolio decision-making process were selected, with the top eight down-selected and compared in more detail in order to determine their suitability for PPM decision making.

In summary, this investigation demonstrated that specific MCDM techniques are better suited to, and designed for, particular circumstances/scenarios while other applications need to completely ignore them. Also, it was study determined that there is no single standard MCDM method that can both support a PPM's strategic decision making and deal with all its challenges. Moreover, not all portfolio decision-making specifications can be accomplished using current techniques. A few, such as those working with both quantitative and qualitative values might be achieved in the case of a customised application. This review indicated that using particular techniques significantly increases a planning procedure's performance and it would be better to apply more than one MCDM technique or even a hybrid method. There is some evidence that it might be beneficial to choose and implement multiple MCDM methods (Bell et al., 2001; Kangas et al., 2001; Salminen et al., 1998), with those more useful for PPM problems a combination of MADM and MODM techniques.

The capabilities of the AHP and DEA methods to deal with any type of judgement specifications or factors with both quantitative and qualitative data, the simplicity of their outcomes and their relatively low levels of complexity when managing preferences leads to the conclusion that they are the most effective approaches (of the numerous methods examined during this study) for the targeted process. They can provide better solutions related to PPM decisions and, in particular, offer the prospect of re-evaluation. Some techniques take significant amounts of a decision makers time and usually are not capable of ranking options. The ANP, DRSA, ELECTRE, PROMETHEE, TOPSIS and VIKOR methods were omitted given that, despite the fact that they may take even less time than the AHP or DEA, their solution procedures would still be complicated for a large group of targets while their procedures for a sensitivity examination would be challenging. The evaluation results showed that the AHP and DEA are slightly easier to use than the other methods but, to apply the former for the purpose of PPM decision making would require modifications to it or possibly its integration with other methods that can support both infinite and qualitative data. Although it is possible that a hybrid method could be customised for this specific problem, there are still many questions and limitations which need further investigation, such as the requirements for obtaining feedback about the quality of a prediction or reliability/accuracy of a solution.

In accordance with the outcomes discussed in this study, details of attempts to improve them which involve applying the selected methods, both individually and in an integrated decision support system format, and examining them in real decision-making scenarios requires further investigation.

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ANNEX A - MCDM METHODS REFERENCES

Additive Ratio Assessment (ARAS) (e.g., Zavadskas & Turskis, 2010); Additive Value Function (AVF) (e.g., Stewart, 1996); Aggregated Indices Randomization Method (AIRM) (e.g., Dotsenko, Makshanov, & Popovich, 2014); Analytic hierarchy process (AHP) (e.g., Saaty, 1980b); Analytic Network Process (ANP) (e.g., Saaty, 2001); ARGUS (e.g., De Keyser & Peeters, 1994); Artificial Neural Network (ANN) (e.g., Wang, 2003); Axiomatic design (AD) (e.g., Suh, 1998); Balanced Scorecard (BSC) (e.g., Kaplan & Norton, 1995); Best Worst Method (BWM) (e.g., Marley, 2009); Chance Constraint DEA (CCDEA) (e.g., Cooper, Huang, & Li, 2004); Characteristic Objects METhod (COMET) (e.g., Sałabun, 2015); Choosing By Advantages (CBA) (e.g., Suhr, 1999); COmplex Proportional ASsessment (COPRAS) (e.g., Zavadskas & Kaklauskas, 1996); Corporative Game Theory (CGT) (e.g., Steffen & Uzunova, 2016); Comprehensive Algorithm (CA) (e.g., Zhao & Fernald, 2005); Compromise Programming (CP) (e.g., Zeleny, 1973); Corrected Ordinary Least Squares (COLS) (e.g., Banker, Gadh, & Gorr, 1993); Data Envelopment Analysis (DEA) (e.g., Cooper, Seiford, & Zhu, 2004); Decision EXpert (DEX) (e.g., Bohanec & Rajkovič, 1990); Decision matrix (DM) (e.g., Hawass, 1997); Dependence-based Interval-valued ER (DIER) (e.g., Fu & Yang, 2012); Dominance-based Rough Set Approach (DRSA) (e.g., Greco, Matarazzo, & Słowiński, 2007); ELimination and Choice Translating REality (ELECTRE) (e.g., Figueira, Mousseau, et al., 2005); Evidence Reasoning (ER) (e.g., Zhang, Da Xu, Zhang, & Li, 2003); Evidential Reasoning approach (ERA) (e.g., Yang & Singh, 1994); Failure Mode and Effect Analysis (FMEA) (e.g., Hollenback, 1977); Fuzzy Set Theory (FST) (e.g., Zimmermann, 2010); Genetic Algorithm (GA) (e.g., Tanaka, Watanabe, Furukawa, & Tanino, 1995); GAIA (e.g., Hayez, Mareschal, & De Smet, 2009; Lidouh, De Smet, & Zimányi, 2009); Goal Programming (GP) (e.g., Lee, 1972); Grey Relation Analysis (GRA) (e.g., Hsia & Wu, 1998); Hasse Diagram Technique (HDT) (e.g., Bruggemann & Voigt, 2008; Simon, Kübler, & Böhner, 2007); House of Quality (HOQ) (e.g., er Tapke, son Muller, Johnson, & Sieck, 1997); Index Decomposition Analysis (IDA) (e.g., Ang & Zhang, 2000); Inner Product of Vectors (IPV) (e.g., Wang, Yang, Waters, & Zhang, 2011); Integer Linear Programming (ILP) (e.g., Abara, 1989); Interactive Minimax Reference Point (IMRP) (e.g., Yang, Xu, & Yang, 2012); Interpretive Structural Modeling (ISM) (e.g., Malone, 1975); IRIS (e.g., Dias, Mousseau, Figueira, Clímaco, & Silva, 2002); Lexicographic Goal Programming (LGP) (e.g., Rees, Clayton, & Taylor, 1985); Linear Programming (LP) (e.g., Dantzig, 1998); Linear Programming Techniques for Multidimensional Analysis of Preference (LINMAP) (e.g., Srinivasan & Shocker, 1973); Measuring Attractiveness by a categorical Based Evaluation Technique (MACBETH) (e.g., Bana e Costa, Corte, & Vansnick, 2011); Multicriterion Q-analysis (MCQA) (e.g., Duckstein, Kempf, & Casti, 1984; Eder, Duckstein, & Nachtnebel, 1997); Meta-heuristics (MH) (e.g., Osman & Kelly, 1996); Mixed Integer Programming (MIP) (e.g., Wolsey, 2008); Monte Carlo Simulation (MCS) (e.g., Mooney, 1997); Multi-attribute Global Inference of Quality (MAGIQ) (e.g., McCaffrey, 2005); Multi-attribute Utility Theory (MAUT) (e.g., Mateo, 2012); Multi-attribute Value Theory (MAVT) (e.g., Hostmann, Bernauer, Mosler, Reichert, & Truffer, 2005); Multicriterion Analysis of Preferences by means of Pairwise Alternatives and Criterion comparisons (MAPPAC) (e.g., Matarazzo, 1984); Multi-objective Optimization by Ratio Analysis plus Full Multiplicative Form (MULTIMOORA) (e.g., Brauers & Zavadskas, 2010); Multi-objective Optimization on the basis of Ratio Analysis (MOORA) (e.g., Brauers & Zavadskas, 2006); Multi-objective Programming (MOP) (e.g., Zografos & Davis, 1989); Multiplicative Exponent Weighting (MEW) (e.g., Zhengkun, L. et al. 2012); Novel Approach to Imprecise Assessment and Decision Environment (NAIDE) (e.g., Cancelliere, Giuliano, & Longheu, 2003; Naidu, Sawhney, & Li, 2008); Nonlinear Programming Model (NLP) (e.g., Tyteca, 1981); Ordered Weighted Averaging (OWA) (e.g., Yager, 1988); Organization, Rangement Et Synthese De Donnes Relationnelles (ORESTE) (e.g., Chatterjee & Chakraborty, 2013); Potentially All Pairwise Rankings of all possible alternatives (PAPRIKA) (e.g., Dalgaard, Heikkilae, & Koskinen, 2014); Preemptive Goal Programming (PGP) (e.g., Wang & Parkan, 2007); Preference Ranking Global frequencies in Multicriterion Analysis (PRAGMA) (e.g., Matarazzo, 1988); Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) (e.g., Mareschal, Brans, & Vincke, 1984); Principal Component Analysis (PCA) (e.g., Jolliffe, 1986); Pugh Evaluation Matrix (PEM) (e.g., Pugh & Clausing, 1996); Quality function deployment (QFD) (e.g., Chan & Wu, 2002); REMBRANDT (e.g., Lootsma, 1992); Rough Set Approach (RSA) (e.g., Pawlak & Sowinski, 1994); Simple Additive Weighting (SAW) (e.g., Afshari, Mojahed, & Yusuff, 2010); Stochastic Multi-criteria Acceptability Analysis (SMAA) (e.g., Lahdelma & Salminen, 2001); Simple Multi-attribute Rating Technique (SMART) (e.g., Valiris, Chytas, & Glykas, 2005); Stochastic Programming (SP) (e.g., Birge & Louveaux, 2011); Superiority and Inferiority Ranking (SIR) (e.g., Jian-qiang, 2004); Total Cost of Ownership (TCO) (e.g., Ellram & Siferd, 1998; Ferrin & Plank, 2002); Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (e.g., Chen, 2000); Theory of Inventive Problem Solving (TRIZ) (e.g., Altshuller & Shulyak, 1996); Tratement des Actions Compte Tenu de l'Importance des Crite'res (TACTIC) (e.g., Vansnick, 1986); Utility Theory Additive (UTA) (e.g., Jacquet-Lagreze & Siskos, 1982); Value Analysis (VA) (e.g., Miles, 1961); Value Engineering (VE) (e.g., Caijiang, Kehua, & Yongmei, 2002); VIP (e.g., Dias & Clímaco, 2000); VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (e.g., El-Santawy, 2012); Weighted Linear Assignment Method (WLAM) (e.g., Zhou, Jia, Xie, Chang, & Tang, 2012); Weighted Product Model (WPM) (e.g., Savitha & Chandrasekar, 2011); Weighted Sum Model (WSM) (e.g., Goh, Tung, & Cheng, 1996); ZAPROS (e.g., Larichev, 2001; Tamanini & Pinheiro, 2008); Zero-One Goal Programming (ZOGP) (e.g., GAME & TWO-PERSON, 1996) and Z-W (e.g., Fang, 2008).

ANNEX B - TOP EIGHT PPM MCDM METHODS COMPARISON TABLE

		Requirements	AHP	ANP	DEA	DRSA	ELECTRE	PROMETHEE	TOPSIS	VIKOR
Main Criteria	1	*Supporting Sensitivity Analysis* [1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes and No
	2	*Supporting Dependencies* [2]	Yes	Yes	Yes	Yes and No	Yes	Yes	Yes	Yes
	3	*Supporting Decision Traceability*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	4	*Simplicity Level* [3]	3	2	3	2	1	2	1	1
Beneficial Criteria	5.1	*Supporting Quantitative Data*	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
	5.1	*Supporting Qualitative Data*	No	No	Yes	Yes	No	No	No	No
	5.2	*Supporting Infinite number of values*	No	No	Yes	No	No	No	No	No
	5.3	*Supporting Tradeoffs / Conflict*	No	No	Yes	No	No	No	No	No
	5.4	*Supporting Group Decision*	No	Yes	Yes	No	No	No	No	No
	5.5	*Supporting Hierarchical Structure*	Yes	Yes	No	No	No	No	No	No
Beneficial Sub-criteria	6.1	*Supporting Thresholds/Setting Parameters* [4]	No	No	Yes	Yes	Yes	Yes	No	Yes
	6.2	*Allowing criteria weighting* [5]	Yes	Yes and No	Yes	No	No	Yes	Yes	Yes
	6.2	*Allowing alternative weighting* [5]	Yes	Yes and No	Yes	No	No	No	No	No
	6.3	*Supporting rank reversal*	No	No	Yes	No	No	No	No	No
	6.4	*Supporting sub-criteria*	Yes	Yes	Yes	No	No	Yes	No	Yes
Additional consideration during the selection process	7.1	*Type of Problem*	Ranking	Ranking	Ranking / Classification	Classification	Ranking / Classification	Ranking	Ranking	Ranking
	7.2	*Some Advantages*	Can be used in almost any type of subject; Easy to use; scalable; hierarchy structure can easily adjust to fit many sized problems; lots of tools are available; not data intensive.	Can get ranking of a set of alternatives in terms of a finite number of decision criteria. Allows grouping of criteria.	It does not require pre-estimated variables. It is capable of handling multiple inputs and outputs; efficiency can be analysed and quantified; weights assigned to outputs and inputs are not allocated by users.	Handles missing values and qualitative and qualitative data. The method is not limited to a specific field and could be used for a wide variety of real-life problems; does not require any data transformation; and is able to handle uncertainty.	They avoid compensation between criteria and any normalization process. Takes uncertainty and vagueness into account. Does not need criteria weights.	Easy to use; does not require assumption that criteria are proportionate; allows to operate directly on the variables included in the decision matrix without requiring any normalisation; User friendly tools available.	Has a simple process; easy to use and program; the number of steps remains the same regardless of the number of attributes; allows selecting only one solution as the “best” one and it is able to manage each kind of variables and each type of criteria; and There are also multiple tools that support this method.	Evaluates several possible alternatives according to multiple conflicting criteria and rank them from the worst to the best one; it is not necessary to perform consistency test; and simple to use and implement.
	7.3	*Some Disadvantages*	Problems due to interdependence between criteria and alternatives; can lead to inconsistencies between judgment and ranking criteria; rank reversal problem;only supports qualitative values; a limited number of criteria can be applied.	Only a limited number of criteria and alternatives can be applied. This method suffers from the rank reversal problem. It may be very difficult to create own implementation of ANP in Excel spreadsheet. it ignores the different effects among clusters.	Does not deal with imprecise data; assumes that all input and output are exactly known; the results can be sensitive depending on the inputs and outputs; DEA does not work with negative or zero values for inputs and outputs.	Limited by the previous experience; DRSA could suffer from rank reversal	Its process and outcome can be difficult to explain in layman’s terms; sometimes is unable to identify the preferred alternative; does not have these characteristics; outranking causes the strengths and weaknesses of the alternatives to not be directly identified. Criteria Weights are not supported.	Does not provide a clear method by which to assign weights; is needed that each criterion is of the benefit type; handle only quantitative and missing values; and suffers from the rank reversal problem.	Its use of Euclidean Distance does not consider the correlation of attributes; difficult to weight and keep consistency of judgment; it does not support uncertain or missing values; and suffers from rank reversal problem.	Not tools available for this method. It is not able to handle incomplete and uncertain information. Suffers from the rank reversal problem
	7.4	*Area of Applications*	Performance-type problems, resource management, government, corporate policy and strategy, public policy, political strategy, planning, supplier selection, and…	Logistic services, services selection, manufacturing performance, IT system project selection, hazardous substance management, forest management, planning, and …	Economics, medicine, utilities, road safety, agriculture, construction, water resources, retail, business problems, banking, operational efficiency, aviation, and …	Medicine, Education, Finance, IT, Medical practice, Cryptography, IGS, and…	Energy, economics, environmental, water management, transportation problems, and …	Environmental, hydrology, water management, business and finance, chemistry, logistics and transportation, manufacturing and assembly, energy, agriculture, and …	Supply chain management and logistics, engineering, manufacturing systems, business and marketing, environmental, human resources, water resources, and …	Multi-criteria optimisation of complex systems, business management, water resources, material selection, supplier selection, forestry, land subdivisions, and ...
	7.5	*Integrated methods*	ANP, DEA, ELECTRE, PROMETHEE, TOPSIS, VIKOR	AHP, DEA,PROMETHEE, TOPSIS, VIKOR	AHP, ANP, PROMETHEE, TOPSIS, VIKOR	AHP, ANP, TOPSIS	AHP, PROMETHEE	AHP, ANP, DEA, ELECTRE	AHP, ANP, DEA, VIKOR	AHP, ANP, DEA, TOPSIS
	7.6	*Learning dimension*	Difficult	Difficult	Possible	Difficult	Difficult	Possible	Possible	Difficult
References		*Literature References*	Saaty, 1980	Saaty, 2001	Charnes et al., 1994	Greco et al., 2007	Benayoum et al.1966	Mareschal et al. 1984	Lai et al. 1994	Opricovic et al. 2004

Comparison Summary

	Methods	Score	Rank
1	AHP	11	2
2	ANP	9	3
3	DEA	15	1
4	DRSA	7	5
5	ELECTRE	6	8
6	PROMETHEE	9	4
7	TOPSIS	6	7
8	VIKOR	7	6

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NOTE:

[1] DEA, DSRA, ELECTRE as well as PROMETHEE are able to manage unknown data better than AHP, ANP and TOPSIS through possibility distributions together with thresholds management.
[2] DRSA can only support the interdependencies between alternatives.
[3] 1= Complex; 2= Moderate; 3= Simple
[4] PROMETHEE is subject to the time-intensive thresholds verification, however it is easier to learn and apply instead of ELECTRE.
[5] ANP undermines the outcomes of weighing the clusters.

ANNEX C - MCDM METHODS AVAILABLE SOFTWARE

Method	Software name	Links
AHP	Expert Choice:	http://www.expertchoice.com/
	Mind Decider:	http://www.minddecider.com
	HIPRE 3+:	http://sal.aalto.fi/en/resources/downloadables/hipre3
	MAkeItRational:	www.makeitrational.com/
	Transparent Choice:	www.transparentchoice.com/
	Decision Analysis Module for Excel (DAME):	http://ironcake.blogspot.com.au/p/download-dame.html
	ChoiceResults:	http://choiceresults.win7dwnld.com/
	123AHP (Online):	http://123ahp.com/Izracun.aspx
	Decisions Lens:	http://www.decisionlens.com
	Super Decisions:	http://www.superdecisions.com
ANP	ANP SOLVER:	http://kkir.simor.ntua.gr/anpsolver.html
	WEB ANP SOLVER:	http://kkir.simor.ntua.gr/web-anp-solver.html
	Decisions Lens:	http://www.decisionlens.com
	Super Decisions:	http://www.superdecisions.com
DEA	DEA-Solver-Pro:	www.saitech-inc.com
	Frontier Analyst:	www.banxia.com
	OnFront:	www.emq.com
	Warwick DEA:	www.deazone.com
	DEA Excel Solver:	www.deafrontier.com
	DEAP:	http://www.uq.edu.au/economics/cepa/deap.htm
	EMS: Efficiency Measurement System:	http://www.holger-scheel.de/ems/
	PIONEER 2:	http://faculty.smu.edu/barr/pioneer
	Win4DEAP:	http://www8.umoncton.ca/umcm-deslierres_michel/dea/install.html
	DEAFrontier:	http://www.deafrontier.net/software.html
DSRA	4eMka2:	http://idss.cs.put.poznan.pl/site/60.html#c80
	jMAF:	http://www.cs.put.poznan.pl/jblaszczynski/Site/jRS.html
ELECTRE	ELECTRE III/IV:	http://www.lamsade.dauphine.fr/~mayag/links.html
	ELECTRE TRI:	http://www.lamsade.dauphine.fr/~mayag/links.html
PROMETHEE	Visual PROMETHEE Academic:	http://www.promethee-gaia.net/software.html
	PROMETHEE:	www.smart-picker.com
TOPSIS	Triptych:	www.stat-design.com/Software/Triptych.html
VIKOR	N/A	No software available.
Multi-Software	SANA (Electre I & 3, Topsis, Promethee II):	http://nb.vse.cz/~jablon/sanna.htm
	Decision Deck:	http://www.decision-deck.org/
	DECERNS (AHP, PROMETHEE and TOPSIS):	http://deesoft.ru/lang/en

ANNEX L – PUBLICATION III

Using Analytic Hierarchy Process as a Decision-Making Tool in Project Portfolio Management

D. Danesh, M. J. Ryan, A. Abbasi

Abstract**—**Project Portfolio Management (PPM) is an essential component of an organisation's strategic procedures, which requires attention of several factors to envisage a range of long-term outcomes to support strategic project portfolio decisions. To evaluate overall efficiency at the portfolio level, it is essential to identify the functionality of specific projects as well as to aggregate those findings in a mathematically meaningful manner that indicates the strategic significance of the associated projects at a number of levels of abstraction. PPM success is directly associated with the quality of decisions made and poor judgment increases portfolio costs. Hence, various Multi-Criteria Decision Making (MCDM) techniques have been designed and employed to support the decision-making functions. This paper reviews possible options to enhance the decision-making outcomes in organisational portfolio management processes using the Analytic Hierarchy Process (AHP) both from academic and practical perspectives and will examine the usability, certainty and quality of the technique. The results of the study will also provide insight into the technical risk associated with current decision-making model to underpin initiative tracking and strategic portfolio management.

Keywords**—**Analytic hierarchy process, decision support systems, multi-criteria decision-making, project portfolio management.

I. Introduction

As organisations progressively transform into project forms, projects tend to be the key delivery tool for organisational strategy [1]-[5]. These projects are influenced by several drivers, such as competitive demands, greater complexity of organisational plans, along with the increasing accessibility of resources and software products [6], [7]. Generally, the role of Project Portfolio Management (PPM) is to evaluate, select, and prioritise new projects, as well as to revise priority, and possibly eliminate and reduce projects in progress [8]. By managing and analysing all projects and their interrelationships from a portfolio level, the goal of PPM is to enhance the overall efficiency of the project portfolio. Project investments decisions play an essential strategic role in the majority of businesses, particularly project-based businesses [9].

PPM is an essential portion of strategic management practice since it involves decisions concerning which actions a business needs to undertake to best achieve strategic targets. In other words, PPM is an organisational functionality of increasing value in a growing challenging project concept [10]-[12]. The literature emphasises that PPM is basically a strategic decision-making method that engages determining, reducing, as well as diversifying risk; identifying and addressing variations; along with recognising and accepting together with making trade-offs [12], [13]. The importance of the position of the project portfolio with the public as well as private sector strategy has been introduced more frequently as an essential activity for organisations, leading PPM to assume a significant role in competitive strategy as well as, to present itself as an impacting element in the long-term outcomes of the business [14]. An essential factor in PPM would be to assess which is the group of projects that maximises the success and achievement of strategic targets. PPM is then an active decision practice where an amount of new analysis items and improvement is constantly updated.

Although PPM is not directly focused on assuring good results in obtaining strategic goals and objectives, an effective PPM practice will be able to improve the probabilities of choosing and then completing the assignments that best achieve organisational goals and promote accomplishing the organisation's perspective. Fundamental aspects in obtaining such targets are (1) choosing the projects that best promote strategic targets, (2) analysing efficiency throughout execution to make sure the portfolio continues to be on target to provide strategic advantages as well as (3) modifying strategy along with the portfolio whenever adjustments in strategy or functionality require. To examine efficiency at the portfolio level, it is essential to identify the capability of single projects and combine the findings in a mathematically meaningful process which displays the strategic significance of the associate projects.

This paper proposes a practical study that aims to determine the inhibitors for decision-making when managing a complex portfolio and to provide an examination of the Analytic Hierarchy Process (AHP) method to indicate the characteristics of the approach in dealing with the MCDM problem. This paper also aims to improve organisations' knowledge of MCDM methods and the interdependencies within a project portfolio, thereby improving their capability to take strategic portfolio decisions.

In this paper, the academic perspective of the AHP technique is introduced through a literature review and the

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works according to this methodology is reviewed. The shortcomings of AHP and issues in using this method when exclusively used to deal with the MCDM problems is also explained accompanied by a practical case study of the way this process works. This study will describe the experiences of an organisation in implementing the proposed method of visually identifying and demonstrating information to assist strategic decision-making; and will examine the usability, certainty and quality of the technique in a real portfolio life cycle.

II. Literature Review

A. Project Portfolio Management (PPM) and Challenges

There are various methodologies for portfolio management. The best-suited models indicate an activity of regular selection of available project proposals, along with the re-evaluation of existing projects which are in implementation stage, therefore, enabling the compliance with the strategic targets of the organisation without exceeding available resources, nor violating business constraints, and responding to the minimal requests of the organisation in accordance with the different requirements [15]. A few of such requests might be: possible potential revenue, potential acceptance, and quantity of assets.

Recently, PPM has received interest as a means of aligning projects with strategy in addition to ensuring sufficient resourcing for projects, prompting businesses in different sectors to improve their PPM abilities [16], [17]. PPM procedures assist organisations to control their projects using a variety of tools or methods built to produce and evaluate project information as well as to drive decision-making to manage a well-balanced portfolio which is in parallel with key objectives [12]-[14]. The publications signifies that the effective management of project portfolios transcends the techniques employed, realising that the business framework, individuals together with tradition are likewise essential elements of an organisation's total ability to handle its project portfolio [18]. Studies frequently implies that PPM requires to be developed over time [14], [19] and different procedures and tools are designed for PPM which require to customised and specified for optimum outcomes [20]. The remarkable increase of best practice researches and growth techniques emphasises the existing link within PPM and final results improvement [21]-[24]. The remarkable increase of best practice researches and strong focus on PPM processes and techniques emphasises the existing link between growth and outcomes of PPM; and likewise, the ability to improve PPM outcomes as reported in different studies. A number of researches suggested the need for a mutual link between projects and strategic levels of the organisations instead of one way relationship from strategic level to projects level, as PPM procedures obtain from both strategic and Projects levels [3]-[5], [25]-[27]. PPM functions are proven to enable the mixture of top-down strategic objective with bottom-up strategy progress in a number of different scientific experiments [28]-[30]. Such research has revealed that PPM is a critical strategic functionality responsible for delivering and shaping strategy. This responsibility assists to describe the level of executive as well as scientific desire for comprehending and strengthening PPM decision-making abilities.

Portfolio decisions are in charge of guaranteeing resource adequacy and agility, and also to better implementing adjustment at the portfolio level rather than the project level [31], [32]. Having said that, PPM decisions depend on limitations in human intellectual ability to assess a number of different data in restricted time. PPM techniques and procedures are created to support these types of decision-making by offering a pure perspective of the project portfolio, making sure that information are obtainable and providing representation strategies and resources to simplify examination of project details [13], [14], [33]. Classic metrics and strategies emphasise efficiency and performance driven by cost, schedule, quality, or scope [34] while they do not examine, monitor, or track portfolios/projects to provide the strategic benefit.

The challenges of the execution and delivery of PPM are related to the uncertainties established by turbulences in the industry, sudden technological variations, and utilisation of uncommon resources shared among the many areas of the organisation [35], [36]. To be able to confirm the possible implementation of the portfolio, PPM needs to visualise options and potential outcomes of project decisions across a portfolio. Decision-making quality is a key element of a successful project portfolio [37]. Organisational achievement relies on proper PPM strategies techniques and tools that enhance the quality associated with these portfolio-level decisions. Projects interconnections together with the activities relations elevate the complexity of PPM decision-making and needs to be regarded alongside financial, strategic, risk, resource and other elements. Portfolios of complex and interdependent projects are significantly common and there is certainly an identified requirement for advanced methods to recognise and handle the associations between projects. Research in portfolio management identifies that decisions are depending on various criteria like product, market, and financial, knowing that over-emphasising a single measure is linked to poorer performance [38], [39].

B. Portfolio Decision-Making Tools

Dealing with a complex portfolio of projects with uncertainty is much more complicated when compared to the classic project management [40] especially throughout the control of project interconnectivities [41], [42] that could be one of the PPM’s shortcomings [43].

Different systems, applications, or methods are frequently presented and analysed in PPM research [15], [44]-[46]. Nevertheless, assessing the impact of a different application or technique is complicated since every single organisational nature is unique and there might be other aspects that affect project efficiency. Despite several studies in organisational environment, a reliable environment within which results can be generalised has not yet been provided.

Several studies indicate that strategic PPM decisions are consumed in group sessions applying graphical applications, however, these tools must to be specially developed or modified according to individual organisations needs or desires for highly valuable decisions [14], [47]-[52]. For example, portfolio maps provide projects and their options on two axes, supported by extra information such as variations and risk [14], [50], [51]. Although these mapping tools offering a portfolio level perspective, they are generally looking at projects independently. On the other hand, project interconnectivities might result in unexpected responses in the procedures [40]-[42], indicates the importance of the projects dependencies to make effective decisions [53], [54]. The use of classic PPM tools is no longer accepted as project portfolio complexity is increasing dramatically and most of projects are no longer considered independently or, if there are independent projects, their independencies should be fully understood for successful decisions [53], [54]. There is a variety of organisations that collect project interconnectivities data, however there is limited ability to use or apply this information or identify multistage dependencies [45], [55]. To meet these challenges, particularly as complexity rises, experts participated in developing different decision-making systems [40]. This research also employs controlled experimentation to test the ability of a decision-making model (AHP) to improve project portfolio decision-making knowledge among PPM decision makers.

C. Multi-Criteria Decision Making (MCDM) Overview

Decision-makers are no longer considering just one single criterion to make a decision. To develop ongoing communication and come up with viable choices, organisations consider multiple criteria in their decision practice. Decision difficulties such as ranking, selection and sorting challenges are sometimes complicated since they often consist of various criteria.

MCDM is a structure for analysing decision issues indicated by complex multiple targets [56], [57]. MCDM also can handle long-term time options, unknown aspects, risks, and complicated value concerns. The MCDM practice generally defines targets, selects the requirements to determine the targets, specifies options, modifies the measure values, assigns weights to the requirements, uses a mathematical algorithm to score options, and selects an option [58]-[61]. MCDM has been employed in different fields such as policy examination [62], [63], food security [64], policy examination [65], resource management [66]-[68], portfolio and financial assets management [69], location selection [70], procurement and best supplier selection [71], forest management [72], evaluation of business units performances [73], health care system [74], finance [75], energy [76], and environmental risk assessment [77].

Currently, there are more than 100 MCDM techniques and methodologies that are used to support decision-making. Each method has its own advantages and disadvantages, and its fitness depends on the situation. Usually portfolios with complex independencies and a large number of criteria or alternatives are managed in a hierarchical format and for the same reason a preferred method requires to support a hierarchical structure. As a result, those MCDM techniques that assume a single level of attributes and not support a hierarchical structure have been omitted.

D. Analytic Hierarchy Process (AHP)

According to [78]: "the human mind uses hierarchies as the prevailing method for classifying what we observe". The AHP method is one such approach that presents a solution to shape key decisions into hierarchies of targets, in addition to evaluate those to support difficult choices, like selection of project portfolios for an organisation. AHP seems to be one of the most popular and appropriate among the remaining MCDM techniques for solving the portfolio decision problems because of its simplicity and applicability to multilevel hierarchies.

AHP, developed in the 1980 [79], is among the most common MCDM methods and is well suited to modelling quantitative considerations and has discovered extensive purposes in so many different fields like preference, assessment, designing as well as improvement and decision-making, etc. [80]. AHP presents the relative priority of particular indicators [81]-[83].

AHP employs hierarchical (or network) system to indicate a decision problem [79]. The system is designed in such a manner that the total goal is at the top level, requirements at the center level(s), and alternatives decisions at the bottom. The AHP approach presents an organised structure for arranging preferences at each level of the hierarchy employing pairwise analysis [84]. The feature vector that is obtained is then compared by determining the matrix elements to find the relative value of the same unit on the different levels and then rank the value of each option [79], [85]. The hierarchical equation first introduced by [86] and practised in [87], [88]. The 1-9 ratios are based on Stevens and Fechner studies [89], [90] which the value of objects in each level is simulated by [91].

TABLE I
COMPARATIVE JUDGMENT TABLE

	Intensity Scale	
Less important than	Extremely less important	1/9
		1/8
	Very strong less important	1/7
		1/6
	Strongly less important	1/5
		1/4
	Moderately less important	1/3
		1/2
	Equal Importance	1
More important than		2
	Moderately more important	3
		4
	Strongly more important	5
		6
	Very strong more important	7
		8
	Extremely more important	9

The AHP method has been widely applied for performance evaluation and used by various researchers to solve different decision-making problems and the growth in AHP-related publications is enormous [80], [92]-[99]. AHP has been employed in many areas like designing, preferencing, optimisation, resource delegation, problem solution, etc. [100].

E. AHP Mathematical Logic and Processes

AHP incorporates decision-makers' inputs and defines a process for decision-making. The AHP method procedure contains the following steps [79]:

a) Decomposition (structuring or construction) of the decision problem into factors in accordance with their characteristics along with the development of a hierarchical model having different levels. The structuring step breaks down a situation into related clusters.
b) Making comparative judgments (measuring or priority analysis). The measuring step compares the relative importance of each factor in a group to each of the other factors of the cluster 'with regard to the parent of the cluster' [101] to obtain the preferences of those aspects.
c) Combining (synthesising or consistency verification): The synthesising step is an AHP advantage and incorporates the measuring step results into a group of mathematically result. AHP combines such outcomes applying accurate mathematical techniques for calculating eigenvectors [102]. In this step, the AHP method receives the priority weights of factors by calculating the eigenvector of matrix A, $w=(w_1,w_2,...,w_s)^T$, which is related to the largest eigenvalue, $\lambda_{\max}$.

$$Aw = \lambda_{\max} w \tag{1}$$

A is an $n \times n$ pairwise comparison matrix, where n is the number of factors considered for examination. Likewise, matrix B for the priority weights of sub-factors,

$$e_h = (e_{h1}, e_{h2}, ..., e_{hs'})^T .$$

B is an $m \times m$ pairwise comparison matrix, where m is the number of options evaluated.

$$Be_h = \lambda_{\max} e_h \tag{2}$$

Saaty, T. L. [79] described a statistical equation to examine the consistency of the respondent (Consistency index - *CI*):

$$CI = \mu = \frac{\lambda_{\max} - n}{n-1} \tag{3}$$

where n is the dimension of the matrix and $\lambda_{\max}$ is the maximal eigenvalue.

The Random Index (or Random Indices) (*RI*) is the average of the *CI* for a large number of randomly generated matrices. The values of *RI* for small problems ($n \le 10$) can be found in Table II, developed by [103].

The Consistency Ratio (*CR*) is a critical function of the AHP which aims to avoid the potential for inconsistency in the criteria weights. To decide if the inconsistency in a comparison matrix is practical the CR is determined by:

$$CR = \frac{\lambda_{\max} - N}{(N-1)RI} \tag{4}$$

The *CR* of less than 0.1 or even slightly above 0.1 is regarded as sufficient [79]. Values greater than 0.1 are found unreliable and in these situations, the comparison scores need to be reconsidered.

TABLE II
RANDOM INDEX FORM

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

III. CASE STUDY

This study used an actual example of the PPM process to investigate the usability, reliability and characteristic of the AHP method in a real portfolio life cycle, and then used it as a baseline in the evaluation process for this research. The selected organisation was working in engineering management industry and dealing with complex construction projects in Australia. The experiment aimed to select the project that would best support portfolio objectives by determining the efficiency of individual projects and combining the measurements which displayed the strategic significance of the member projects. AHP adopted to assess which project would maximise the success and achievement of strategic targets in the organisations portfolio.

We have collected the historical information of five projects decision making time, cost, quality, risk and work health and safety (WH&S) factors. Also, the decisions made by executives on those requirements are studied and utilised to establish a framework of portfolio. Five evaluation criteria (n = 5) and five alternatives (to evaluate) have been considered as input for the AHP evaluation process to describe the AHP mechanism. If more criteria are required to be considered, then this example can be expanded accordingly. The AHP model for our study is illustrated in Fig. 1.

A. Pairwise Comparison

The decision-maker first built the pairwise comparison matrix for the five factors (n=5) and five alternatives to be evaluated (m=5) using the intensity scales presented in Table I comparison judgment table.

$$Aw = \begin{bmatrix} 1 & 3 & 3 & 5 & 2 \\ 1/3 & 1 & 1 & 1 & 1 \\ 1/3 & 1 & 1 & 1 & 2 \\ 1/5 & 1 & 1 & 1 & 1 \\ 1/2 & 1 & 1/2 & 1 & 1 \end{bmatrix} \tag{5}$$

The weight vector $w = (0.431, 0.138, 0.167, 0.127, 0.137)^T$

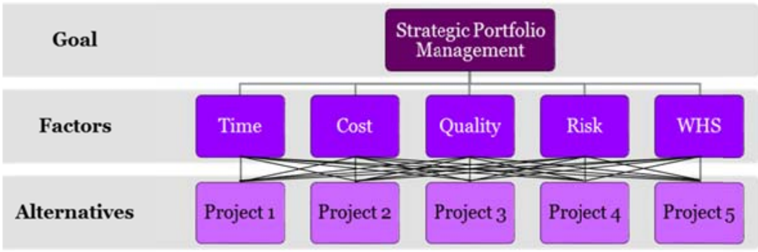

Fig. 1 AHP model

TABLE III
PAIRWISE COMPARISON MATRIX (FACTORS)

Factor	Time	Cost	Quality	Risk	WHS
Time	1	3	3	5	2
Cost	1/3	1	1	1	1
Quality	1/3	1	1	1	2
Risk	1/5	1	1	1	1
WHS	1/2	1	1/2	1	1
Total	**2.367**	**7.000**	**6.500**	**9.000**	**7.000**

B. Normalisation

From the comparison matrix, the priority or weights of each parameter has been calculated (Table IV (A)) by totaling values in each column. Each value is then divided by the total value of the column. For example, considering 'Time' factor, 'Time' value (1) divided by total value of 'Time' column (2.367) gives the value of 0.423; or in the case of 'Cost' factor, 3 / 7= 0.429 and so on.

TABLE IV (A)
PARAMETER WEIGHTS

Factor	Time	Cost	Quality	Risk	WHS
Time	**0.423**	0.429	0.462	0.556	0.286
Cost	0.141	**0.143**	0.154	0.111	0.143
Quality	0.141	0.143	**0.154**	0.111	0.286
Risk	0.085	0.143	0.154	**0.111**	0.143
WHS	0.211	0.143	0.077	0.111	**0.143**
Total	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

TABLE IV (B)
PARAMETER WEIGHTS

Factor	Total (Factors)	Weight Vector	%
Time	2.154	0.431	**43.08%**
Cost	0.692	0.138	**13.83%**
Quality	0.834	0.167	**16.69%**
Risk	0.635	0.127	**12.70%**
WHS	0.685	0.137	**13.70%**

'Total (Factors)' is the total and 'Weight Vector' is the average of all factors in each raw. The total of each column in Table IV (A) must be equal to one (1) otherwise the calculation is not correct. As indicated in Table IV (B), the highest weight vector is 0.431 which is related to the 'Time' factor of projects.

C. Consistency Analysis

Consistency index (*CI*) is calculated through multiplying each pairwise comparison column by the associated weight. The total value of each row is then divided by the identical weight, and by averaging them the $\lambda_{\max}$ value is identified in Table V. The Random Index is selected from Table II (*n*=5, so, *RI*=1.12).

TABLE V
CONSISTENCY MEASURE (FACTORS)

Consistency Measure	
Time	5.236
Cost	5.154
Quality	5.093
Risk	5.159
WHS	5.118
$\lambda_{\max}$	**5.152**

$$\lambda_{\max} = 5.152 \tag{6}$$

$$CR = \frac{\lambda_{\max} - N}{(N-1)RI} = \frac{5.152 - 5}{(5-1)1.12} = 0.034 \tag{7}$$

$$\text{CR= 3\%} \tag{8}$$

$$\text{Consistency= OK} \tag{9}$$

Priority vectors also applied to each sub-factors (Projects) which are on their own a composite amount of other factors. For instance – in Fig. 1, all factors are composite parameters (Time, Cost, Quality, Risk and WHS). Thus, priority vectors have to be created for all five factors. An example of 'Time' factor is shown in Table VI:

TABLE VI
PAIRWISE COMPARISON MATRIX FOR 'TIME' FACTOR

Time	Project 1	Project 2	Project 3	Project 4	Project 5
Project 1	1	3	1	2	1
Project 2	1/3	1	1	1	1
Project 3	1	1	1	1	1
Project 4	1/2	1	1	1	1
Project 5	1	1	1	1	1
Total	**3.833**	**7.000**	**5.000**	**6.000**	**5.000**

$$Be_{Time} = \begin{bmatrix} 1 & 3 & 1 & 2 & 1 \\ 1/3 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1/2 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \tag{10}$$

TABLE VII
CONSISTENCY MEASURE (SUB-FACTORS)

	Consistency Measure
Project 1	5.224
Project 2	5.087
Project 3	5.153
Project 4	5.106
Project 5	5.153
λ_{max}	**5.144**

$$\lambda_{max} = 5.144 \quad (11)$$

$$CR = \frac{\lambda_{max} - N}{(N-1)RI} = \frac{5.144 - 5}{(5-1)1.12} = 0.032 \quad (12)$$

CR= 3% (13)

Consistency= OK (14)

D. Portfolio Summary

Five projects have been scored on the five factors described in Fig. 1. Assigning accurate weight to each element is a key factor that impacts the outcome of this experiment. Table VIII indicates weights and scores of the portfolio in summary.

TABLE VIII
PORTFOLIO SUMMARY

Summary	Time		Cost		Quality		Risk		WHS		Final Score	Final Score
	Weight (w_{Time})	Score (Be_{Time})	Weight (w_{Cost})	Score (Be_{Cost})	Weight ($w_{Quality}$)	Score ($Be_{Quality}$)	Weight (w_{Risk})	Score (Be_{Risk})	Weight (w_{WHS})	Score (Be_{WHS})	(Be_{Total})	(%)
Project 1	0.431	0.285	0.138	0.337	0.167	0.299	0.127	0.236	0.137	0.191	0.2752	27.52%
Project 2	0.431	0.159	0.138	0.252	0.167	0.199	0.127	0.275	0.137	0.228	0.2029	20.29%
Project 3	0.431	0.194	0.138	0.185	0.167	0.245	0.127	0.179	0.137	0.191	0.1989	19.89%
Project 4	0.431	0.168	0.138	0.114	0.167	0.130	0.127	0.119	0.137	0.225	0.1558	15.58%
Project 5	0.431	0.194	0.138	0.112	0.167	0.127	0.127	0.191	0.137	0.166	0.1672	16.72%

The score matrix B is:

$$Be_{Total} = (Be_{Time}, Be_{Cost}, Be_{Quality}, Be_{Risk}, Be_{WHS}) = \begin{bmatrix} 0.285 & 0.337 & 0.299 & 0.236 & 0.191 \\ 0.159 & 0.252 & 0.199 & 0.275 & 0.228 \\ 0.194 & 0.185 & 0.245 & 0.179 & 0.191 \\ 0.168 & 0.114 & 0.130 & 0.119 & 0.225 \\ 0.194 & 0.112 & 0.127 & 0.191 & 0.166 \end{bmatrix} \quad (15)$$

As mentioned in Section A (pairwise comparison) and shown in Table VIII, the priority weights of factors have been identified:

$$w = (0.431, 0.138, 0.167, 0.127, 0.137)^T \quad (16)$$

Hence, the final score vector is:

$$v = w.\, e_{Total} = (0.2752, 0.2029, 0.1989, 0.1558, 0.1672)^T \quad (17)$$

As a result, 'Project 1' with a total score of 27.52% (as shown in Table IX and Fig. 2) is the project that maximises our portfolio's strategic targets success.

TABLE IX
PROJECTS RANKING

Projects	%	Rank
Project 1	27.52%	1
Project 2	20.29%	2
Project 3	19.89%	3
Project 4	15.58%	5
Project 5	16.72%	4

IV. RESULT AND DISCUSSION

A. Identified Advantages

The main function of the AHP method is the utilisation of pairwise comparisons that help decision-makers to weight coefficients and simply examine choices with ideal [104]. It is scalable, which enables it to simply modify in dimension to support decision-making issues as a result of its hierarchical format. AHP can be applied for dealing with decision-making issues in almost any kind of issue. Given that AHP is amongst the very first techniques employed in multi-criteria decision examination, there are a number of tools which make full use of this approach. An additional advantage is the fact that inconsistency in decisions is permitted and is allowed to be assessed [105]. In the event that consistency fails, the eigenvector continues to create a number of priorities which are all acceptable approximation, allowing 10% error [102]. Utilising a Consistence Index, unreasonable results can be eliminated, allowing weights to be identified [106]. Other advantage of AHP is its convenience, flexibility and the capability to verify inconsistencies and analyse a problem where sub-problems are hierarchised applying different factors and making the qualitative index into quantitative index. Therefore, significant and complicated problems with contentious requirements and factors can be considerably simplified. Where quantitative data are restricted, the experts' decisions to define the weights of the factors as well as the scores of the options could be greatly valuable. AHP is a reliable method for decision procedures and help decision-makers to assess the criteria's weights and chosen the best alternative [107].

The consistency verification in AHP, allows decision-makers to stay away from unreliable decisions as a consequence of personal judgments. AHP presents a precise and effective strategy for determining the aspect weights which also considers the characteristics of human decision-making. So, inputs from customers and other professionals with regards to the related advantages of the individual factors is employed in the development of the comparison matrix which eventually produced the factor weights. The end result of AHP is weights in the ratio basis that is much more usable and accurate compared to ordinal scales generated by some other methodologies. It is actually less difficult to evaluate the variables/factors two simultaneously and determine their relative benefits (that is just what exactly is conducted in AHP) instead of to evaluate several criteria as well as sub-criteria all together and seek to precisely determine their weight values. AHP is truly very simple to apply and has a consistency checking function included in the method designed to omit the potential inconsistencies discovered in the factors weight.

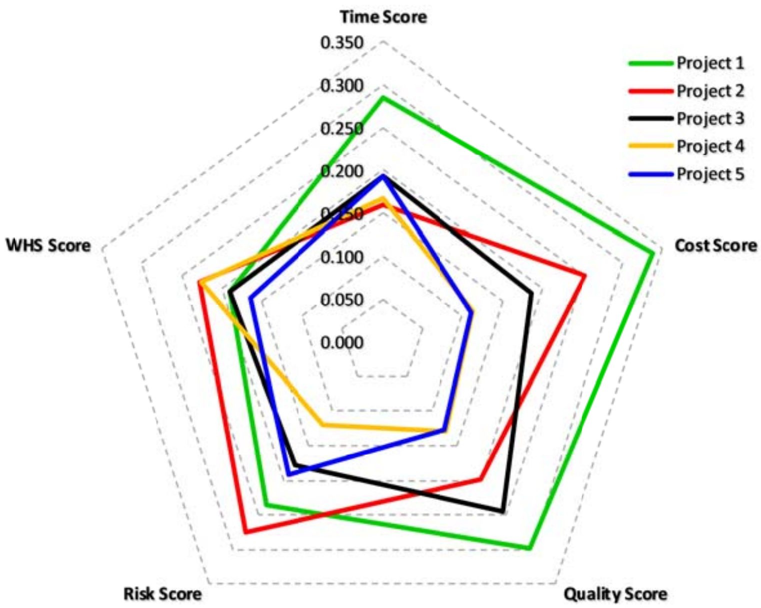

Fig. 2 Projects Ranking Diagram

The broad applicability of AHP results from its functionality, simplicity, and great flexibility, and more importantly it is capable of be incorporated with methods such as mathematical programming to have the ability to evaluate both qualitative and quantitative aspects [98]. Individual acceptability and assurance in the examination offered by AHP is much higher than other decision methods [108]. Apart from being applied as a standalone application, AHP has been combined with several other methods and techniques for many practical functions such as by [109] which investigated a problem employing binary non-linear programming approach.

B. Identified Problems

Even though the AHP is a well-known technique, it possesses a number of disadvantages, and a number of changes have been recommended for improvement. AHP is a subjective method as it depends on the opinions of experts [106]. In addition, its approach has issues associated with the interdependency between criteria and alternatives. Given that the AHP technique depends on setting up priorities between criteria and alternatives employing pairwise reviews, it just facilitates quantitative values as input values to matrices (i.e. qualitative values, and missing data are not verified using this method). The downside of employing AHP might also be the ability to employ a restricted number of criteria. As it is crucial to perform $n\times(n-1)/2$ analysis it is recommended not to use more than 10 criteria.

One of AHP's biggest criticisms is that the method suffers from the rank-reversal problem. As a consequence of the comparisons of ratings, adding up options towards the end of the practice may result in the finalised ratings to reverse. There are some publications in the area of project management, [110]-[112] that criticise AHP model as not following rank-reversal scenarios, in which the ranking of options identified by AHP might possibly be modified by the adding up of a different option for evaluation. Ranks could potentially be reversed when an irrelevant alternative is added to the existing alternatives. Even so, several researchers state that the rank reversal issue can be resolved without making an adjustment to the scores of the current options [113]-[115]. Moreover, one other criticism is the fact that AHP is not an axiomatic structure and the large number of pairwise reviews of the options could make the application of AHP a lengthy task. In the AHP approach, an aspect is compared against the best factor so the finalised selections will only be evaluated.

There are a number of researchers who presented a variety of ways to advance the flexibility of the AHP technique. Boender et al. [116] and Chen et al. [117] added the fuzzy method into AHP. Sugihara and Tanaka [118] as well presented a fuzzy AHP by modifying the simple AHP matrix values into a fuzzy amount to manage the risk in human's decision as well as a number of limited data. Nevertheless, none at all had given a manageable parameter to make the selection of the weightings variable. Generally, the pairwise matrix is not totally consistent due to an excessive number of redundancies in the pairwise reviews. However, as a result of the redundancy in the pairwise reviews, the method is unsupportive to judgmental issues [119].

V. Conclusion and Future Works

To perform PPM effectively, organisations should revise their strategy and prioritise the targets in the strategic plan for effective portfolio decisions. They should map their candidate projects to the objective(s) in addition to prioritise them against all other projects.

Portfolio decisions are complicated [120] and usually require multiple criteria or targets with a great number of requirements as well as capabilities, many of them intangible or involving some level of risk, in an area that may include contradictory goals and contains both quantitative and qualitative factors. The accuracy in estimation of the relevant data through the decision-making practice is essential for the success of the portfolio. Some methods are not able to provide this function where extracting qualitative data from the decision-maker is required. It is desirable that techniques have the capability of handling uncertain, imprecise, or missing information. They need to apply different qualitative and quantitative variables to the portfolio decision-making process.

Yeh [121] stated that AHP technique is very useful once an element hierarchy carries above the three levels. This indicates that, the total aim and target of the problem at the top level, a number of factors which explain options at the center point, and then competing solutions in the end. However, since the portfolio decision-making process may have more than 10 alternatives and criteria, AHP method is not recommended tool to be used alone. AHP do not support missing values and presents consistency in decision given that the consistency index is measured before developing pairwise assessment matrices. Probably the most important steps in decision-making techniques are the precise valuation of the relevant information. This issue is specifically critical in techniques which have to elicit qualitative data from the decision-maker. AHP cannot fulfil this requirement and can only support the values that are quantified. AHP is clearly inferior to other MCDM methods in terms of issue framework since AHP cannot be utilised once several requirements and options are required.

This study has determined that AHP cannot individually support the strategic decision-making for a complex PPM. This review concluded that engaging utilisation of the techniques significantly increases the performance of the planning procedure, considering that it would be better to apply more than only one MCDM technique or even a hybrid method. In particular, a combination of other MCDM methods with AHP appears to be useful; one using quantitative data and the other using qualitative data. Further study can be based on methods that are able to support both quantitative and qualitative information and perhaps an AHP integrated method. However, there are still many questions and limitations which need further investigation. Other requirements like feedback about the quality prediction or reliability/accuracy of the solution also requires further investigations. In order to overcome this problem, future attempts will apply or combine different MCDM theories with AHP to score projects properly. This research can be extended in different ways and the following summarises some of the future directions:

- Applying implemented mixed models,
- Developing a hierarchy profiling model which can combine two models,
- Profiling an integrated model due to extra conformity of such models to the reality.

Then, an executive dashboard of indicators can be proposed as an alternate decision-support tool for decision-makers to measure and track portfolio activities and assess portfolio's performance, risks, inputs, and outputs generated from the proposed model.

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ANNEX M – PUBLICATION IV

A Novel Integrated Strategic Portfolio Decision-Making Model

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ABSTRACTS

This study proposes a novel method for portfolio selection/decision making that combines the Portfolio Theory (PT), Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA) cross-efficiency technique. It takes into account the profits, risks and proficiency of a portfolio and is shown to be useful for selecting one with positive and negative data and subsequently measuring its efficiency using AHP, with a consistency test conducted to verify the objectivity of the results. To test the applicability of the proposed model, it is used to determine the efficiency levels of ten of the largest companies in Australia for the years 2014 and 2015. Two criteria, namely, the expected return and variance, are used to identify the preference status of each company. The results indicate that the proposed model is feasible and adoptable for the contemporary industrial scenario as it simultaneously analyses profits, risks and proficiency.

Keywords: strategic portfolio management, strategic portfolio decision making, Data Envelopment Analysis (DEA), Analytic Hierarchy Process (AHP), integrated DEA and AHP Model.

1. INTRODUCTION

The evaluation of a portfolio's performance requires selecting an appropriate portfolio assessment method(s). As current methods have their own advantages and disadvantages, a constructive review and comparison of existing MCDM methods is required to identify the most suitable one(s) for PPM decision making.

The PT (Markowitz, 1952) is viewed as the premise of many existing assessment models used to choose portfolios in a broad range of applications. Many researchers have extended it by adding many different ideas and limitations as well as targets, such as the cardinality limit or operational expenses, to help it become even more practical (e.g., Arditti, 1975; Ho & Cheung, 1991; Kane, 1982). The principal method used to identify a portfolio's functionality is the DEA which was presented by Charnes, Cooper, and Rhodes (1978) and used for only commercial banks taking into account risk and return procedures. Also, its diversification was evaluated and a way of dealing with it demonstrated (Lamb & Tee, 2012). However, no researchers have incorporated PT with DEA and AHP nor have studies addressed the normalisation of weighting scores.

Unlike the return, the variance as a variable in the PT model can adopt non-negative values which is not convenient for conventional DEA methods that presume positive values for both inputs and outputs. Therefore, these models cannot function if Decision Making Units (DMUs) consist of both positive and negative inputs and outputs. Many different techniques for managing non-positive information have been suggested. To determine the performances of DMUs with negative variables, Portela, Thanassoulis, and Simpson (2004) presented the Range Directional Model (RDM), Tone (2001) the slacks-based measure model (SBM), Sharp, Meng, and Liu (2007) a modified SBM based on the directional distance functionality of Portela et al. (2004) called the modified slacks-based measure model (MSBM), Emrouznejad, Anouze, and Thanassoulis (2010) the Semi-Oriented Radial Measure (SORM) and Cheng, Zervopoulos, and Qian (2013) the Variant of Radial Measure (VRM) Models.

Although the abovementioned methods might be employed as a way of dealing with negative data, they have shortcomings. Moreover, these models may sometimes not present total efficiency rankings for DMUs.

An integrated DEA/AHP method was beneficial and avoided each model's limitations although using a basic DEA model led to the effective units not being reasonably distinguished. In turn, this justified incorporating a peer evaluation mode into the standard DEA model, with a cross-efficiency examination presented by Sexton, Silkman, and Hogan (1986) included. While applications of cross-efficiency in portfolio assessments have been reported to show significant advantages over approaches based on the standard DEA, some challenges have emerged.

The intention of this study is to build a reliable and operational model for examining the overall efficiency and success of a portfolio with regard to their comparative efficiencies influenced by the quality of efficiency outcome. A multi-objective model that applies the PT to identify the expected return and risk, and modifies the DEA-CE to properly score the efficiency of DMUs using AHP are proposed. Then, the portfolio's performance is combined with the PT standard theory. Finally, a comparison table is produced to assist Decision Makers (DMs) to select the best assets characterised by the values of the expected return, risk, Sharpe ratio and efficiency scores obtained from the proposed model. Then, DMs can optimise the portfolio based on the outcomes of an examination and determine whether the modifications enhance the efficiency of original portfolio. The results obtained from the proposed model can assist organisations to understand their advantages and disadvantages, and the current possibilities and options, or threats, of their portfolios.

Section 2 and 3 of this paper briefly reviews the literature describing the PT, AHP, and DEA methods. The challenges are discussed in Section 4 and a new model is proposed in Section 5 to deal with these drawbacks. Furthermore, Section 6 consists of the portfolios of Australia's ten largest firms for the financial year 2014-15, illustrates how the proposed model is applied in relatively large portfolios. The results from the standard models presented in the literature review are then compared with those from the proposed model which shows how well they agree. This study concludes its investigation with a discussion in Section 7 of the requirements for operationalising the proposed method. Finally, its limitations are presented and recommendations for future work identified in Section 8 and 9.

2. PORTFOLIO THEORY (PT)

As DMs may discover completely different assets on which to decide, each with unique risks and returns on investment (Classroom, 2006), it may be difficult for them to select a portfolio that fulfils their requirements. The PT is a decision structure for portfolios influenced by aiming to maximise the estimated profits and minimise the asset risks (Fabozzi, Gupta, & Markowitz, 2002).

In general, the risk element of PT is determined by several mathematical steps and can be minimised through a diversification designed to choose an effective weighted selection of assets that jointly present lower risks than with any specific asset or category of assets. Diversification is the primary reason behind PT and relates specifically to the typical logic of "never placing all your eggs in a single basket". (Fabozzi et al., 2002; McClure, 2010; Veneeva, 2006). Markowitz (1952) verified that a DM can minimise a portfolio's priorities to manage its estimated return and risk (Sciences, 1990). These essential PT terms are discussed further in the following sub-sections.

2.1. Portfolio's Expected Return

The expected return is the weighted average of each asset's estimated returns (Sharpe, 1970). These assets affect the returns of the portfolio, subject to the weight of each asset.

There are various ways of calculating the estimated return of an investment. One would be to calculate the possibilities of various return results and compare them with historical information. To create a portfolio, it is essential to assess the profit of each asset and then the return of the entire portfolio can be estimated (Sharpe, 1970). Also, the expected return is often known as the mean or average return or historical average of an asset's return over a period of time (Benninga, 2010). Developing formulas for a portfolio of assets basically require determining the weighted average of the estimated profits for each asset (Ross, R, & Jaffe, 2002). Eq. (1) demonstrates the expected return of a portfolio and Eq. (2) its actual return.

$$E(R_p) = \sum_{i=1}^{N} x_i E(R_i) \quad (1)$$

where:
$E(R_p) = the\ expected\ return\ of\ the\ portfolio$
$x_i = the\ weighting\ of\ component\ asset\ i$
$E(R_i) = the\ expected\ return\ of\ asset\ i$

$$R_p = \sum_{i=1}^{N} x_i R_i \quad (2)$$

where:
$R_p = actual\ return\ of\ the\ portfolio$
$R_i = actual\ return\ of\ asset\ i$

If a portfolio consists of two assets with return amounts of R_1 and R_2 and weights of w_1 and w_2, the portfolio return will be the weighted average of the two assets' profits as:

$$R_p = w_1 R_1 + w_2 R_2 \quad (3)$$

where:
$R_p = Portfolio\ return$
$w_1 = Weight\ of\ Asset\ 1$
$w_2 = Weight\ of\ Asset\ 2$
$R_1 = Return\ of\ Asset\ 1$
$R_2 = Return\ of\ Asset\ 2$

2.2. Portfolio's Return Risk

A portfolio's return risk is the possibility that an asset's actual return will differ from its expected one (Markowitz, 1952). It consists of the potential loss of a few or even all the primary investments and that of a specific portfolio's return can be identified by different techniques. Although the standard deviation and variance are the two best-known procedures, the former is not only the weighted average of the two assets.

2.2.1. Return Variance

The return variance is the average squared variation between the actual and average return, that is, a "*measure of the squared deviations of a stock's return from its expected return*" (Bradford & Miller, 2009; Ross et al., 2002).

A higher variance indicates higher risks. Whenever several assets are retained as a group in a portfolio, as those reducing in profit are usually compensated by others increasing in profit, the risk is reduced. Therefore, the variance of a portfolio reduces as the quantity of assets increases (Frantz & Payne, 2009). Consequently, with portfolios consisting of many assets, DMs can more effectively minimise their risk which is expressed as:

$$\sigma^2 = \sum_{i=1}^{n} P_i \left[R_i - E\left(R_p\right)\right]^2 \quad (4)$$

where:
$E\left(R_p\right) = expected\ return\ of\ the\ portfolio$
$P_i = the\ probability\ that\ the\ rate\ R\ occurs$
$R = the\ return\ level$
$i = counts\ the\ number\ of\ assets$

2.2.2. Standard Deviation of Return

A portfolio's standard deviation is the variation in its assets which can be a measure of the expected inconsistency of its returns. It needs to be less than the weighted average of the standard deviations of each asset, with a greater one resulting in a higher risk and return (Sharpe, 1970).

The standard deviation can be calculated as:

$$\sigma = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \rho_{ij}\sigma_i\sigma_j} \quad (5)$$

$$where\ \sigma \text{ is also } = \sqrt{w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\sigma_1\sigma_2\rho_{1,2}} \quad or \ \sqrt{w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2Cov_{1,2}}$$

$$or\ simply \quad \sigma = \sqrt{\sigma^2} \quad (6)$$

where:
x = proportions invested in each asset
ρ = correlation coefficients between i and j or asset 1 and asset 2
σ = standard deviation of each asset
w = weight of each asset in the portfolio

In order to define the standard deviation of returns, firstly, the covariance and correlation of the assets need to be identified. The covariance reveals the co-movements of the profits of the assets and, providing that the assets are completely linked, it can reduce the overall risk.

2.2.2.1. Covariance of Return

A portfolio's variability is estimated through its variance and standard deviation. However, when a link between the returns in a portfolio is required, it is critical to determine both its covariance and correlation. As they can determine the connectivity between two random factors (Ross et al., 2002), there is a need to identify the level of risk in the entire portfolio.

As outlined by Markowitz (1959), the risk of a portfolio is not the variance of each of its assets but the covariance of the entire portfolio. The more the assets move in the same direction, the higher the possibility that economic changes will push them all down simultaneously. As the assets in a portfolio are less risky once the covariance between them is low, it is ideal to obtain portfolios with minimal covariances. The covariance is the result of the correlation coefficient and standard deviation of the return (of a pair of assets), as demonstrated in Eq. (7). Also, that between returns can be considered the weighted average of the assets.

$$Cov_{jk} = \rho_{jk}\sigma_j\sigma_k \quad (7)$$

where:
ρ_{ij} = Correlation coefficients
$\sigma_i\sigma_j$ = Standard deviation of each asset

If the returns are correlated, their covariance will be positive but, if they are negatively correlated or not completely connected, it will be adverse or become zero (Ross et al., 2002).

2.2.2.2. Correlation Coefficient of Returns

The correlation coefficient measures the level of connectivity between factors and is the last measure for estimating risk as:

$$\rho_{AB} = \frac{cov_{AB}}{\sigma_A\sigma_B} \quad (8)$$

Correlation is the covariance of assets A and B divided by their standard deviation and is an absolute amount of the co-movement between a pair of assets limited by –1 and +1. A positive correlation of +1 ensures that the assets' returns proceed constantly in a similar direction and are positively correlated. A correlation of zero indicates that the assets have no connection to one another and are uncorrelated. A negative correlation of –1 implies that the returns proceed constantly in opposite directions and are negatively correlated (Ross et al., 2002). The higher the quantity of uncorrelated assets, the lower the risk, with inadequate correlations (between +1 and -1) typically revealing the elimination of risk. A portfolio with low correlation coefficient rates presents a lower level of risk than those with high ones (Hight, 2010).

2.3. Diversification

The principle of PT is to optimise the connection between risk and return by developing portfolios of assets based on their profits and risks as well as their covariance or, perhaps, correlations with different assets. The risk elimination approach consists of using the assets of different financial units, companies and organisations as well as other investment decision groups (Investopedia, 2009). Diversification is carried out by choosing individual shares, asset categories or materials. As every expected return consists of different results, this could be risky, with this association between return and risk optimised via diversification.

Diversification maximises returns and minimises risk by selecting individual assets each of which can respond uniquely to a similar event. Its impact, which represents the connection between correlation and a portfolio (Roger, 2008), is an inadequate outcome of the correlation between assets and is a useful risk elimination approach which does not compromise returns (Hight, 2010). A portfolio that fulfils such factors is considered efficient, with no other portfolio capable of obtaining a larger return with the same degree of risk (Markowitz, 1959). A portfolio is insufficient when it obtains a larger expected return without having a larger risk as well as decreasing risk while offering a similar degree of expected return (Markowitz, 1991).

2.4. Sharpe Ratio (*SR*)

The *SR* is used to examine returns based on different factors and indicates if the returns come from good assets or are the result of additional risk (Gregoriou, Karavas, Lhabitant, & Rouah, 2011). The larger the ratio, the greater the modified efficiency of its risk which is measured as:

$$SR = \frac{E(R_p) - R_f}{\sigma} \qquad (9)$$

where:
$SR = \text{Sharpe Ratio}$
$E(R_p) = \text{Expected Return of the Portfolio}$
$R_f = \text{Risk} - \text{free Rate}$
$\sigma = \text{Volatility of the Portfolio}$

3. Preferred Project Portfolio Management (PPM) Multi-criteria Decision Making (MCDM) Techniques

Many researchers have tried to incorporate DEA in, or apply it, with MCDM techniques and some have actually claimed that DEA alone is a MCDM approach (e.g., Troutt, 1995). However, MCDM is often used prior to decision making or during project implementation whereas DEA is typically applied to assess existing strategies (Adler, Friedman, & Sinuany-Stern, 2002). A smart solution to integrating a MCDM method with DEA is to inject better data into it. Although this can be accomplished by restricting the weight values, choosing ideal input/output goals or perhaps developing hypothetical DMUs, these treatments may not provide complete rankings. The concept of integrating the AHP and DEA is not new, with DEA/AHP methods being widely applied as a solution to the multi-criteria decision-making issue.

3.1. Overview of AHP

The academic perspective of the AHP method is introduced through a literature review and the works previously completed on this methodology reviewed in Danesh, Ryan, and Abbasi (2015). Its shortcomings and issues involved in using it to overcome MCDM problems is described in detail with a practical case study of its processes and directions for future investigation are presented.

3.2. Overview of DEA

DEA has grown to become an effective application for evaluating the performances of DMUs (Ruggiero, 2004) and continues to improve substantially since being created by Charnes et al. (1978). It is a data-oriented method for analysing the relative efficiencies of DMUs using various inputs to generate multiple outputs (Cooper, Seiford, & Zhu, 2004).

DEA was primarily created as the Charnes-Cooper-Rhodes (CCR) model (also called the constant returns to scale (CRS)) by Charnes et al. (1978). Then the Banker-Charnes-Cooper (BCC) model (also known as the variable return to scale (VRS)) was created by Banker, Charnes, and Cooper (1984) to estimate the performances of related financial development models and develop a performance frontier based on the Pareto optimum.

Studies of DEA applications are available in Seiford (1996) and Emrouznejad, Parker, and Tavares (2008). Furthermore, there are several studies which apply the DEA to compare project efficiency (for example, Eilat, Golany, & Shtub, 2008; Hadad, Keren, & Hanani, 2013; Hadad, Keren, & Laslo, 2013; Mahmood, Pettingell, & Shaskevich, 1996; Vitner, Rozenes, & Spraggett, 2006). Ramanathan (2003) presented outstanding introductory material for DEA beginners while a more detailed DEA explanation can be obtained from Cooper, Seiford, and Tone (2006).

Assuming that n is the number of DMUs to be examined and every DMU uses m inputs and generates s outputs, DMU_j requires x_{ij} of input i to generate y_{rj} of output r as:

$$min\,\theta - \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right) \qquad (10)$$

subject to:

$$\sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- = \theta x_{i0} \qquad i = 1, 2, \dots, m;$$

$$\sum_{j=1}^{n} y_{ij}\lambda_j - S_r^+ = y_{r0} \qquad r = 1, 2, \dots, s;$$

$$\lambda_j, S_i^-, S_r^+ \geq 0 \qquad \forall i, j, r$$

where:
λ_j= the weights assigned by the linear program,
θ = the efficiency calculated,
S_i = the input slacks,
S_r = the input slacks and
ε = the non-Archimedean aspect identified to be less than a positive value.

For a better interpretation, the classic model above can be presented as:

$$max\, h_o(u, v) = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \qquad (11)$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \qquad j = 1, \dots, n; \text{and } u_r, v_i \geq 0$$

where:
u, v = the weights to be optimised and
y_{ro}, x_{io} = the observed input/output values of the DMU to be evaluated.

3.3. DEA Cross-efficiency (DEA CE)

Sexton et al. (1986) proposed the cross-efficiency DEA technique that has both self and peer assessment capabilities for DMUs whereby each DMU is examined according to its own weight and those of every other DMU to ensure that it is properly assessed.

Assume that *n* DMUs with *m* inputs and *s* outputs need to be examined, with $x_{ij}(i = 1, \dots, m)$ and $y_{rj}(r = 1, \dots, s)$, and the input and output values of DMU_j $(j = 1, \dots, n)$ and the efficiencies of these DMUs estimated by determining the following CRS model (Charnes et al., 1978):

$$max\ \theta_{kk} = \sum_{r=1}^{s} u_{rk} y_{rk} \tag{12}$$

subject to:

$$\sum_{i=1}^{m} v_{ik} x_{ik} = 1$$
$$\sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} \leq 0 \qquad j = 1, \dots, n$$
$$u_{rk}, v_{ik} \geq 0, \quad r = 1, \dots, s \quad i = 1, \dots, m$$

where:
DMU_k = the DMU under evaluation
$v_{ik}(i = 1, \dots, m)$ = input weights
$u_{rk}(r = 1, \dots, s)$ = output weights

Allowing $u_{rk}^*(r = 1, \dots, s)$ and $v_{ik}^*(i = 1, \dots, m)$ to be the optimal solution to the above equation, $\theta_{kk}^* = \sum_{r=1}^{s} u_{rk}^* y_{rk}$ is known as the CRS efficiency of DMU_k and is the ideal efficiency applicable for the self-assessment of DMU_k . If $\theta_{kk}^* = 1, DMU_k$ is CRS-efficient, otherwise non-CRS-efficient.

$\theta_{jk} = \sum_{r=1}^{s} u_{rk}^* y_{rj} / \sum_{i=1}^{m} v_{ik}^* x_{ij}$ is known as the cross-efficiency of DMU_k to DMU_j by peer assessment, where $j = 1, \dots, n; j \neq k$. As Eq. (12) is solved *n* times for each individual DMU, it is possible to obtain a single CRS-efficiency value as well as (*n*-1) cross-efficiency values for every DMU. The *n* efficiency values form the cross-efficiency matrix shown in Table 1. The averaged *n* efficiency value represents the total efficiency and is often referred to as the average cross-efficiency value. According to the total efficiency value, the *n* DMUs will be fully rated.

Table 1. Cross-efficiency Matrix

DMUs	1	2	…	n	Average Cross-efficiency
1	θ_{11}	θ_{12}	…	θ_{1n}	$(\frac{1}{n}) \sum_{k=1}^{n} \theta_{1k}$
2	θ_{21}	θ_{22}	…	θ_{2n}	$(\frac{1}{n}) \sum_{k=1}^{n} \theta_{2k}$
…	…	…	…	…	…
n	θ_{n1}	θ_{n2}		θ_{nn}	$(\frac{1}{n}) \sum_{k=1}^{n} \theta_{nk}$

where:
$\theta_{kk}(k = 1, \dots, n)$ = the CRS-efficiency values of *n* DMUs
$\theta_{kk} = \theta_{kk}^*$.

There are two main benefits of using a DEA CE assessment: it offers ideal placements of DMUs, and minimises impracticable weight limits (Anderson, Hollingsworth, & Inman, 2002).

3.4. Mathematical Logic and Process of Integrated DEA/AHP

Sinuany-Stern, Mehrez, and Hadad (2000) presented an integrated model in which, initially, a pair-wise assessment of DMUs was performed using an improved DEA method (Eq. (13)). Subsequently, these DMUs were examined by a cross-efficiency approach (Eq. (14)) and then the results applied for the development of a pair-wise assessment matrix for generating the source data required for AHP analyses. The selling point of the DEA/AHP rating model is the fact that each method has its own unique advantages and the AHP pair-wise reviews are the result of a functional pair-wise DEA. This DEA/AHP approach overcomes the DEA's rating inefficiency and minimises the AHP's subjective examination. A comparison matrix is established by applying standard DEA methods and then using the AHP to grade the DMUs.

The DEA is used on DMUs to develop the pair-wise assessment matrix. If there are *n* DMUs and each one has m inputs and s outputs, where X_{ij} is input *i* of unit *j* and Y_{rj} output *r* of unit *j*, the DEA technique is employed to estimate the performance of each pair of DMUs irrespective of the other DMUs, with E_{AA} and E_{BA} are the efficiencies of DMU_A and DMU_B respectively.

$$E_{AA} = \underset{u_r, v_i}{Max} \sum_{r=1}^{s} u_r Y_{rA} \tag{13}$$

$$s.t. \sum_{i=1}^{m} v_i X_{iA} = 1$$

$$\sum_{r=1}^{s} u_r Y_{rA} \leq 1$$

$$\sum_{r=1}^{s} u_r Y_{rB} - \sum_{i=1}^{m} v_i X_{iB} \leq 0 \qquad u_r \geq 0, r = 1 \dots s, v_i \geq 0, i = 1 \dots m$$

$$E_{BA} = \underset{u_r, v_i}{Max} \sum_{r=1}^{s} u_r Y_{rB} \tag{14}$$

$$s.t. \sum_{i=1}^{m} v_i X_{iB} = 1$$

$$\sum_{r=1}^{s} u_r Y_{rB} \leq 1$$

$$\sum_{r=1}^{s} u_r Y_{rA} - E_{AA} \sum_{i=1}^{m} v_i X_{iA} = 0 \qquad u_r \geq \varepsilon, \qquad v_i \geq \varepsilon$$

E_{BB} and E_{AB} are also determined by the same equations (Eq. (13) and (14)) following the efficiency rankings of DMU_A and DMU_B.

$$a_{AB} = \frac{E_{AA} + E_{AB}}{E_{BB} + E_{BA}} \tag{15}$$

Eventually, a pair-wise assessment matrix from the outcomes of Eq. (15) needs to be developed for each set of DMUs' *j* and *k*, with the *j* row and *k* column factor (a_{jk}) in the AHP judging matrices:

$$a_{jk} = \frac{E_{jj} + E_{jk}}{E_{kk} + E_{kj}} \tag{16}$$

$$a_{jj} = 1, \quad a_{kj} = \frac{1}{a_{jk}}$$

The comparison matrix is:

$$\begin{vmatrix} 1 & \frac{E_{AA} + E_{AB}}{E_{BB} + E_{BA}} & \cdots & \frac{E_{AA} + E_{An}}{E_{nn} + E_{nA}} \\ \frac{E_{BB} + E_{BA}}{E_{AA} + E_{AB}} & 1 & \cdots & \frac{E_{BB} + E_{Bn}}{E_{nn} + E_{nB}} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{E_{nn} + E_{nA}}{E_{AA} + E_{An}} & \frac{E_{nn} + E_{nB}}{E_{BB} + E_{Bn}} & \cdots & 1 \end{vmatrix}$$

4. Portfolio Selection Challenges

In the standard DEA model, as each DMU is evaluated using only its own weight, it should not consider other sets of weights possibly chosen by its competing peers. While this mechanism is valid in the context of efficiency evaluation itself, it is not appropriate when we use DEA for portfolio selection. As, in this situation, each DMU is exposed to the risk of a change in weight, this needs to be considered more seriously which, in turn, justifies incorporating a peer evaluation mode into the standard DEA model, with cross-efficiency evaluation a potential contender.

Standard DEA models presume that the values of each of the inputs or outputs of DMUs are only positive; in other words, they cannot examine non-positive data. Although some DEA software does permit applying negative inputs and outputs in a few DEA models, typically, the weights of the negative outputs and inputs are absolute zeroes. To eliminate this issue, a number of models have been designed with the intention of enhancing the distinguishing factor of DEA.

The idea behind the CCR (a.k.a. CRS) DEA model (Banker et al., 1984) is the fact that, as every part of an efficient DMU can also be efficient, it is merely justifiable for positive information. With negative inputs/outputs, the VRS additive method of Banker et al. (1984) (a.k.a. BCC) is applied mainly as a translation-invariant model according to Ali and Seiford (1990). Despite this, the application of radial methods of performance in the VRS DEA method is challenging and impossible without transforming the data. The output performance ranking relies on the degree of interdependency of the non-positive output vector. Also, the output radial efficiency ranking is difficult to analyse and translate when there are negative inputs/outputs. However, the additive model fails to produce a performance estimate which can really be interpreted or easily rank a DMU's efficiency.

Portela et al. (2004) presented the Range Directional Measure (RDM) method for determining the performances of DMUs with positive and non-positive variables in accordance with a directional distance function without the need to modify the information. The outcomes of their method were very similar to those of radial DEA which is an advantage of the RDM method compare to the additive approach. The Modified Slack-Based Measure (MSBM), which can deal with both negative outputs/inputs, was developed by Sharp et al. (2007). It can handle the Slack-based Measure (SBM) model's transformation challenge suggested in the study by Tone (2001) based on the directional distance functionality of Portela et al. (2004). Emrouznejad et al. (2010) proposed the Semi-Oriented Radial Measure (SORM) for managing factors that obtain both positive and negative DMUs. This model considers that every input/output is a total of two factors, one using negative and the other positive data. Cheng et al. (2013) recommended the Variant of the Radial Model (VRM) in which the initial data of the ranked DMUs are changed to definite values to evaluate the level of enhancement required to achieve an efficient frontier.

Although the abovementioned methods might be employed as a way of dealing with negative data, they have shortcomings. Specifically, the additive model cannot present an efficiency estimate while the RDM technique is generally limited once the DMUs under consideration are considered to have the highest rates for outputs or the lowest for inputs and its efficiency rankings do not include all types of inefficiency. Portela et al. (2004) demonstrated that their method is equally unit- and translation-invariant with 1–ß regarded as a measure of performance. However, they mention that ß fails to encapsulate all types of inefficiency given that its ideal values for certain inputs/outputs might obtain non-zero slacks. The MSBM and SORM models can achieve aggregated targets but have problems if all their inputs or outputs are not positive. The mixed-sign factor in the VRM model is the total summary of two artificial factors ($v = v^1 + v^2$) one of which uses negative and the other positive data. If a variable has a positive mixed-sign factor, the VRM will deal with a monotonic problem (that is, one with values that never increase or decrease). Moreover, these models may sometimes not present total efficiency rankings for DMUs.

Therefore, the standard input-/output-oriented radial models produce inaccurate and problematic results because of their disadvantages when determining the significance of negative information in the optimisation procedure.

The standard DEA has a disadvantage in the Pareto concept, that is, when almost all DMs or MCDM techniques would choose a solution, a DEA may view several DMUs as equally efficient (Sinuany-Stern, Mehrez, & Hadad, 2000). Basically, it could generate too many, or even an unlimited number of, ideal options or solutions (Shang & Sueyoshi, 1995). Whenever the quantity of inputs/outputs increases, so do the number of DMUs which can obtain a performance ranking of one as they are specially examined in relation to other DMUs.

Although Sinuany-Stern et al. (2000) presented a combined DEA/AHP method for arranging DMUs, the selection method could not obtain efficient/inefficient ratings when several inputs and outputs were involved, thereby unreasonably selecting an efficient DMU from inefficient ones. The pair-wise assessment matrix established by Eq. (16) of Sinuany-Stern et al. (2000) consisted of many 'one' variables (Guo, Liu, & Qiu, 2006; Oral, Kettani, & Lang, 1991; Sinuany-Stern et al., 2000; Zhang, Li, & Liu, 2005) signifies that a pair of DMUs is regarded as equally efficient. Consequently, many similarities in a pair-wise assessment matrix can cause strict selection of DMUs since the rating weights generated from this matrix can be similar, or even identical, to those of other DMUs.

As a performance analysis using DEA involves both inputs and outputs, a decision matrix of $n \times n$ requires n DMUs and n outputs. The results are regarded as outputs since they have the features of outputs and a DMU obtaining a high score is preferable to those with lower ones. As a DEA cannot be generated by only outputs, it needs a minimum of one input.

5. Proposed Model

As DMs usually apply various techniques to make portfolio decisions, there is no classic portfolio selection method with easily specified steps and procedures which may be used in all projects. Standard DEA/AHP models are not able to use negative values or simultaneously obtain an efficiency ranking that can be easily employed to assess DMUs. Also, the basic application of only cross-efficiency ranking in portfolio decisions may lead to inadequately expanded portfolios in terms of their efficiency regarding several input/output aspects. The concept of the proposed model is simple: the portfolio with the lowest risk at a given expected return (on investment) can be found with a higher efficiency rank.

The proposed model is based on the PT of Markowitz (1952), integrated DEA/AHP method of Sinuany-Stern et al. (2000) and standard DEA cross-efficiency model (DEA CE) of Sexton et al. (1986). However, it does not have the disadvantages of former techniques and improves the accuracy of an efficiency assessment. As, in the standard DEA/AHP, the outcomes of the comparison model are calculated by DEA with the DM not involved in the weighting process, the parameters are entered by the DEA to produce the answer. Using the PT, this study develops a model that enables DMs to modify the expected return and obtain the best portfolio with a minimum risk for that amount which guarantees efficient ratings once negative values are applied. The new methodology determines the cross-efficiency of the DMUs and generates a pair-wise assessment matrix in accordance with each DMU's weights and the outcomes of the assessments of two DMUs. Then, it is normalised using the AHP to produce the final efficiency ranks. Also, it provides objectives which are much easier to obtain than those of other approaches.

This study proposes the following five-stage model for prioritising DMU's efficiencies in order to select appropriate portfolios.

5.1. Step 1 - Developing Portfolio

As a first step, the data required to estimate a portfolio's efficiency need to be collected, based on which a portfolio of several DMUs is created. Monthly, quarterly and/or annual information is necessary to develop portfolios with different timeframes. Although DMs usually develop portfolios for a year or more, this study collects only weekly data for convenience, based on which one week's average growth is calculated as:

$$One\ week\ growth = 100 \times \left(\left(\frac{v_2}{v_1} \right) - 1 \right) \tag{17}$$

where:
$v_2 =$ current week's amount; and
$v_1 =$ previous week's amount.

5.2. Step 2 - Calculating Portfolio's Parameters

A return, which consists of the money received in different periods and is the difference between buying and selling, is not usually obvious. This uncertainty in the rate of expected return is defined as the deviation of return which is called risk. An investor's aim would be to obtain the highest likely return on an asset with the least potential risk. According to this logic, the expected return is considered an output and any deviation from it an input that leads to the selection of the best asset.

This step identifies the expected return (on investment) and risk for a portfolio using Eqs. (1) and (5). The process begins by a DM having a certain amount of funds to spend. Given that a portfolio is an accumulation of assets, it is more beneficial to choose the best portfolio. Therefore, a DM needs to identify the expected return and standard deviation which implies that the DM desires to both increase the expected return and decrease the level of risk.

The fundamental problem of a portfolio can be introduced in two means: whether the DM wishes to reduce the variance related to a specified expected return (R_{min}) as:

$$min \sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \rho_{ij} \sigma_i \sigma_j \qquad (18)$$

subject to:

$$\sum_{i=1}^{n} x_i E(R_i) \geq R_{min}$$
$$\sum_{i=1}^{n} x_i = 1$$
$$x_i \geq 0 \qquad i = 1, \dots, n$$

or increase the expected return in a specified variance as:

$$max \sum_{i=1}^{n} x_i E(R_i) \qquad (19)$$

subject to:

$$\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \rho_{ij} \sigma_i \sigma_j \leq \sigma_{max}$$
$$\sum_{i=1}^{n} x_i = 1$$
$$x_i \geq 0 \qquad i = 1, \dots, n$$

This process is adequate for realising that both the return and variance should be considered when establishing an ideal project portfolio (Siew, 2016), with either the expected return or risk tending to be estimated using historic information. The expected return is determined through applying the mathematical aspect of returns and the risk through applying variances/standard deviations of the returns during past periods. According to the PT, if the expected return on investment i is $E(R_i)$ and the value given to this investment (x_i), the expected return on the investment in a portfolio can be identified in Eq. (1) as:

$$E(R_p) = \sum_{i=1}^{n} x_i E(R_i)$$

where:

$$\sum_{i=1}^{n} x_i = 1$$

As previously mentioned, the standard deviation or variance can signify the level of investment risk and an investment variance is determined in accordance with Eq. (4) as:

$$\sigma^2 = \sum_{i=1}^{n} P_i\,[R_i - E(R_p)]^2$$

The standard deviation demonstrates the average variation of an investment's profit from the mean of the sample with regard to the same measures using Eq. (6) as:

$$\sigma = \sqrt{\sigma^2}$$

5.3. Step 3 – Collecting Input and Output Data for DMUs

To rank the efficiency level of a DMU, the two criteria of the variance and expected return are considered the input and output respectively. After Steps 1 and 2, financial input/output parameters are identified.

5.4. Step 4 – Proposed Integrated DEA Cross-efficiency/AHP Model

5.4.1. **Phase 1:** pair-wise comparison matrix

A pair-wise comparison matrix is formed using the DEA method as follows.

The CRS classic model is implemented for each *n* of DMUs as (1,2,…,n) (Eq. 20): given that there are *n* DMUs all with m inputs and s outputs, the applicable performance of a specific one (DMU_k ($k \in \{1,2,\dots,n\}$)) is gained by determining:

$$\theta_{kk} = max\frac{\sum_{r=1}^{s} u_{rk}y_{rk}}{\sum_{i=1}^{m} v_{ik}x_{ik}} \tag{20}$$

subject to:

$$\frac{\sum_{r=1}^{s} u_{rk}y_{rj}}{\sum_{i=1}^{m} v_{ik}x_{ij}} \le 1 \quad j = 1,2,\dots,n$$
$$u_{rk}, v_{ik} \ge 0, \quad r = 1,\dots,s \quad i = 1,\dots,m$$

where:
j is the DMU factor;
j =1,2,...,*n* the output factor;
r =1,..., *s*;
i the input factor *i* =1,...,*m*;
y_{rj} the amount of the r^{th} output for the j^{th} DMU;
x_{ij} the significance of the i^{th} input for the j^{th} DMU;
u_{rk} the weight directed at the rth output; and
v_{ik} the weight provided to the i^{th} input.
Note that DMU_k is efficient providing $\theta_{kk} = 1$.

DMU_k prefers weights that maximise the output to input ratio depending on the limitations. An applicable efficiency rating of one implies that the DMU of interest is efficient and a lower rating that it is inefficient. Eq. (20) can be changed into a linear programming approach in which the best value of the target performance considers the related performance of DMU_k.

As in Eq. (12), the standard cross-efficiency can be formulated as:

$$\theta_{kk} = max\ \sum_{r=1}^{s} u_{rk}y_{rk} \tag{21}$$

subject to:

$$\sum_{i=1}^{m} v_{ik}x_{ik} = 1$$
$$\sum_{r=1}^{s} u_{rk}y_{rj} - \sum_{i=1}^{m} v_{ik}x_{ij} \le 0 \quad j = 1,\dots,n$$

$$u_{rk}, v_{ik} \geq 0, \quad r = 1, \dots, s \quad i = 1, \dots, m$$

Considering the standard cross-efficiency (Eq. (12)) and standard DEA/AHP (Eqs. (13) and (14)), the modified DEA cross-efficiency/AHP evaluation is proposed as:

$$\theta_{kk}^{*} = \theta_{kk} = max \; \sum_{r=1}^{s} u_{rk} y_{rk} \tag{22}$$

subject to:

$$\sum_{i=1}^{m} v_{ik} x_{ik} = 1$$
$$\sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} = 0 \qquad j = 1, \dots, n$$
$$u_{rk}, v_{ik} \geq 0, \quad r = 1, \dots, s \quad i = 1, \dots, m$$

The second constraint of the standard DEA/AHP (Eq. (13)) demonstrates that a top portion of its objective characteristic is excluded to offer the possibility of an overall assessment of two DMUs without restricting the evolving ranking. As , when this restriction remains, the final efficiency scores are often equal, proper differences between the DMUs cannot be observed. An additional modification is the inequality in the last constraint in Eq. (13) and the second in Eq. (21) which is changed to equality in Eq. (22). If the inequality in Eq. (21) remains in its original format in Eq. (22), it would certainly remain an equality for every option in Eq. (22). Since only the optimal solutions to Eq. (22) need to be considered, that constraint can be considered an equality.

Employing the same theory for Eq. (13) and Eq. (21), as well as omitting the second demand in Eq. (14), i.e., a top portion of the objective characteristic, the following modified condition is demonstrated for Eq. (14):

$$\theta_{hk} = max \; \sum_{r=1}^{s} u_{rh} y_{rh} \qquad\qquad h = 1, \dots, n \tag{23}$$

subject to:

$$\sum_{i=1}^{m} v_{ih} x_{ih} = 1$$
$$\sum_{r=1}^{s} u_{rh} y_{rk} - \theta_{kk}^{*} \sum_{i=1}^{m} v_{ih} x_{ik} = 0$$
$$u_{rh}, v_{ih} \geq 0, \quad r = 1, \dots, s \quad i = 1, \dots, m$$

In some cases, constructing a pair-wise comparison matrix using Eq. (16) of Sinuany-Stern et al. (2000) is problematic as applying this approach may comprise many elements with ‘one’ values (Guo et al., 2006; Oral et al., 1991; Sinuany-Stern et al., 2000; Zhang et al., 2005). An outcome of 'one' for a pair-wise assessment signifies that the DMUs are not seen as different. Consequently, many DMUs in a pair-wise assessment matrix might influence the assessment and ranking of DMUs since the rating weights generated from this matrix might be similar or even identical to each another. Therefore, unlike Eq. (16), an $n \times n$ matrix of the entries ($A = [a_{kj}]$) is constructed by:

$$a_{kj} = \theta_{kj} \tag{24}$$

5.4.2. **Phase 2:** ranking using AHP method

In this phase:

a. In a pair-wise assessment matrix, the sum of each column has to be calculated.
b. Each element in the column’s sum is divided and a new matrix called a normalised matrix is generated.
c. Balancing the data and AHP mean normalisation of data is the next step for ensuring that the information is similar across the assessments and in units, and contains no misalignment, with this mean indicating the ranking weight of each DMU. There are two steps for normalising the mean:

firstly, the mean of the information group for every input and output must be identified, with the mean of the elements in each row of the normalised matrix estimated as:

$$\bar{M}_i = \frac{\sum_{n=1}^{N} M_{ni}}{N} \qquad (25)$$

where:
$\bar{M}_i$ = mean value for column *i*;
N = number of DMUs; and
M_{ni} = value of DMU *n* for the input or output *i*.

In the next stage, all the values in an individual column are divided by the total mean values in each line, with the formula to be applied for every single unit:

$$MNorm_{ni} = \frac{M_{ni}}{\bar{M}_i} \qquad (26)$$

where:
$MNorm_{ni}$ is the normalised significance for the value related to DMU_n as well as the input or output in column *i*.

5.4.3. **Phase 3:** consistency ratio test

Finally, for the objectivity of the results to be identified as a numerical value and to a specific standard degree of an option, a consistency test needs to be conducted using the AHP. Saaty (1980) suggested a Consistency Index (CI) which is applied to show how consistent the pair-wise comparison matrices and, for an assessment matrix, is estimated as:

$$CI = \frac{\lambda_{max} - n}{n-1} \qquad (27)$$

where:
λ_{max}= greatest eigenvalue of the assessment matrix; and
n = size of the matrix.

The Consistency Ratio (CR) (Saaty, 1980) is known as the ratio between the consistency of an individual assessment matrix and that of a random one as:

$$CR = \frac{CI}{RI(n)} \qquad (28)$$

where *RI(n)* is a random index (Saaty, 1977) that relies on *n*, as demonstrated in Table 2.

Table 2. Random Index (RI)

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

As suggested by Saaty (1980), if the CR of an assessment matrix is equivalent to or even lower than 0.1 (10%), it will be a reliable result for ranking and can be accepted while, if not, there is no consistency and the initial data set should be fixed.

5.5. Step 5 – Testing Portfolio's Efficiency Results

5.5.1. Phase 1 – Portfolio's actual risk and return

The original purpose of portfolio development is to diversify non-systematic risks. The actual portfolio return is described as:

$$R_p = \sum_{i=1}^{N} x_i R_i$$

It can also be calculated by multiplying all the expected return values by their weights and then summing them.

The following formula describes the portfolio risk calculation explained in Eq. (4):

$$\sigma^2 = \sum_{i=1}^{n} P_i \, [R_i - E(R_p)]^2$$

Firstly, the correlations among the DMUs need to be estimated for which the CORREL function in Excel can be used. To simplify the evaluation, more matrices need to be evaluated based on Eq. (4), including the share, weights multiplication, risk and risk multiplication matrices. Once their values are identified, the value of correlation, weights multiplication, and risk multiplication matrices are multiplied to develop the final multiplication matrix. The total result of all the DMUs in the final multiplication matrix yields σ^2 and, to obtain the portfolio risk, the following square root is required.

$$\sigma = \sqrt{\sigma^2}$$

5.5.2. **Phase 2 -** Checking Sharpe Ratio (*SR*)

The *SR* is indicative of the additional profit over risk as:

$$SR = \frac{E(R_p) - R_f}{\sigma}$$

As a risk-free rate, the ten-year treasury yield at the end of the year is divided into the total of week's number; for example, assuming that this yield at the end of 2014 is equal to 1.98% and the number of our weekly data is 50, a risk-free rate can be calculated by:

$$R_f = \frac{1.98\%}{50} = 0.039\%$$

This coefficient is calculated for all the DMUs in the portfolio. It is suggested that DMs select the portfolios with the largest *SR* since it considers a greater return for risk.

5.5.3. **Phase 3 -** Checking Beta (β)

β details the connection between a project/asset and its portfolio/market returns as:

$$\beta_a = \frac{Cov\ (r_a - r_p)}{Var\ (r_p)} \qquad (29)$$

where:
R_a is the return of the asset/project;
R_p the return of the portfolio/market;
Cov the covariance of the asset/project and portfolio/market return; and
Var the portfolio/market variance.

This study uses the COVAR and VAR functions in Excel to calculate the covariance and variance, respectively, and β for each DMU and portfolio.

The value for the project/asset shifts correspondingly like the portfolio/market factor whenever β is equal to one. On the other hand, there is no connection between the project/asset and portfolio/market when β is zero. In the event that β is equal to minus one, the project/asset and portfolio/market values are shifted in opposite directions. If β is greater than one, the value of the project/asset increases by 1% for each 1%

portfolio/market movement. When β is less than one, the value of the project/asset drops by 1% whenever the portfolio/market value increases by 1%; but increases by 1% whenever the portfolio/market decreases by 1%.

5.5.4. **Phase 4 -** Decision Making

Finally, DMs are able to review the provided portfolios along with the trade-off between level of return, risk of the portfolio with efficiency score in addition to select the portfolio with highest efficiency and level of return with a minimum risk. Individual DMs might select different ways of efficiency selection between portfolios. To minimise the variance related to a specified expected return, R_{min} must be considered:

$$min\, \sigma^2 \tag{30}$$

subject to:

$$E(R_p) \geq R_{min}$$

$$\sum_{i=1}^{n} x_i = 1$$

$$x_i \geq 0 \qquad i = 1, \ldots, n$$

or, in order to maximise the expected return provided a specified variance:

$$max\, E(R_p) \tag{31}$$

subject to:

$$\sigma^2 \leq \sigma_{max}$$

$$\sum_{i=1}^{n} x_i = 1$$

$$x_i \geq 0 \qquad i = 1, \ldots, n$$

6. TESTING THE PROPOSED MODEL: A CASE STUDY OF AUSTRALIA'S TEN LARGEST COMPANIES

Australia's exports of resource and energy commodities have increased substantially over the last few years, supported by approximately $400 billion in investment between 2003 and 2014. Also, seven mega-projects with a total value of more than $40 billion are currently under development in Australia. Once these projects enter production, they will be another boost to Australia's exports of resource and energy services.

A case study involving the ten largest Australian companies outlined on the Australian stock market and Forbes (2016) listed in Table 3 is conducted to identify the best-performing ones that could provide the foundations of economic growth.

Table 3. TEN LARGEST FIRMS IN AUSTRALIA (FY2014-15)

	Company Name	Code
1	BHP Billiton Ltd	BHP.AX
2	National Australia Bank Ltd	NAB.AX
3	Commonwealth Bank of Australia	CBA.AX
4	Rio Tinto Ltd	RIO.AX
5	ANZ Banking Group Ltd	ANZ.AX
6	Westpac Banking Corp.	WBC.AX
7	Telstra Corp Ltd	TLS.AX
8	Macquarie Group Ltd	MQG.AX
9	Woolworths Ltd	WOW.AX
10	AMP Ltd	AMP.AX

6.1. Step 1 - Developing Portfolio

As a first step, a portfolio consisting of the ten firms needs to be created using the 2014 weekly data required to estimate their stocks and are obtained from the financial records accessed through Yahoo Finance (Yahoo, 2016) and the Australian Securities Exchange (AXS, 2016) (for the period 01 January 2014 to 29 December 2014). Later, the portfolio determined by the outcomes of the examination is adjusted to optimise it and verify whether the modifications assisted in enhancing the efficiency of the original portfolio and compared with the S&P factor in 2015. As outlined in Wikinvest (2016), the "*S&P/ASX 200 Index is the investable benchmark for the Australian Securities Exchange. It measures the performance of the 200 largest index eligible stocks listed on the exchange. The index is float-adjusted, covering approximately 80% of Australian equity market capitalisation*".

This study examines the companies' weekly records shown in Table 4 with the intention of developing a portfolio for one week.

Table 4. Companies' 2014 Financial and S&P/ASX Data

No.	Date	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP	S&P/AXS 200
1	1/1/14	35.29	33.00	77.16	68.36	32.21	32.12	5.27	55.00	34.00	4.39	5350.10
2	6/1/14	34.05	32.89	77.18	63.65	31.56	32.00	5.26	54.81	34.36	4.43	5312.40
3	13/1/14	35.41	32.10	75.06	66.32	31.03	31.39	5.24	53.96	34.19	4.49	5305.90
4	20/1/14	34.61	32.17	74.34	65.16	30.65	30.91	5.15	55.88	33.98	4.33	5240.90
5	27/1/14	34.17	31.63	73.83	65.64	30.13	30.66	5.14	54.09	34.07	4.27	5190.00
6	3/2/14	33.72	31.18	73.12	65.96	29.45	31.04	5.01	54.87	34.97	4.24	5166.50
7	10/2/14	35.24	32.46	75.58	67.90	31.34	32.53	5.20	55.36	35.50	4.52	5356.30
8	17/2/14	36.60	32.86	74.77	70.23	31.82	33.08	5.25	55.34	36.32	5.00	5438.70
9	24/2/14	35.86	33.05	74.26	66.84	32.14	33.24	5.05	56.27	36.07	4.83	5404.80
10	3/3/14	35.25	33.05	75.59	64.94	32.58	33.67	5.07	56.84	36.36	5.00	5462.30
11	10/3/14	33.32	32.66	74.84	61.50	31.87	33.42	5.01	54.25	36.32	4.92	5329.40
12	17/3/14	33.25	32.98	75.25	61.37	32.25	33.37	5.00	54.83	35.80	4.92	5338.10
13	24/3/14	33.77	33.60	76.72	63.24	32.82	34.20	5.03	57.65	35.60	4.96	5366.90
14	31/3/14	35.28	33.66	76.57	63.72	33.37	34.37	5.06	57.96	35.96	5.06	5422.80
15	7/4/14	35.15	33.61	76.94	64.11	33.85	34.43	5.05	56.37	36.04	5.14	5428.60
16	14/4/14	35.60	33.64	77.15	63.37	33.88	34.70	5.13	55.97	37.09	5.18	5454.20
17	21/4/14	35.77	34.07	78.46	62.98	34.67	35.54	5.18	56.54	37.74	5.16	5531.00
18	28/4/14	34.83	32.88	78.71	60.98	34.34	34.63	5.20	58.70	36.60	5.13	5458.10
19	5/5/14	34.89	32.71	79.07	60.95	32.72	34.70	5.22	60.12	36.84	5.25	5460.80
20	12/5/14	35.58	31.86	79.97	61.95	32.94	34.05	5.29	58.88	37.10	5.33	5479.00
21	19/5/14	35.18	31.93	80.87	60.54	33.60	33.96	5.38	59.30	37.57	5.26	5492.80
22	26/5/14	34.58	31.86	81.15	59.30	33.49	34.19	5.34	60.03	37.53	5.29	5492.50
23	2/6/14	33.86	31.90	81.33	59.40	33.67	34.32	5.23	60.10	37.04	5.34	5464.00
24	9/6/14	32.98	31.59	81.29	57.60	33.75	34.03	5.21	59.98	36.48	5.35	5405.10
25	16/6/14	33.59	31.52	80.98	58.51	33.98	33.92	5.17	60.50	35.40	5.34	5419.50
26	23/6/14	34.03	31.42	81.03	60.06	33.60	33.94	5.26	60.46	35.66	5.36	5445.10
27	30/6/14	35.11	32.09	81.51	62.60	33.78	34.17	5.34	60.44	36.42	5.41	5525.00
28	7/7/14	35.12	32.03	80.79	62.14	33.35	33.72	5.33	59.26	35.97	5.39	5486.80
29	14/7/14	35.87	32.51	80.83	64.29	33.42	33.67	5.43	60.00	35.95	5.27	5531.70
30	21/7/14	36.44	32.90	81.84	65.09	33.75	34.05	5.45	58.62	36.00	5.42	5583.50
31	28/7/14	35.89	33.23	82.37	65.40	33.56	33.82	5.44	57.71	36.46	5.37	5556.40
32	4/8/14	35.27	32.17	79.70	66.43	32.26	32.81	5.39	55.65	35.67	5.23	5435.30
33	11/8/14	36.49	33.00	80.76	65.29	32.39	33.86	5.58	57.03	36.12	5.37	5566.50
34	18/8/14	35.32	32.78	80.18	65.40	33.47	34.65	5.71	58.38	37.02	5.77	5645.60
35	25/8/14	34.27	33.49	80.88	62.63	33.43	34.80	5.56	58.30	36.16	5.88	5625.90
36	1/9/14	33.31	33.14	80.86	61.30	33.34	34.52	5.64	57.75	36.31	5.66	5598.70
37	8/9/14	33.44	32.58	79.80	61.89	32.83	34.02	5.54	57.95	35.25	5.57	5531.10
38	15/9/14	33.15	32.25	77.39	61.59	31.92	32.95	5.41	58.42	35.07	5.59	5433.10
39	22/9/14	31.92	31.11	74.85	60.11	30.99	31.67	5.31	57.79	34.50	5.62	5313.40
40	29/9/14	31.26	31.36	76.24	58.80	31.64	32.37	5.39	57.22	34.45	5.46	5318.20
41	6/10/14	30.19	30.36	74.40	57.26	31.22	32.03	5.29	55.83	33.73	5.22	5188.30

42	13/10/14	31.21	31.54	76.13	59.37	31.93	32.88	5.38	57.49	34.76	5.16	5271.70
43	20/10/14	31.53	32.60	78.35	60.05	33.02	33.98	5.50	59.75	34.83	5.56	5412.20
44	27/10/14	31.73	33.29	80.05	60.41	33.50	34.54	5.63	61.17	36.00	5.85	5526.60
45	3/11/14	32.23	31.60	82.31	60.70	32.88	34.60	5.77	62.36	34.48	5.90	5549.10
46	10/11/14	31.07	31.10	81.33	60.05	32.33	32.81	5.80	60.34	33.72	5.75	5454.30
47	17/11/14	29.62	30.70	79.66	56.41	31.82	32.03	5.65	58.45	31.60	5.56	5304.30
48	24/11/14	28.89	31.01	80.29	59.10	31.92	32.33	5.69	58.43	31.12	5.64	5313.00
49	1/12/14	28.43	30.82	81.20	57.14	32.10	32.79	5.67	60.40	30.84	5.68	5335.30
50	8/12/14	26.59	30.39	81.30	53.67	31.00	31.83	5.70	58.30	29.86	5.42	5219.60
51	15/12/14	27.08	31.07	83.26	56.29	31.68	32.26	5.89	57.82	30.00	5.48	5338.60
52	22/12/14	27.07	31.75	84.46	56.59	32.00	32.68	5.91	58.35	30.50	5.47	5394.50
53	29/12/14	27.44	31.96	85.19	58.00	32.09	32.94	5.97	58.29	30.68	5.50	5411.00

One week's average growth (Eq. (17)) is the simple growth over the previous week expressed as a percentage as:

1 week growth = 100*((V2/V1)-1)

Considering the company BHP, its one-week growth from 1/1/2014 (V1=35.29) to 6/1/2014 (V2=34.05) is:

100*((34.05/ 35.29)-1) = -3.5%

The portfolio information for the ten companies is presented in Table 5:

Table 5. PORTFOLIO DATA

Company	**Acronym**	**Last price (as at 29/12/14)**	**No. of Shares**	**Position**	**Shares**
BHP Billiton	BHP	$27.44	45.619	$1,252	14.89%
National Australia Bank	NAB	$31.96	34.638	$1,107	13.17%
Commonwealth Bank	CBA	$85.19	16.517	$1,407	16.74%
Rio Tinto	RIO	$58.00	10.483	$608	7.23%
ANZ Banking Group	ANZ	$32.09	30.19	$969	11.52%
Westpac Banking Corp.	WBC	$32.94	37.095	$1,222	14.53%
Telstra Corp Ltd	TLS	$5.97	116.451	$695	8.27%
Macquarie Group	MQG	$58.29	6.031	$352	4.18%
Woolworths	WOW	$30.68	21.107	$648	7.70%
AMP	AMP	$5.50	26.862	$148	1.76%
Total				**$8,407**	**100.0%**

Where:

The number of shares (volume at 29/12/2014) is the quantity of stocks managed in a portfolio over a particular time frame. (Note: '*Volume is an important indicator in technical analysis as it is used to measure the worth of a market move. If the markets have made a strong price move either up or down, the perceived strength of that move depends on the volume for that period. The higher the volume during that price move, the more significant the move*'(Investopedia, 2016)).

6.2. Step 2 - Calculating Portfolio Parameters

Weekly share values, S&P indices and weekly changes for all DMUs are measured, with the values of the expected return, risk and variance identified using Eqs. (1), (2) and (23). As a simple example, those of the expected return are the average weekly returns of the companies and those of the risks the standard deviations of these returns calculated using the STDEV function in Excel. Table 6 lists the portfolios' parameters.

Table 6. PORTFOLIO PARAMETERS

Company	Shares	Expected Return (Re)	Risk (σ)	Variance (σ^2)
BHP Billiton	14.89%	-0.45%	2.63%	0.07%
National Australia Bank	13.17%	-0.04%	1.93%	0.04%
Commonwealth Bank	16.74%	0.20%	1.57%	0.02%
Rio Tinto	7.23%	-0.27%	2.91%	0.08%
ANZ Banking Group	11.52%	0.01%	2.04%	0.04%
Westpac Banking Corp.	14.53%	0.07%	1.94%	0.04%
Telstra Corp Ltd	8.27%	0.25%	1.70%	0.03%
Macquarie Group	4.18%	0.14%	2.18%	0.05%
Woolworths	7.70%	-0.18%	1.96%	0.04%
AMP	1.76%	0.48%	3.04%	0.09%
S&P		**0.03%**	**1.42%**	**0.02%**

6.3. Step 3 – Collecting Input and Output Data for DMUs

To rate the sampled businesses, the two factors considered are the two financial parameters, the expected return and variance considered as the output and input respectively, as shown in Table 7.

Table 7. INPUT/OUTPUT DATA

Company	Input 1 (Variance)	Output 1 (Expected Return)
BHP Billiton	0.689124	-4.48616
National Australia Bank	0.373543	-0.43002
Commonwealth Bank	0.246631	2.026055
Rio Tinto	0.844466	-2.73763
ANZ Banking Group	0.416069	0.131739
Westpac Banking Corp.	0.376906	0.667096
Telstra Corp Ltd	0.287517	2.542196
Macquarie Group	0.476039	1.351179
Woolworths	0.386048	-1.78282
AMP	0.925884	4.78745

6.4. Step 4 – Proposed Integrated DEA Cross-efficiency/AHP Model

Using Eqs. (22), (23) and (24), we develop the following comparison matrix (Table 8):

Table 8. COMPARISON MATRIX

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10
DMU1	1.000	5.655	-0.792	2.008	-20.560	-3.678	-0.736	-2.294	1.410	-1.259
DMU2	0.177	1.000	-0.140	0.355	-3.636	-0.650	-0.130	-0.406	0.249	-0.223
DMU3	-1.262	-7.136	1.000	-2.534	25.945	4.641	0.929	2.894	-1.779	1.589
DMU4	0.498	2.816	-0.395	1.000	-10.239	-1.832	-0.367	-1.142	0.702	-0.627
DMU5	-0.049	-0.275	0.039	-0.098	1.000	0.179	0.036	0.112	-0.069	0.061
DMU6	-0.272	-1.537	0.215	-0.546	5.590	1.000	0.200	0.624	-0.383	0.342
DMU7	-1.358	-7.681	1.076	-2.727	27.925	4.996	1.000	3.115	-1.915	1.710
DMU8	-0.436	-2.466	0.346	-0.876	8.964	1.604	0.321	1.000	-0.615	0.549
DMU9	0.709	4.012	-0.562	1.425	-14.585	-2.609	-0.522	-1.627	1.000	-0.893
DMU10	-0.794	-4.492	0.629	-1.595	16.330	2.921	0.585	1.822	-1.120	1.000
Total	**-1.787**	**-10.10**	**1.416**	**-3.588**	**36.735**	**6.572**	**1.315**	**4.098**	**-2.519**	**2.249**

Eqs. (25) and (26) are applied to develop the AHP mean normalisation matrix shown in Table 9:

Table 9. AHP MEAN NORMALISATION MATRIX

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10
DMU1	-0.560	-0.560	-0.560	-0.560	-0.560	-0.560	-0.560	-0.560	-0.560	-0.560
DMU2	-0.099	-0.099	-0.099	-0.099	-0.099	-0.099	-0.099	-0.099	-0.099	-0.099
DMU3	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706
DMU4	-0.279	-0.279	-0.279	-0.279	-0.279	-0.279	-0.279	-0.279	-0.279	-0.279
DMU5	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027
DMU6	0.152	0.152	0.152	0.152	0.152	0.152	0.152	0.152	0.152	0.152
DMU7	0.760	0.760	0.760	0.760	0.760	0.760	0.760	0.760	0.760	0.760
DMU8	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244
DMU9	-0.397	-0.397	-0.397	-0.397	-0.397	-0.397	-0.397	-0.397	-0.397	-0.397
DMU10	0.445	0.445	0.445	0.445	0.445	0.445	0.445	0.445	0.445	0.445
Total	-5.597	-0.990	7.063	-2.787	0.272	1.522	7.602	2.440	-3.970	4.445
Efficiency	-0.560	-0.099	0.706	-0.279	0.027	0.152	0.760	0.244	-0.397	0.445
Consistency	10	10	10	10	10	10	10	10	10	10
Rank	10	7	2	8	6	5	1	4	9	3

A consistency test of the above results is conducted using Eq. (27):

CI = (10-10)/(10-1) = 0

As, according to Table 2, the random index (RI)) for 10 DMUs is equal to 1.49, the consistency ratio is:

CR=0/1.49 = 0
0% <= 10% OK

The consistency test using Eq. (28) is performed and a total consistency ratio of zero obtained which cannot often be ensured to work with a mixed professional group. As this result is much less than the upper boundary of 10% suggested by Saaty (1980), we can rely on the ranking result and select the alternative 'DMU 7 - Telstra Corp Ltd' as the best company with the lowest possible risk and highest return on investment.

6.5. Step 5 – Testing the Portfolio Efficiency Results

6.5.1. Phase 1 - actual risk and return of portfolio

The actual portfolio return can be found using Eq. (2):

$R_p = -0.03\%$

As the estimated portfolio return is below the S&P return of 0.03% and the portfolio is unable to defeat this index on a weekly basis, the risk is calculated using Eq. (4). However, the correlations between the shares should be determined as a first step and are shown in Table 10.

Table 10. CORRELATION MATRIX

	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	1.000	0.433	0.369	0.749	0.455	0.497	0.520	0.334	0.445	0.480
NAB	0.433	1.000	0.603	0.319	0.689	0.729	0.392	0.360	0.534	0.385
CBA	0.369	0.603	1.000	0.215	0.656	0.730	0.663	0.444	0.342	0.349
RIO	0.749	0.319	0.215	1.000	0.327	0.316	0.447	0.168	0.352	0.375
ANZ	0.455	0.689	0.656	0.327	1.000	0.752	0.517	0.369	0.435	0.505
WBC	0.497	0.729	0.730	0.316	0.752	1.000	0.507	0.520	0.576	0.560
TLS	0.520	0.392	0.663	0.447	0.517	0.507	1.000	0.219	0.455	0.439
MQG	0.334	0.360	0.444	0.168	0.369	0.520	0.219	1.000	0.246	0.339
WOW	0.445	0.534	0.342	0.352	0.435	0.576	0.455	0.246	1.000	0.450

AMP	0.480	0.385	0.349	0.375	0.505	0.560	0.439	0.339	0.450	1.000

Considering ANZ and BHP as examples and applying Eq. (17), the changes in returns for ANZ and BHP are estimated as:

$$\text{BHP's one} - \text{ week growth} = 100 \times \left(\left(\frac{v_2}{v_1} \right) - 1 \right)$$

…

$$\text{BHP's one} - \text{ week growth} = 100 \times \left(\left(\frac{v_{53}}{v_{52}} \right) - 1 \right)$$

Using the CORREL function in Excel, the following correlation matrix can be developed.

$$= CORREL\big((BHP_1 : BHP_{53}), (ANZ_1 : ANZ_{53})\big) = 0.455$$

To simplify a valuation, five more matrices are examined based on the portfolio risk formula in Eq. (4) and the results shown in Table 11 to Table 15.

The share values of each firm can be obtained from Table 6.

Table 11. Shares Matrix

BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%
14.89%	13.17%	16.74%	7.23%	11.52%	14.53%	8.27%	4.18%	7.70%	1.76%

Using the values in this matrix, the weights multiplication one is created and the results shown in Table 12. Considering the CBA and BHP firms as examples, their weights multiplication values are estimated using the following process.

$$\text{The weights multiplication values of CBA and BHP} = 0.1489 \times 0.1674 = 0.0249$$

Table 12. Weights Multiplication Matrix

	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	0.022	0.020	0.025	0.011	0.017	0.022	0.012	0.006	0.011	0.003
NAB	0.020	0.017	0.022	0.010	0.015	0.019	0.011	0.006	0.010	0.002
CBA	0.025	0.022	0.028	0.012	0.019	0.024	0.014	0.007	0.013	0.003
RIO	0.011	0.010	0.012	0.005	0.008	0.011	0.006	0.003	0.006	0.001
ANZ	0.017	0.015	0.019	0.008	0.013	0.017	0.010	0.005	0.009	0.002
WBC	0.022	0.019	0.024	0.011	0.017	0.021	0.012	0.006	0.011	0.003
TLS	0.012	0.011	0.014	0.006	0.010	0.012	0.007	0.003	0.006	0.001
MQG	0.006	0.006	0.007	0.003	0.005	0.006	0.003	0.002	0.003	0.001
WOW	0.011	0.010	0.013	0.006	0.009	0.011	0.006	0.003	0.006	0.001
AMP	0.003	0.002	0.003	0.001	0.002	0.003	0.001	0.001	0.001	0.000

Table 13 presents the risk matrix created using the risk values identified in Table 6.

Table 13. Risk Matrix

BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%
2.63%	1.93%	1.57%	2.91%	2.04%	1.94%	1.70%	2.18%	1.96%	3.04%

The risk multiplication matrix (Table 14) is created using the values identified in Table 13. Considering the ANZ and RIO firms as examples, their risk multiplication values are estimated using the following process.

The risk multiplication values of ANZ and RIO $= 0.029 \times 0.020 = 0.001$

Table 14. Risk Multiplication Matrix

	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	0.001	0.001	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.001
NAB	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
CBA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RIO	0.001	0.001	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.001
ANZ	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
WBC	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
TLS	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
MQG	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
WOW	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
AMP	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001

At this point, the values of the correlation, weights multiplication and risk multiplication matrices are multiplied to develop the final matrix presented in Table 15. Considering the WBC and CBA firms as examples, their final multiplication values are estimated by:

The final multiplication values of WBC and CBA $= 0.7299 \times 0.0243 \times 0.0003 = 0.00001$

Table 15. Final multiplication matrix

	BHP	NAB	CBA	RIO	ANZ	WBC	TLS	MQG	WOW	AMP
BHP	0.00002	0.00000	0.00000	0.00001	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
NAB	0.00000	0.00001	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
CBA	0.00000	0.00000	0.00001	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
RIO	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
ANZ	0.00000	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000
WBC	0.00001	0.00001	0.00001	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
TLS	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
MQG	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
WOW	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
AMP	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Then, the total of all the values in Table 15 are calculated to find σ^2, that is:

$\sigma^2 = 0.00024$

The square root of Eq. (6) is estimated to obtain the portfolio risk as:
$\sigma = \sqrt{\sigma^2} = 1.5\%$

It is obvious that the portfolio risk exceeds the S&P index of 1.42%.

6.5.2. Phase 2 - Checking Sharpe Ratio (*SR*)

In this step, we calculate the *SR* of the return to risk, as:

$$SR = \frac{E(R_p) - R_f}{\sigma}$$

This study obtains ten years of Australian treasury yield value for the *SR* right to the end of 2014 (Investing, 2016) and breaks it into the total weeks value of a portfolio recorded to obtain:

$$R_f = 1.98\% / 53 = 0.03736\%$$

Then, the coefficient for every share in the portfolio and the S&P index are measured, as shown in Table 16.

Table 16. Portfolio Coefficient

Company	Expected Return (R_e)	Risk (σ)	Risk-free rate (R_f)	Sharpe Ratio (*SR*)
BHP Billiton	-0.449%	2.625%	0.037%	-18.512%
National Australia Bank	-0.043%	1.933%	0.037%	-4.158%
Commonwealth Bank	0.203%	1.570%	0.037%	10.522%
Rio Tinto	-0.274%	2.906%	0.037%	-10.706%
ANZ Banking Group	0.013%	2.040%	0.037%	-1.186%
Westpac Banking Corp.	0.067%	1.941%	0.037%	1.512%
Telstra Corp Ltd	0.254%	1.696%	0.037%	12.789%
Macquarie Group	0.135%	2.182%	0.037%	4.481%
Woolworths	-0.178%	1.965%	0.037%	-10.975%
AMP	0.479%	3.043%	0.037%	14.506%
Portfolio	**-0.026%**	**1.542%**	**0.037%**	**-4.095%**
S&P index	**0.032%**	**1.418%**	**0.037%**	**-0.405%**

It is suggested that DMs select the portfolios with the maximum possible *SRs* since it is considered that they have a larger excess return for risk. Considering this theory, at this stage, AMP appears to be the best option and BHP the worst.

6.5.3. Phase 3 - Checking Beta (β)

In this stage, to determine the connection between the returns of a project/asset and portfolio/market, Beta (β) is estimated using Eq. (29), with the results shown in Table 17.

Table 17. Beta (β) Calculations

Company	Covariance	Variance	Beta
BHP Billiton	0.00027	0.00020	1.34
National Australia Bank	0.00019	0.00020	0.96
Commonwealth Bank	0.00016	0.00020	0.82
Rio Tinto	0.00022	0.00020	1.11
ANZ Banking Group	0.00022	0.00020	1.10
Westpac Banking Corp.	0.00023	0.00020	1.13
Telstra Corp Ltd	0.00018	0.00020	0.87
Macquarie Group	0.00015	0.00020	0.77
Woolworths	0.00017	0.00020	0.86

AMP	0.00029	0.00020	1.45
Portfolio	**0.00021**	**0.00020**	**1.04**

6.5.4. Phase 4 - Decision Making

Details of all the parameters are presented in Table 18.

Table 18. CALCULATED PARAMETERS

Company	Shares	Expected Return (Re)	Risk (σ)	Sharpe Ratio	Beta
BHP Billiton	14.9%	-0.4%	2.6%	-0.19	1.34
National Australia Bank	13.2%	0.0%	1.9%	-0.04	0.96
Commonwealth Bank	16.7%	0.2%	1.6%	0.11	0.82
Rio Tinto	7.2%	-0.3%	2.9%	-0.11	1.11
ANZ Banking Group	11.5%	0.0%	2.0%	-0.01	1.10
Westpac Banking Corp.	14.5%	0.1%	1.9%	0.02	1.13
Telstra Corp Ltd	8.3%	0.3%	1.7%	0.13	0.87
Macquarie Group	4.2%	0.1%	2.2%	0.04	0.77
Woolworths	7.7%	-0.2%	2.0%	-0.11	0.86
AMP	1.8%	0.5%	3.0%	0.15	1.45
Portfolio		**-0.03%**	**1.54%**	**-0.041**	**1.040**
S&P index		**0.03%**	**1.42%**	**-0.004**	

The first point to note is that the *SR* is below the S&P value which implies that the latter offers a more desirable connection between the return and risk. Also, as the portfolio possesses a Beta equivalent of 1.04, once the portfolio/market improves, our portfolio improves much faster.

The following adjustments are made based on the values extracted from Table 18.

- The values of shares with the lowest *SR*s are reduced (BHP, RIO and WOW).
- The value of a share with the largest Beta value is maximised (AMP).
- The value of a share with the largest *SR* is maximised (also AMP).
- The other values shown in Table 5 are retained.

The portfolio presented in this case study is also tested with data collected from 2015. Applying the above adjustments to Table 5, a new modified version of this table is presented in Table 19, including the adjustments to the numbers of shares for BHP, RIO, WOW and AMP.

Table 19. NEW PORTFOLIO WITH MODIFIED SHARE VALUES

Company	Synonym	Last price (as at 2014)	Shares No.	Position	Shares
BHP Billiton	BHP	$27.4445	**7**	$192	2.3%
National Australia Bank	NAB	$31.9631	34.638	$1,107	13.2%
Commonwealth Bank	CBA	$85.1885	16.517	$1,407	16.7%
Rio Tinto	RIO	$58	**3.5**	$203	2.4%
ANZ Banking Group	ANZ	$32.09	30.19	$969	11.5%
Westpac Banking Corp.	WBC	$32.9358	37.095	$1,222	14.5%
Telstra Corp Ltd	TLS	$5.97	116.451	$695	8.3%
Macquarie Group	MQG	$58.29	6.031	$352	4.2%
Woolworths	WOW	$30.68	**5**	$153	1.8%
AMP	AMP	$5.5	**383**	$2,107	25.1%
Portfolio				$**8,407**	**100%**

The share quantities for BHP, RIO, WOW and AMP are modified to obtain ones almost equal to the totals in Table 5. In this step, the weekly returns for the current as well as newly modified portfolios are estimated with the average ones and results for the S&P index shown in Table 20.

Table 20. Average Weekly Returns

	OLD	NEW	S&P index
2015 average weekly return	-0.157%	0.003%	-0.026%

There is no doubt that the improvements help as the new portfolio demonstrates better performance than the old one and outperforms the S&P index. Table 21 refers to the average weekly performances of the shares in 2014:

Table 21. Average weekly performances in 2014

Company	Change (2014)
BHP Billiton	-0.45%
National Australia Bank	-0.04%
Commonwealth Bank	**0.20%**
Rio Tinto	-0.27%
ANZ Banking Group	**0.01%**
Westpac Banking Corp.	**0.07%**
Telstra Corp Ltd	**0.25%**
Macquarie Group	**0.14%**
Woolworths	-0.18%
AMP	**0.48%**

The weight of AMP is improved and, surprisingly it is among the preferred portfolios together with MQG, CBA and WBC. The weights of BHP, RIO and WOW are decreased and BHP is the worst-performing stock followed by RIO and WOW.

The expected return, risk, *SR* and efficiency of each portfolio are compared based on Eqs. (30) and (31) assumptions, as presented in Table 22 and Table 23.

In this step, DMs review the portfolios' values and the trade-offs between their expected return, risk, *SR* and efficiency scores and can select the portfolio with the highest possible return and lowest possible risk while considering the efficiency scores. These values are shown in Table 22.

Table 22. Comparison of Results

DMUs No.	Company	Expected Return (Re)	Risk (σ)	Sharpe Ratio	Efficiency Score
1	BHP Billiton	-0.4%	2.6%	-0.19	-0.5597
2	National Australia Bank	0.0%	1.9%	-0.04	-0.0990
3	Commonwealth Bank	0.2%	1.6%	0.11	0.7063
4	Rio Tinto	-0.3%	2.9%	-0.11	-0.2787
5	ANZ Banking Group	0.0%	2.0%	-0.01	0.0272
6	Westpac Banking Corp.	0.1%	1.9%	0.02	0.1522
7	Telstra Corp Ltd	0.3%	1.7%	0.13	0.7602
8	Macquarie Group	0.1%	2.2%	0.04	0.2440
9	Woolworths	-0.2%	2.0%	-0.11	-0.3970
10	AMP	0.5%	3.0%	0.15	0.4445

Table 23. Ranking Scores

DMUs No.	Company	Expected Return (Re)	Risk (σ) (1=low, 10=high)	Sharpe Ratio	Efficiency Score
1	BHP Billiton	10	8	10	10
2	National Australia Bank	6	3	7	7
3	Commonwealth Bank	3	1	3	2
4	Rio Tinto	9	9	8	8
5	ANZ Banking Group	6	6	6	6
6	Westpac Banking Corp.	4	4	5	5
7	Telstra Corp Ltd	2	2	2	1

8	Macquarie Group	4	7	4	4
9	Woolworths	8	5	9	9
10	AMP	1	10	1	3

World demand for Australian resource and energy exports remains strong and, for most products, is expected to increase in coming years. However, the ongoing downturn in production and trading costs has led many finance, resource and energy organisations to apply expense reduction policies to remain successful, with limiting their exploration funds undoubtedly one principal approach. The focus of companies has clearly shifted from developing new projects to ensuring the commercial viability of existing assets. Australia's total exploration expenses in 2014-15 (i.e., minerals and petroleum) reduced by 22% from $5.4 billion in 2013-14.

In an environment of tight finances and falling prices, companies have been forced to re-evaluate their project development plans in order to identify cost savings. The result is a downward trend in the number and value of both committed and uncommitted projects in Australia over the last four years. The benefits of agreed projects are declining which, in turn, are not mitigated by new forthcoming funds and are being significantly delayed as a result of undesirable market situations.

The slowing growth in demand in key markets and the increasing supply of most products have led to lower product prices in 2015. This trend has impacted on the finance and development of resource and energy projects in Australia. According to empirical results from this case study, in December 2014, six companies (CBA, ANZ, WBC, TCL, MQG and AMP) with a combined average weekly performance value of 1.15% progressed to be the top six companies with higher average weekly performance; this is two companies more and 0.15% higher than recorded in December 2015. This decrease in value is due to the closure of some major projects, especially in the mining industry, and different cost reduction policies used in many organisations to remain profitable. Business investment is cyclical and, although the level of investment in the resource and energy sectors in Australia is decreasing, there are significant opportunities for investment in coming years. Advances in technology and the ongoing growth in demand in highly populated emerging economies will continue to support the higher consumption of commodities, such as base metals, rare earth elements, gold, silver and uranium, in future. However, Australia must remain competitive with other countries to guarantee continuing financial investment and ensure that it remains one of the best places for attracting capital.

The result from the case study shows that eight companies have lower performance scores than Telstra Corp Ltd and Commonwealth Bank of Australia which suggests that, in particular, they must enhance their expected returns while focusing on possible risks. It is clear that the proposed model has the capacity to select the portfolio with the highest efficiency while considering the *SR* and risk factor at a given expected return, as proven in Table 23. The majority of DMUs resulting from the proposed model are identical with the results from the PT *SR*s. Although the efficiency results for DMUs 3, 7 and 10 are different, the proposed model scores all DMUs by simultaneously considering the risk, expected return and *SR* and identifying the best companies with the highest expected returns and *SR*s, and lowest possible risks.

6.5.5. Comparing results from standard methods and proposed model

In this step, this study compares and tests the standard ranking methods discussed in this study with the new proposed method in parallel using the same data presented in our case study.

This study selected portfolios 49 times using different methods by applying:

1. Standard DEA Input-oriented (I) Constant Returns to Scale (CRS)
2. DEA I-CRS Cross-efficiency (CE)
3. DEA Output-oriented (O) - CRS
4. DEA I- Variant Returns to Scale (VRS)
5. DEA O-VRS
6. Range Directional Measure (RDM)+
7. RDM-
8. Slack-based Model (SBM)
9. Modified Slack-based Model (MSBM)
10. Semi-oriented Radial Measure (SORM) I-CRS

11. SORM O-CRS
12. SORM I-VRS
13. SORM O-VRS
14. Variant of the Radial Measure (VRM) I-CRS
15. VRM O-CRS
16. VRM I-VRS
17. VRM O-VRS
18. Radial Supper-efficiency Model (RSEM) I-CRS
19. RSEM O-CRS
20. RSEM I-VRS
21. RSEM O-VRS
22. Scale Efficiency Measure (SEM) I-VRS
23. SEM O-VRS
24. Radial Models with Value Judgements (RMVJ) I-CRS
25. RMVJ O-CRS
26. RMVJ I-VRS
27. RMVJ O-VRS
28. Additive Model (AM) I-CRS
29. AM I-VRS
30. Free Disposal Hull Models (FDHM) I-CRS
31. FDHM I-VRS
32. Cost Efficiency Models (CEM) O-CRS Cost Efficiency
33. CEM O-CRS Technical Efficiency
34. CEM O-CRS Allocative Efficiency
35. CEM O-CRS Profit Efficiency
36. CEM O-CRS Revenue Efficiency
37. CEM O-VRS Cost Efficiency
38. CEM O-VRS Technical Efficiency
39. CEM O-VRS Allocative Efficiency
40. CEM O-VRS Profit Efficiency
41. CEM O-VRS Revenue Efficiency
42. Standard DEA/AHP Linear Programming (LP)
43. Standard DEA/AHP Average Efficiency (Avg.)
44. Standard DEA/AHP Total
45. Proposed DEA CE/AHP Model Avg. with 2 Criteria
46. Proposed DEA CE/AHP Total with 2 Criteria
47. Proposed DEA CE/AHP LP with 3 Criteria
48. Proposed DEA CE/AHP Avg. with 3 Criteria
49. Proposed DEA CE/AHP Total with 3 Criteria

Although the proposed model can identify efficient and inefficient DMUs using only two criteria (variance as input and expected return with negative data as output), other standard DEA methods are not able to estimate efficiency among DMUs using these criteria. DMUs 1, 2, 4, 9 are not semi-positive and should have a minimum of one positive input as well as one positive output to be used in the standard models.

If both the variance and expected return values are considered outputs, a minimum of one input is necessary as DEA methods cannot be completely created with outputs. A dummy input with a value equal to one for all the DMUs and the expected return and variance as two outputs are considered for comparing other standard methods, as demonstrated in Table 24:

Table 24. Input/ Output data with dummy inputs

Company	**Input**	**Output 1** (Expected Return)	**Output 2** (Variance)
BHP Billiton	1	-4.48616	0.689124
National Australia Bank	1	-0.43002	0.373543
Commonwealth Bank	1	2.026055	0.246631
Rio Tinto	1	-2.73763	0.844466
ANZ Banking Group	1	0.131739	0.416069

Westpac Banking Corp.	1	0.667096	0.376906
Telstra Corp Ltd	1	2.542196	0.287517
Macquarie Group	1	1.351179	0.476039
Woolworths	1	-1.78282	0.386048
AMP	1	4.78745	0.925884

The expected return is often treated as an output since more of this variable is desired and can become negative for the respective period whereas the variance involves only the variables in the model that take non-negative values. Although some methods can score efficiency using the above three criteria (RDM, SORM, VRM and MSBM), the rest cannot deal with negative data. While we also apply these criteria to the proposed model, the results are far from the reality. Considering only the Consistency Ratio (CR) clearly shows that this arrangement of the criteria needs to be changed as the CR for our proposed model using them is 53.3% which is far greater than the acceptable one of 10% proposed by Saaty (1980) in Eq. (28). The DMUs' ranking scores are neither acceptable nor justifiable as they are not even close to the results we identified from the PT; for example, based on them, BHP is the second-best company compared with the others in terms of efficiency, with the results from the PT and proposed model clearly showing a huge discrepancy.

As standard DEA methods cannot handle non-positive data, there is a need for a solution to this issue. A possible and, perhaps, simplest approach is to treat negative outputs as positive inputs and vice versa (e.g., Scheel, 2001; Seiford & Zhu, 2002). Therefore, the negative inputs/outputs in the proposed model are shifted to positive values by changing the original results obtained from a new problem (Cooper, Seiford, & Tone, 2007). Then, modified positive input/output data are presented for further investigation.

Drawing upon the above-described approach, if a vector of input or output data consists of a mix of positive and negative numbers, this approach will require dividing this vector into two sub-vectors. One will hold the positive numbers and replace the negative values with zeroes (or very small positive values) while the other one will retain the absolute values of the negative elements and substitute zeroes (or very small positive values) for positive numbers. Then, the context will dictate which sub-vector needs to be maximised (minimised) and reside on the output (input) side.

To deal with the negative data from Output 1 (the expected return) in Table 24, these data are shifted to positive values by changing the original results in a new problem (Input 2). Modified positive input/output data are shown in Table 25.

Table 25. INPUT/OUTPUT DATA WITH POSITIVE VALUES

Company	**Input 1**	**Input 2**	**Output 1** (Expected Return)	**Output 2** (Variance)
BHP Billiton	1	4.48616	0	0.689124
National Australia Bank	1	0.43002	0	0.373543
Commonwealth Bank	1	0	2.026055	0.246631
Rio Tinto	1	2.73763	0	0.844466
ANZ Banking Group	1	0	0.131739	0.416069
Westpac Banking Corp.	1	0	0.667096	0.376906
Telstra Corp Ltd	1	0	2.542196	0.287517
Macquarie Group	1	0	1.351179	0.476039
Woolworths	1	1.78282	0	0.386048
AMP	1	0	4.78745	0.925884

Although applying the data in Table 25 to the remaining models shows that they can estimate efficiency scores, some models are infeasible. Numerical errors may lead to some minor changes in model constraints that can cause Linear Programming (LP) to become infeasible. In this case, we need to scale the data or change the tolerance value to reduce numerical errors. Moreover, some models are not always feasible; for example the Radial Super-efficiency Model (RSEM)-VRS or any models with weight restrictions. There are also other restrictions, such as epsilon which limits the lower bound of the LP variables, with the results are not justifiable in this scenario.

The results have been compared as shown in Table 26 and discussed in the followings.

Table 26. COMPARISON OF RESULTS FROM STANDARD MODELS

Models	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10
1	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
2	0.521	0.282	0.313	0.638	0.323	0.327	0.377	0.445	0.292	1.000
3	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
4	1	1	1	1	1	1	1	1	1	1
5	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
7	93.461	64.412	66.730	99.227	69.681	64.844	78.005	76.395	66.005	0.000
8	0.000	0.202	0.000	1.000	0.620	0.579	0.474	0.679	0.613	1.000
9	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	1.000
10	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
11	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
12	1	1	1	1	1	1	1	1	1	1
13	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
14	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
15	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
16	1	1	1	1	1	1	1	1	1	1
17	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
18	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	2.440
19	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	2.440
20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
21	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	2.440
22	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
23	1	1	1	1	1	1	1	1	1	1
24	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
25	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
26	1	1	1	1	1	1	1	1	1	1
27	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
28	9.510	5.770	3.441	7.606	5.166	4.669	2.884	3.886	7.110	0.000
29	9.510	5.770	3.441	7.606	5.166	4.669	2.884	3.886	7.110	0.000
30	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
31	1	1	1	1	1	1	1	1	1	1
32	0.035	0.138	0.423	0.069	0.449	0.407	0.531	0.514	0.046	1.000
33	0.744	0.403	0.423	0.912	0.449	0.407	0.531	0.514	0.417	1.000
34	0.047	0.341	1.000	0.075	1.000	1.000	1.000	1.000	0.111	1.000
35	76.656	18.296	5.419	38.469	4.385	5.024	4.172	3.611	57.860	1.000
36	0.744	0.403	0.266	0.912	0.449	0.407	0.311	0.514	0.417	1.000
37	0.047	0.341	1.000	0.075	1.000	1.000	1.000	1.000	0.111	1.000
38	1	1	1	1	1	1	1	1	1	1
39	0.047	0.341	1.000	0.075	1.000	1.000	1.000	1.000	0.111	1.000
40	57.054	7.381	2.293	35.086	1.971	2.045	2.215	1.856	24.125	1.000
41	0.744	0.403	0.266	0.912	0.449	0.407	0.311	0.514	0.417	1.000
42	0.091	0.086	0.088	0.100	0.090	0.087	0.092	0.099	0.084	0.182
43	1.057	1.188	1.153	0.961	1.120	1.171	1.074	1.021	1.213	0.580
44	0.093	0.086	0.088	0.103	0.090	0.087	0.092	0.098	0.083	0.180
45	-0.179	-1.010	0.142	-0.359	3.673	0.657	0.132	0.410	-0.252	0.225
46	-0.560	-0.099	0.706	-0.279	0.027	0.152	0.760	0.244	-0.397	0.445
47	0.114	0.038	0.104	0.104	0.042	0.056	0.129	0.091	0.054	0.268
48	0.729	2.925	2.045	0.696	9.285	2.424	1.747	1.441	1.374	0.580
49	0.151	0.057	0.073	0.142	0.063	0.062	0.089	0.085	0.072	0.207

There are several methods that produce identical ranking scores in the same order for the DMUs under consideration; for example, Methods 1 (DEA I-CRS), 3 (DEA I-CRS), 5 (DEA O-VRS), 10 (SORM I-CRS), 11 (SORM O-CRS), 13 (SORM O-VRS), 14 (VRM I-CRS), 15 (VRM O-CRS), 17 (VRM O-VRS), 22 (SEM I-VRS), 24 (RMVJ I-CRS), 25 (RMVJ O-CRS), 27 (RMVJ O-VRS), 30 (FDHM I-CRS) and 33 (CEM O-CRS Tech.Effic).

Also, Methods 18 (RSEM I-CRS), 19 (RSEM O-CRS) and 21 (RSEM O-VRS) have the same ranking scores as do Methods 36 (CEM O-CRS Rev.Effic) and 41 (CEM O-VRS Rev.Effic). The efficiency results obtained from these methods are also very close to those from the previous groups of models, that is, Methods 28 (AM I-CRS) and 29 (AM I-VRS) in one group and 34 (CEM O-CRS Alloc.Effic), 37 (CEM O-VRS Cost.Effic) and 39 (CEM O-VRS Alloc.Effic) in another.

Moreover, the efficiency levels of DMUs cannot be estimated by some methods which estimate zero values for them; for instance, Methods 6 (RDM+) and 20 (RSEM I-VRS) consider all the DMUs inefficient (zero) while Methods 7 (RDM-), 8 (SBM), 28 (AM I-CRS) and 29 (AM I-VRS) identify the values for DMUs 1, 3 and 10 as zero. As the efficiency results for all DMUs in Methods 4 (DEA I-VRS), 12 (SORM I-VRS), 16 (VRM VRS IO), 23 (SEM O-VRS), 26 (RMVJ I-VRS), 31 (FDHM I-VRS) and 38 (CEM O-VRS Tech.Effic) are equal to one, because these DMUs cannot be considered different, they are viewed as equally efficient.

Only the results obtained from 36 of the 49 methods (1, 2, 3, 5, 9, 10, 11, 13, 14, 15, 17, 18, 19, 21, 22, 24, 25, 27, 30, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48 and 49) are considered for further investigation. Those that cannot estimate the efficiency of DMUs (zero values) and those incapable of differentiating between DMUs (equally efficient with values of one) are omitted from further investigation.

There are significant differences between the proposed method and the other standard models concerning their performance scores for effective organisations. The above results demonstrate that the proposed approach is a promising tool for portfolio selection as a means of fundamental analysis. Our results also show that the DEA cross-efficiency approach in the new method is more effective than that based on the simple use of cross-efficiency scores, at least for this particular application. Overall, our findings consistently support the effectiveness of our approach.

7. RESULTS AND CONCLUSIONS

This study proposed a model based on the PT, standard DEA cross-efficiency and standard DEA/AHP methods. It simultaneously takes into account the efficiency, expected return, *SR* and risk of a portfolio. Moreover, the AHP and PT models are considered tools for testing efficiency to check the accuracy of the proposed model.

The proposed model is inspired by considering that the standard basic use of DEA scores in portfolio selection per se suffers from the problem of the resultant portfolios not being well diversified which is exacerbated by the DEA cross-efficiency evaluation being integrated with the AHP. This study discovered that this problem is due to the basic utilisation of DEA assessment in portfolio selection not taking into account shifts or improvements in weights. This issue is addressed by integrating a modified DEA cross-efficiency and AHP assessment into the PT method in which those risks are simultaneously taken into consideration.

As standard DEA methods presume positive inputs/outputs for DMUs, the DEA models for non-negative data in the literature cannot be employed to establish the cross-efficiency of these DMUs. All existing methods for measuring efficiency with negative data have some disadvantages whereas the proposed model evaluates the Pareto-Koopmans efficiency of DMUs when the inputs and outputs can be either positive or negative.

As an illustration of the recommended method, a case study using the actual financial data from 2014 to 2015 of Australia's 10 largest companies in the Australian share market were taken into consideration. Its fundamental aim was neither to provide perspectives of those companies nor present grading advice but to concentrate on explicitly representing an integrated method for rating those organisations according to a variety of factors. The accuracy of the proposed model has been defined by comparing the results obtained from 49 standard main and sub-models including the proposed method, with the outcomes revealing that the proposed model presents much better efficiency scores with higher accuracy. It scores efficient DMUs with much better ranking levels than inefficient ones. Therefore, there is certainly better agreement among its rankings and the efficiency specifications taken from the DEA, that is, the proposed model scores effective DMUs which cannot be considered by standard models. Simultaneously, it scores inefficient DMUs while ensuring that efficient ones have better ranking levels.

The results obtained using this method show the reality of the weights generated. They appears to be much more reasonable with financial and organisational clarity since this study used a modified DEA cross-efficiency evaluation instead of a standard DEA method. The proposed model perceives the subjective and objective aspects and makes the options far more practical and, in general, provides better objectives than the available methods presented in the literature review.

8. Limitations

That DMs are simply ready to take higher levels of risk given considerably better than expected returns is often contradicted by their decisions. Usually, investment methods require that they undertake an investment considered risky to minimise the total risk with no noticeable improvement in expected returns (McClure, 2010). Moreover, DMs possess particular powers which could outweigh considerations regarding the delivery of returns.

The PT presumes all the data from DMs regarding their investments are regularly received. However, in fact, world markets represent data irregularly and some DMs may be much better informed than others (Bofah, unknown) which may explain why organisations usually purchase below market value.

Another key idea is that DMs have an almost infinite capability to lend at a risk-free interest rate. In reality, each DM carries credit limitations and only the government can frequently access interest-free funds (Morien, unknown). The PT aims to minimise the risk on returns while taking no notice of environmental or strategic aspects. In reality, there is no factor called a risk-free asset (McClure, 2010).

Although the PT considers the possibility of choosing portfolios that different efficiencies than others, market records verified that there are no tools for accomplishing this (McClure, 2010).

A company's investment outlook is based on a project-level analysis of a number of factors to assess the probability that a project moves to the development stage. Usually, case studies draw on projects currently in the development phase or being assessed as having a good possibility of progressing to closure. Projects for which information can be obtained are evaluated according to their positions in terms of applicable management expenses and their internal return levels. Given that an examination is possibility-dependent, there is some doubt regarding the results of the projects considered and their progression to the closing phase. Moreover, typically, estimates created at a project level may not be incorporated since some of the data employed may be addressed as commercial-in-confidence.

9. Future Work

This study might be extended in several potential ways, as summarised in the following.

1. Even if the case study presented in this document empirically promotes the success and ability of the suggested method for portfolio selection, other sorts of objectives or perhaps restrictions may be included in future models (e.g. skewness and kurtosis).
2. It is likely to choose only DMUs with at least moderately good performances for all measures and exclude those with good performances on only a subset. As this leads to the selection of a specialised portfolio comprising similar DMUs, it lacks diversification. As Tofallis (1996) demonstrated, in the event that two DMUs obtain the same variable degrees, they will use the same weights and increase each other's cross-efficiency ranking. If the remaining DMUs do not have similar variable degrees, they will be disadvantaged since they are separated in the cross-efficiency assessment. Consequently, either one or both DMUs might become the more efficient given that they successfully provide large ranks to one another. If one DMU's factor levels are very different from those of the others, it has significantly less potential to become efficient. This phenomenon is aggravated as the distribution of DMUs' locations is skewed which, again, leads to the selection of a specialised portfolio consisting of relatively similar DMUs that, in turn, lacks diversification.
3. For an in-depth view of risk, a Monte Carlo simulation consisting of an organised process of sensitivity investigation that clearly includes the uncertainties in methods, such as financial estimations or schedules, in which statistical computations often turn out to be complex or unrealistic when the quantity of tasks increases, might be employed (Cooper, Edgett, & Kleinschmidt, 2001). Rather than conducted as an examination, a Monte Carlo simulation may be applied like a random sampling

technique to approximate values. According to several approximated results and their specific likelihoods, such a simulation operates on many random, feasible what-if situations in an iterative loop to display possibilities. Its obtained outcome forms the technique's overall submission which is why it is very easy to understand (Schuyler, 2001).

4. As the quality of the outcomes of the DEA is dependent on its collected inputs/outputs, quality measures, such as satisfaction and/or awareness levels, may also be incorporated in the model. As the DEA uses a variety of inputs/outputs, collecting these parameters is a challenging task. Although this is referred to mainly as a DM's personal decision, as there may be better ways of selecting the input/output factors for an efficient examination, experts may establish a structure for this task.
5. As not every new portfolio can be implemented from development to closure, only those in the probability phases may be selected for further investigation. More research on the quality of a company's finances, resources and operating costs, and its capability to attract finance and returns on investment would be beneficial for determining the possibility of each project providing the prospect of obtaining future investment from the particular industry's market.

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ANNEX N – PUBLICATION V

COMPLEX PORTFOLIO DECISION MAKING: AN INNOVATIVE STRATEGIC PORTFOLIO MANAGEMENT TOOL

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ABSTRACT
Since the successful delivery of a portfolio depends on the quality of the decisions made while creating and managing it, organisations are searching for better decision support tools. Often, there are too many decision makers (DMs) in large organisations which may create diffused, and sometimes confused, decisions and lead to unstructured portfolios and poor selection and feedback mechanisms. To improve the effectiveness of portfolio decisions, a fundamental change is required to visualise their interdependencies and assist DMs in the selection of the most efficient projects/programs/investments. To capture the full extent of an organisation's portfolio, an executive management system called the Strategic Portfolio Management Tool (SPMT) is proposed as an alternative decision support system for DMs. It is an integrated model that combines the Portfolio Theory (PT), Analytic Hierarchy Process (AHP), and Data Envelopment Analysis (DEA) Cross-efficiency techniques, and simultaneously considers the profit, risks and proficiency of a portfolio. The test results obtained for an investment portfolio indicate that the proposed system is practicable and adoptable, and provides enhanced situational awareness and the capacity to quickly analyse and cross-examine information through existing dashboards and reports. SPMT identifies problems early in a portfolio's lifecycle so that timely remedial actions can be undertaken if necessary.

Keywords: Strategic Management and Leadership, Decision Support Systems, Project Portfolio Management, Multiple Criteria Decision Making, Data Fusion and Visualisation.

1. INTRODUCTION

The increasing difficulty of delivering capital programs in large organisations has also led to a focus on the more comprehensive and effective management of programs and portfolios (Prieto, 2008). The successful delivery of organisational objectives is significantly linked to the effective collection of projects in portfolios (Better & Glover, 2006; Bridges, 1999; Cooper, Edgett, & Kleinschmidt, 2000; Project Management Institute, 2006; Radulescu & Radulescu, 2001; Sommer, 1999). Organisation needs to choose options and projects using an adaptable decision-making practice (Bessant, Von Stamm, & Moeslein, 2011; Blichfeldt & Eskerod, 2008; Wheelwright, 1992; Wheelwright & Clark, 1992). The Decision Makers (DMs) need to incorporate different types of decision making methods considering the existing challenges within the project portfolio management (PPM). The issues regarding project, program and portfolio management highlighted in a number of studies (Artto, 2001a, 2001b; Danesh, Ryan, & Abbasi, 2016b; Rintala, Poskela, Artto, & Korpi-Filppula, 2004; Staw & Ross, 1987). These challenges can be addressed using Multi Criteria Decision Making (MCDM) methods.

Although PPM is currently a widely researched subject, specifically in the area of product development (Bible & Bivins, 2011; Cooper, Edgett, & Kleinschmidt, 2001), few studies have addressed the use of MCDM in PPM decision making. Although some research has been conducted in both the private and public sectors to determine the effects of different MCDM techniques on the success or failure of a decision

(Coles, 2012; Cooper, 1980; Defence & Black, 2011), little attention has been paid to usability issues in a real PPM experiment. Furthermore, while various MCDM techniques and tools have been studied for either ranking or classification purposes, only a few have actually been used for PPM (Ehrgott, Klamroth, & Schwehm, 2004).

Organisations have various means by which individual projects can be reported and analysed at the portfolio level. Portfolio assessments are reported through the organisational hierarchy up to the Senior Executive and then to the Corporate Committee. However, as the data used to report on projects/programs are derived from various source systems, there are usually many DMs with different opinions. Therefore, an organisation needs a simple but powerful decision support system to positively transform planned objectives into decisions. A system's functionality is related to its business functionality and efficiency as well as the quality of DMs' decisions. The capability to present proper instruction and management procedures is essential for businesses, without which, there is absolutely no obligation or, perhaps, appropriate portfolio decisions. In large organisations with many committees, a lack of clarity in responsibilities may lead to inadequate processes or judgements. How an organisation undertakes choices and the way in which they adopt them are important drivers of organisational functionality. The capability to transform organisational goals into successful decisions is a key aspect of a successful business. Therefore, the procedure a business employs to establish its decision process is the foundation of business governance while the quality of decisions has a significant influence on an organisation's capabilities in all its aspects.

There are some decision-support systems to manage decisions; however, most of those systems are intended to deal with specific characteristics, environments or problems at a specific industry. Moreover, the majority of organisations are searching for a decision-making system that could have the capacity to fulfil the specifications of different types of portfolio decisions. This study intends to support organisations with that requirement.

2. Research Gap

Although there are many portfolio management procedures and templates, they do not support a decision-making function for selecting efficient projects/programs and do not encourage the agile decisions required by a strategic portfolio management life cycle. Moreover, decision-making systems and their functionality have not been extensively discussed.

Instead of investigating the methods and tools through which judgements are made, most assessments focus on the procedures for organisational decision-making. Only a few studies have assessed methods for selecting a portfolio's efficient options, providing ways of presenting recommendations and options to DMs or investigating the possibility of generating options and reports to track a portfolio's final results; for example, the ISO9000 Standard clearly describes good management practice but does not state how procedures and controls should be operated. It is very flexible and designed to be tailored to suit an organisation, recognising variations in its portfolios, programs and projects. A major function of a decision-making process is to provide greater efficiency and ensure that the quality of the system is properly maintained and continually developed. Therefore, a decision-support system that can outline the key elements of a portfolio noting that, by definition, each project will be different, is required.

As the majority of large organisations have complex portfolio management systems with their own strengths and weaknesses, there is concern about the need for a highly effective strategic decision-making system. Existing systems are under pressure and their lack of a capability to fully deal with portfolio challenges impacts on businesses' reputations and may result in poor outcomes. Current situations can consist of delivery problems for projects, inadequate procurement judgements, and poor budget management and decision making when handling daily activities. Moreover, current portfolio agreements increase executives' management strengths by limiting a DM's capability to manage portfolio decisions and performance in selecting projects/programs. This will probably impact on the visibility of the supervision and perhaps monitoring of projects/programs under investigation in a total portfolio.

Therefore, for several reasons, strategic portfolio management and decision-support systems should become more responsive, effective and easier to use. As improvements in a portfolio's efficiency and decision making will help to eliminate its risks, an effective decision-making system is required to assist DMs.

3. AIM

This study aims to propose a decision-making model that supports individuals in setting specific, measurable, achievable and relevant decision outcomes. It applies an integrated Multi-Criteria Decision Making (MCDM) method for the Project Portfolio Management (PPM) that highlights errors as soon as they arise in a portfolio and provides the appropriate information to the DMs responsible to assist them in decision making. It also aims to provide DMs with a tool they can use to view both summary and detailed data to help them interpret and understand the constituent elements (projects/programs/investments) of a portfolio. This new tool will provide a clear and timely understanding of emerging issues and risks in the delivery of a portfolio by highlighting them so that organisations can respond in an effective, efficient and coordinated manner to guide remedial actions. This will provide organisations with the capability to receive timely and specific identification of significant exceptions, make suitable decisions and then manage effective remediation with the support of senior management. In keeping with the primary goal of this study, the focus is on highlighting underperforming projects/programs/investments in a portfolio. By identifying and remediating issues early in its life cycle, the proposed tool aims to prevent a portfolio from becoming a matter of concern.

This study will not provide DMs with the business logic and portfolio methodology for interpreting the data presented in the new decision making system. An in-depth review of PPM, MCDM methods and the proposed integrated PPM MCDM approach are provided in studies conducted by Danesh et al. (2016a; 2016b; 2016c).

4. PROPOSED DECISION SUPPORT SYSTEM

4.1. AN OVERVIEW

The first step in assessing an organisation's functions is to select an appropriate assessment model and present the results comprehensively to assist DMs to accurately examine the functions. Inadequate data management along with the insufficient use of decision-making methods and the lack of visibility and transparency of the cost and risk, significantly impacts on the portfolio's final results. Although these visibilities are critical when the presentation of projects/programs/investments is required to demonstrate portfolio efficiency, there is still no effective decision-making tool.

Although many organisations have tried to deal with these issues, they are limited by highly complicated methods for estimating portfolio efficiency. Consequently, there are no really effective systems for comprehensively providing decision options to DMs for simultaneously applying to a model portfolio's challenges, risks, profits and efficiencies of its projects/programs/investments. Therefore, systems intended to be primarily for PPM decision making still have problems with a lack of information and direction which means that they are of little use in practice. Similarly, there are only a few decision-making applications that can assist in the collection of information and suggesting decision options to DMs. In fact, it seems that organisations concentrate more on data administration than decision supervision. Considering the current complications in the information setting processes of most complex organisations and the requirement to rationalise the considerable amounts of individual decision applications used in a variety of portfolios equally, little work has been conducted recently on developing comprehensive decision-making applications or finding effective supervision processes for determining decision options.

Decision-making methods must recognise that an organisation's services are seen collectively and strive for organisational cohesion. However, current decision-making applications do not present a simple preference system or decision path that can easily extend from a portfolio to operational (project/investment) level. Organisations could establish more robust portfolio decision-making and proper portfolio decision options through the following approaches.

1. Having committees with individual ownership focused on supporting DMs' liability.
2. Having a suitable MCDM methodology for PPM.
3. Establishing a mechanism for improving the quality of key decisions in a non-adversarial way by visualising and estimating portfolio variables for the efficient assessment of options.

This study begins with the premise that any new decision-support approaches for dealing with the current challenges must fulfil the following specifications.

- A new model should assist the development of a portfolio structure that consistently and carefully immediately identifies the cause of inefficiency.
- A new model should be simple and transparent in relation to determining which projects/programs/investments are efficient in a portfolio.
- The system must be capable of providing a structure for comparing, ranking and weighting data and distributing these findings and data over multiple departments to receive contextual information collected from several sources including divisions, PMO offices and Head Offices. This information will then enable a de-centralised distribution algorithm to make decisions on exactly how the framework is allocated over the areas.
- A new model must provide the best possible, clear and simple decision-making structure by providing the correct data for DMs to enable them to guarantee efficient decisions in portfolios with large numbers of variables and difficult selection options.

4.2. Strategic Portfolio Management Tool (SPMT)

Data visualisation is a powerful format for presenting data to assist both strategic decision making and DMs to manage their portfolios more comprehensively. An executive project portfolio dashboard can demonstrate complicated components of selected issues in an organisation in a simple and highly effective manner (Meyer, 1991). A mixture of DMs' abilities and visual representations of information can provide a powerful perspective of the decision issue which will help to improve PPM decision making. Data visualisations have been proven to improve the examination and data, and strategic thinking and planning processes (Mikkola, 2001; Warglien & Jacobides, 2010). As stated by Ware (2005): '*the power of a visualisation originates from the idea that it is likely to have a far more complex concept structure represented externally in a visual display rather than might be organised in visual and verbal working memories'*.

Recent studies have found that data visualisation can assist in both the consideration and maintenance of strategic data (Kernbach & Eppler, 2010). Advancements in information technology and computer science, especially software-based tools, have provided many new options for collecting and presenting information (Dansereau & Simpson, 2009). Computer-based applications with visual interfaces, such as pattern finding, incorporate the advantages of methods with DMs' ideas (Tergan & Keller, 2005).

As few studies explain the application of PPM data visualisations, more research is required to identify how PPM MCDM selection methods are applied in reality and what forms of visualisation enhance decisions.

4.3. SPMT Overview

The SPMT is a decision-support system designed specifically to assist DMs in complex portfolio decision making. It maps all portfolios' alternatives and compares them to identify their efficiency scores. It highlights the business need to provide DMs and project personnel with clear metrics to track the performances of their projects/programs in a portfolio in terms of the organisation's goals and policies. Subsequently, it is used to assist DMs to select the most efficient projects/programs/investments for a portfolio.

The SPMT is an agile, enterprise-wide, decision-support management tool. It supports evidence-based decision making by giving DMs the ability to manage and share decisions about projects/programs during a portfolio's life cycle. As the authoritative source of information on an organisation's projects, it helps executives manage this life cycle by providing situational awareness (decision options) to DMs and other stakeholders in an organisation. It is a customised tool developed on the basis of the integrated PPM MCDM method presented in a study conducted by Danesh et al. (2016c). It also supports situational awareness at portfolio levels by aggregating data across projects/programs and providing a narrative regarding the development of an appropriate business case and stakeholder commentary during various stages in the process.

4.4. SPMT GOAL

The primary goal of the SPMT is to serve as the central source of truth for the management of portfolio data and selection of suitable projects/programs/investments for management personnel at all levels using an integrated PPM MCDM model. Figure 1 summarises the effects expected to be supported by the SPMT and the mechanisms that will facilitate them.

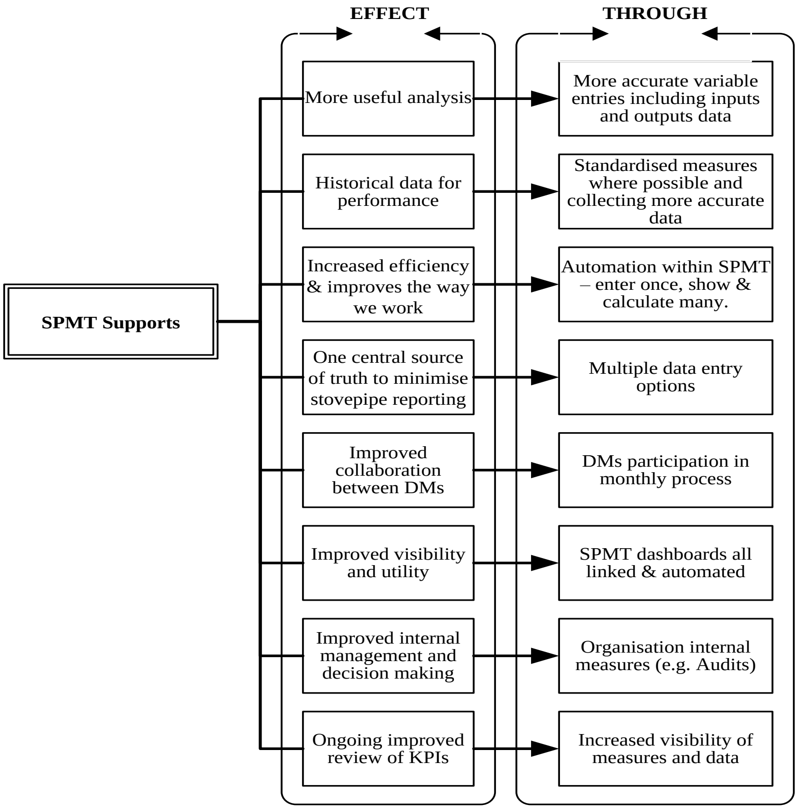

Figure 1. EXPECTED EFFECTS OF SPMT

4.5. SPMT STRUCTURE

The SPMT system requires a set of performance criteria against which projects/programs can be measured. Based on them, any inefficient projects/programs that exceed performance thresholds are reported to senior stakeholders. SPMT provides DMs with collaborative opportunities and increases the visibility of a portfolio's performance. The SPMT requires engagement with a wide range of stakeholders, such as:

- project/program/investment management teams for project/product/investment updates;
- a senior leadership team for clearance of the report;
- external stakeholders for pre-committee consultations at the working level; and
- organisational investment committee members for final clearance.

The SPMT defines the weights of each project/program/investment in a portfolio on a weekly basis (as the default) and offers the opportunity for DMs to review and provide input to the review process. In a mega-portfolio, each sub-portfolio/program measure can be assigned to a single DM (a subject-matter expert) who is responsible for that month's performance. DMs can also review the data, make decisions in groups, discuss or change these decisions and develop overall Key Performance Indicators (KPIs).

The SPMT seeks to meet the diverse needs of all stakeholders during the portfolio management process through a series of dashboards which aim to summarise the portfolio's performance. These dashboards are generated via the data entered by the DMs and their service partners. They are introduced into the SPMT to provide DMs with a brief snapshot of a portfolio's current performance. The SPMT helps DMs determine exactly which challenges should be expected regarding a portfolio's performance and details the options for resolving them which leads to the recommendation of further examination. Figure 2 presents the structure of the proposed SPMT decision-support system.

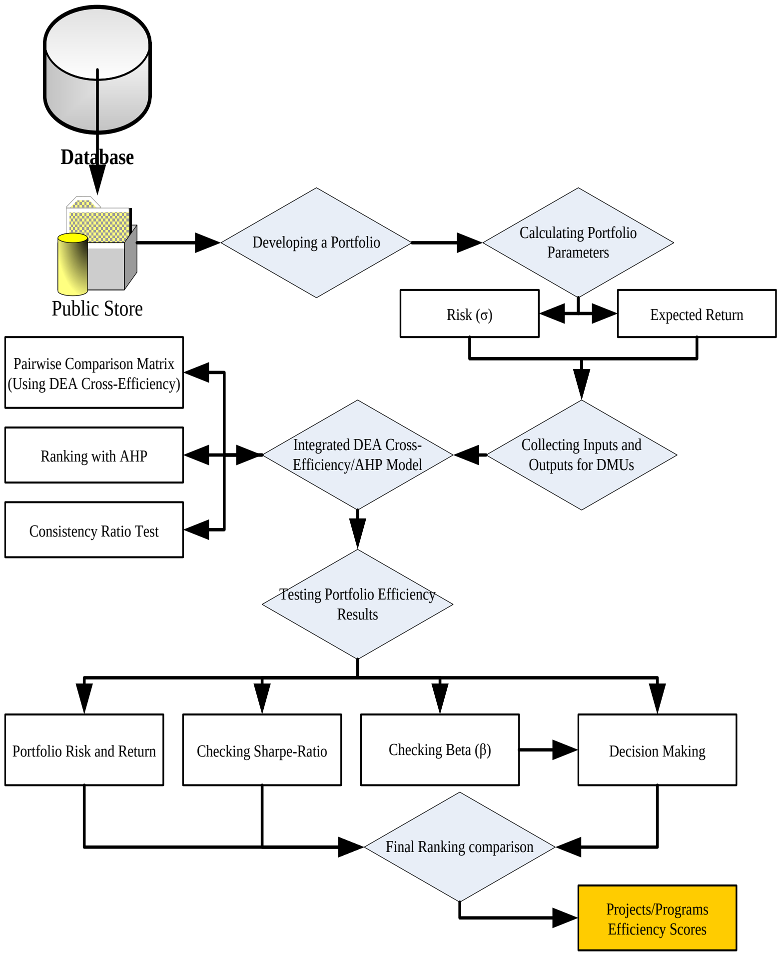

Figure 2. FLOWCHART OF SPMT DECISION PROCESS

5. CASE STUDY

The proposed SPMT decision-support system is based on the processes described in Figure 2 which prioritise the efficiency of DMUs for selecting the appropriate projects/programs/investments in portfolios as follows.

In the first step, the data required to create a portfolio of several DMUs are collected, with the primary source for the SPMT the Yahoo (2016) finance reporting system which includes weekly/monthly online reporting and projects/programs values. These data are populated every day and can be classified and modified by the relevant assets or country codes before being used in the system and, if required, be inserted manually.

Using the PT method of Markowitz (1952), the expected return (on investment) and risk are identified to calculate a portfolio's parameters. Two criteria, the expected return and variance, are used to rank the efficiency levels of DMUs and a pair-wise comparison matrix formed using the modified DEA cross-efficiency assessment presented in Danesh et al. (2016c). This integrated method is then applied through three phases. Phase 1 develops a pair-wise comparison matrix and then, in Phase 2, all the DMUs are ranked using the AHP method proposed by Saaty (1980) and a new normalised matrix generated using the AHP model. To ensure that the information is similar across assessment and in units, and there is no misalignment in the information collected, the AHP is able to balance the data with a mean normalisation of them conducted in the same phase. Then, a consistency test is carried out in Phase 3 using the AHP method to identify the objectivity of the results. By multiplying the expected return values by their weights and then summing them, the system identifies the actual portfolio return. Likewise, the connection between the asset and market returns (β factor) and *SR* is determined using the PT method. Finally, the DMs can review the portfolios and trade-off between the levels of return and the risk of the portfolio according to the efficiency score to select the portfolio with the highest efficiency and return level and minimum risk. A detailed explanation of the integrated PPM MCDM method used to develop SPMT is available in the study conducted by Danesh et al. (2016c).

To test the applicability of the new system, the top five largest portfolios presented in the Dog-of-the-Dow (2016) for the 2015-2016 year are selected to identify the most efficient. A list of the portfolios used in this case study presented in Table 1 and the related financial data (from 02 January 2015 to 28 December 2015) in Table 2.

Table 1. PROGRAM NAMES (2015-16)

	Program Name	**Synonym**
1	Apple	AAPL
2	Alphabet	GOOGL
3	Microsoft	MSFT
4	Berkshire Hathaway	BRK-A
5	Amazon.com	AMZN

Table 2. PORTFOLIO DATA (PERIOD 02 JAN 2015 TO 28 DECEMBER 2015)

Date	AAPL	GOOGL	MSFT	BRK-A	AMZN	S&P 500
2/01/2015	109.33	529.55	46.76	223600	308.52	2058.2
5/01/2015	112.01	500.72	47.19	224675	296.93	2044.81
12/01/2015	105.99	510.46	46.24	223615	290.74	2019.42
20/01/2015	112.98	541.95	47.18	223751	312.39	2051.82
26/01/2015	117.16	537.55	40.4	215865	354.53	1994.99
2/02/2015	118.93	533.88	42.41	224880	374.28	2055.47
9/02/2015	127.08	551.16	43.87	222555	381.83	2096.99
17/02/2015	129.5	541.8	43.86	223100	383.66	2110.3
23/02/2015	128.46	562.63	43.85	221180	380.16	2104.5
2/03/2015	126.6	572.9	42.36	218811	380.09	2071.26
9/03/2015	123.59	553	41.38	217118	370.58	2053.4
16/03/2015	125.9	564.95	42.88	218300	378.49	2108.1
23/03/2015	123.25	557.55	40.97	217000	370.56	2061.02
30/03/2015	125.32	541.31	40.29	216500	372.25	2066.96
6/04/2015	127.1	548.54	41.72	215211	382.65	2102.06
13/04/2015	124.75	532.74	41.62	212982	375.56	2081.18
20/04/2015	130.28	573.66	47.87	214490	445.1	2117.69
27/04/2015	128.95	551.16	48.66	215800	422.87	2108.29
4/05/2015	127.62	548.95	47.75	222880	433.69	2116.1
11/05/2015	128.77	546.49	48.3	218640	426	2122.73
18/05/2015	132.54	554.52	46.9	217000	427.63	2126.06
26/05/2015	130.28	545.32	46.86	214800	429.23	2107.39
1/06/2015	128.65	549.53	46.14	211560	426.95	2092.83
8/06/2015	127.17	547.47	45.97	210760	429.92	2094.11
15/06/2015	126.6	557.52	46.1	212200	434.92	2109.99
22/06/2015	126.75	553.06	45.26	209900	438.1	2101.49
29/06/2015	126.44	547.34	44.4	205923	437.71	2076.78
6/07/2015	123.28	556.11	44.61	209800	443.51	2076.62
13/07/2015	129.62	699.62	46.62	215960	483.01	2126.64
20/07/2015	124.5	654.77	45.94	212032	529.42	2079.65
27/07/2015	121.3	657.5	46.7	214000	536.15	2103.84
3/08/2015	115.52	664.39	46.74	215463	522.62	2077.57
10/08/2015	115.96	689.37	47	213981	531.52	2091.54

17/08/2015	105.76	644.03	43.07	202500	494.47	1970.89
24/08/2015	113.29	659.69	43.93	205344	518.01	1988.87
31/08/2015	109.27	628.96	42.61	196501	499	1921.22
8/09/2015	114.21	655.3	43.48	198329	529.44	1961.05
14/09/2015	113.45	660.92	43.48	192200	540.26	1958.03
21/09/2015	114.71	640.15	43.94	194620	524.25	1931.34
28/09/2015	110.38	656.99	45.57	195500	532.54	1951.36
5/10/2015	112.12	671.24	47.11	199650	539.8	2014.89
12/10/2015	111.04	695.32	47.51	200469	570.76	2033.11
19/10/2015	119.08	719.33	52.87	206584	599.03	2075.15
26/10/2015	119.5	737.39	52.64	204596	625.9	2079.36
2/11/2015	121.06	761.6	54.92	203100	659.37	2099.2
9/11/2015	112.34	740.07	52.84	197825	642.35	2023.04
16/11/2015	119.3	777	54.19	204600	668.45	2089.17
23/11/2015	117.81	771.97	53.93	201624	673.26	2090.11
30/11/2015	119.03	779.21	55.91	204500	672.64	2091.69
7/12/2015	113.18	750.42	54.06	195757	640.15	2012.37
14/12/2015	106.03	756.85	54.13	194720	664.14	2005.55
21/12/2015	108.03	765.84	55.67	201137	662.79	2060.99
28/12/2015	105.26	778.01	55.48	197800	675.89	2043.94

As all the programs presented in this case study are US-based, unlike the case study conducted by Danesh et al. (2016c), it uses the 10Y US Treasury yield (Government, 2016) at the end of 2015 (2.24% as at 28/12/2015) and divides it by the number of weeks in a year to obtain a weekly risk-free return.

Snapshots of the SPMT reports, including the efficiency results for the programs studied, are presented in Table 3, Table 4, Table 5 and Figure 3.

Table 3. Portfolio Parameters

Program	Budget $ (end 2015)	Number of Projects	Position $	Share in portfolio
AAPL	$105.26	30871100	$3,249,492,048	37.02%
GOOGL	$778.01	1634200	$1,271,423,958	14.49%
MSFT	$55.48	24605900	$1,365,135,332	15.55%
BRK-A	$197800	300	$59,340,000	0.68%
AMZN	$675.89	4188900	$2,831,235,684	32.26%
Portfolio			**$8,776,627,022**	**100.0%**

Table 4. Portfolio Inputs and Outputs

DMUs	Program	Input (σ^2)	Output (Re)
1	AAPL	1.345621	-0.069013
2	GOOGL	2.195640	8.417433
3	MSFT	1.763206	4.157062
4	BRK-A	0.406220	-2.154931
5	AMZN	2.074424	16.164779

Programs	Share in portfolio	Expected return (Re)	Risk (σ)	Sharpe ratio (SR)	Beta	Efficiency
AAPL	37.02%	-0.007%	3.668%	-0.013	1.331	-0.0059
GOOGL	14.49%	0.842%	4.686%	0.171	1.400	0.4443
MSFT	15.55%	0.416%	4.199%	0.089	1.581	0.2733
BRK-A	0.68%	-0.215%	2.015%	-0.128	0.817	-0.6149
AMZN	32.26%	1.616%	4.555%	0.346	1.077	0.9032
Portfolio		**0.704%**	**3.31%**	**0.200**	**1.301**	**1.000**
S&P index		**0.004%**	**1.89%**	**-0.020**		

Figure 3. Portfolio Results

Table 5. Portfolio Ranking Scores

Programs	Expected return (Re)	Risk (σ)	Sharpe ratio	Efficiency
AAPL	4	2	4	4
GOOGL	2	5	2	2
MSFT	3	3	3	3
BRK-A	5	1	5	5
AMZN	1	4	1	1

5.2. Results

The results shown in Figure 3 and Table 5 illustrate that four programs have lower performance scores than AMZN in our portfolio.

To gain a sense of the efficiency scores and the level of improvement applied to this portfolio, a chart is generated using Yahoo (2016) for the period of this case study (2015-2016). All five programs are included to demonstrate how well the proposed system can estimate the efficiency scores while suggesting future necessary improvements and adjustments to the portfolio.

Figure 4 clearly shows that the program efficiency orders in this chart are identical to the results presented in Table 5.

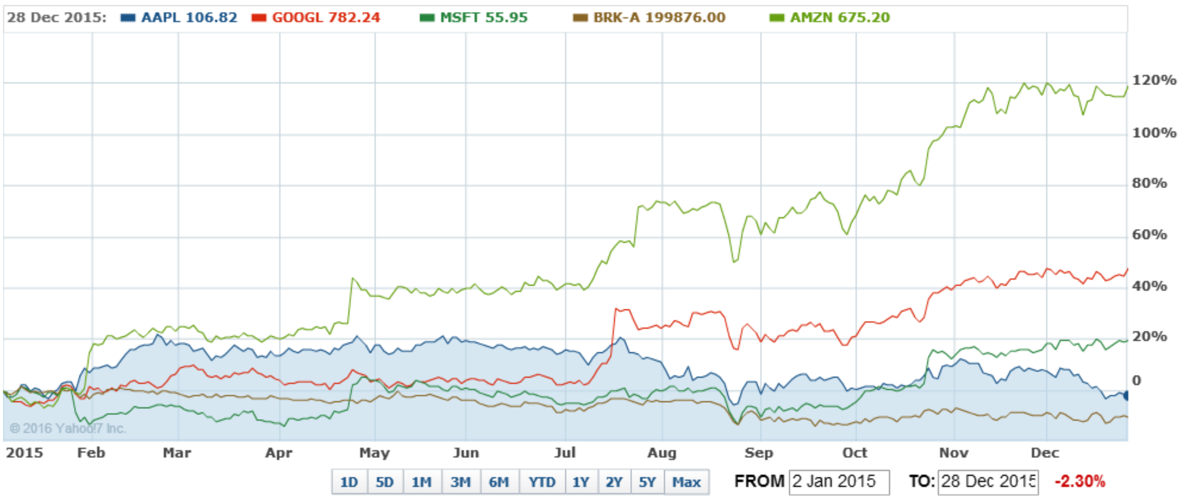

Figure 4. Portfolio Comparison Chart (Period 2/1/2015 to 28/12/2015)

In Figure 3, the SPMT identified that the lowest SR of -0.128 and lowest Beta value of 0.817 belong to the BRK-A program, the AMZN program has the largest SR value of 0.346 and the MSFT program has the largest Beta value of 1.581. As a result of these investigations and to improve the existing portfolio, the number of projects in the BRK-A program is reduced while those in the AMZN and MSFT programs are increased.

To check the accuracy of the decision and changes made to improve the portfolio in 2015, a chart comparing all five programs is generated for 2016 using Yahoo (2016). The results show that the three programs improved in 2016 (AMZN, BRK-A and MSFT) are among the top three programs in the portfolio. Therefore, the proposed SPMT is fully capable of selecting the programs that require improvement; for example, while the BRK-A program is ranked fifth in the 2015 portfolio, it is the second most efficient program in 2016. It can be concluded that the decision option proposed by SPMT, suggesting the adjustment in the number of projects in the BRK-A program in 2015 to improve it in 2016, is completely correct, accurate and necessary to improve the entire portfolio. This SPMT recommendation also ensured that the AMZN and MSFT programs remained among the top three most efficient programs in the 2016 portfolio. Figure 5 shows a comparison of the portfolios of all five programs in 2016, including their performance orders.

Figure 5. PORTFOLIO COMPARISON CHART (PERIOD 4/1/2016 TO 23/11/2016)

6. CONCLUSION

To efficiently perform PPM, organisations should revise their strategies and prioritise their targets in their business plans to make good portfolio decisions. They should map their candidate programs/projects/investments to the objective(s) and prioritise them against all other portfolio elements. The evaluation and comparison of an organisation's portfolios must be conducted effectively and the results represent a correct picture of their performances.

This study tried to improve the way in which organisations select major projects/programs/investments in a portfolio, including improvements to their decision-making systems to strengthen the connection between their objectives and decision functionality as well as enhance their cost estimations. The proposed system not only reduces the amount of effort required to reduce portfolio expenses but is more focused on providing a better decision capability at a lower cost by enhancing the PPM decision making and selection processes to eliminate waste.

SPMT provides a simple approach for improving portfolio decisions in an organisation and generates major savings options for reinvesting to establish a highly effective organisation which are crucial for guaranteeing the delivery of organisational targets.

SPMT enables DMs to work smarter rather than harder and can generate automatic reports via the click of a button. It provides valid and verifiable decision information through several reports and dashboards. DMs can easily generate management, project, program and portfolio reports on a range of issues, such as risks and benefits, using historical data, decision scores and funding. This improves situational awareness, facilitates the analysis and presentation of information, and supports timely and informed decision making at the project, program and portfolio levels. A SPMT system can provide valuable information to support portfolio management decisions, such as: project/program risks and issues, benefits, funding, and project dependencies. It can deal with a very large number of DMUs and takes the interdependencies of the criteria into account based on the weight of each criterion during the evaluation process, and supports both quantitative and qualitative information. Most importantly, it can handle both positive and negative data, an option not available in most decision-support systems. It can also drive organisational improvements through increasing performance transparency and improving decisions in project/program reporting to senior stakeholders, combining improved data quality with more independent analyses, and focusing on improving collaboration between DMs and their end-users.

SPMT provides a reliable direction for portfolio management which can present the main cost and risk factors. It can simply enhance PPM decisions to establish superior processes for selecting projects with greater possibilities of returning benefits. It can present the best possible portfolio advice based on which organisations can select the best projects/programs in which to invest their money. The proposed system guarantees the facilitation of data and appropriately enables DMs to generate the most suitable decisions regarding an organisation’s capital investments. SPMT applies the most suitable PPM methods for minimising waste, selecting efficient projects/programs, boosting portfolio delivery and decreasing the cost of risk.

SPMT provides DMs with greater authority to manage their portfolios by applying an integrated MCDM approach that improves decision-making options. It offers DMs adequate rankings, vision and power to adjust and modify a standard portfolio to select the most suitable projects/programs and reduce an organisation’s costs.

The proposed method by Danesh et al. (2016c) can function very well using the proposed tool (i.e., SPMT) and is capable of dealing with a large number of projects and variables. Also, negative data can be applied to it and there is no limit regarding different decision criteria and options. SPMT can produce specific project/program-related profit benchmarks, generate portfolio efficiency scores and illustrate those findings in different reports. The proposed decision tool can simply present PPM performances and determine projects/programs that are not functioning well. By including the applicable values and advantages of every project/program, DMs are able to immediately recognise those with higher efficiency with their levels of risk and benefits. Using these capabilities, DMs can make innovative and practical decisions regarding the essential modifications of and corrections to a portfolio.

7. FUTURE WORK

SPMT identifies projects/programs/investments at the portfolio level. If any other sub-projects within it are deemed reportable, investigations are required by the business to adjust any anomalies. A SPMT solution will enable DMs to adjust the number of projects/programs/investments in a portfolio and it is also beneficial to add comments to their performance reports which include cost and/or schedule variations.

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