Identification and selection of continuous improvement projects

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Identification and Selection of Continuous Improvement Projects

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A Thesis in Fulfilment of the Requirements for the Degree of
Doctor of Philosophy

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For Emma and Rachael

קְנֹה חָכְמָה מַה טּוֹב מֵחָרוּץ וּקְנוֹת בִּינָה נִבְחָר מִכָּסֶף׃

“How much better is it to acquire wisdom than gold!
And to acquire understanding is preferable to silver.”

Proverbs 16:16

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Manufacturing organisations must routinely deliver efficiencies in order to remain competitive. Many have embraced continuous improvement methodologies, such as Lean manufacturing and Six Sigma in order to achieve these goals. However their ability to realise sustainable competitive advantage from continuous improvement is hampered by the lack of structured objective approaches for optimal project portfolio selection that link strategy to targeted improvement efforts. As a consequence, scarce resources are inappropriately allocated, opportunities are lost and there is sub-optimisation of the system as a whole.

There are three gaps in the extant literature (i) the majority of published methodologies begin with a finite set of explicitly defined alternatives and attempt to maximize the portfolio outcomes without any definition of an optimized future state, (ii), portfolios are limited to choices from an a priori set of alternatives and are therefore unlikely to result in an optimal outcome and (iii) the extant methodologies generally do not include appropriate measurement to judge outcomes. Furthermore, there are significant limitations to the approaches used by industry for project selection and a degree of dissatisfaction with the methodologies employed. The most significant of these is the gap between strategy formulation and portfolio generation. A normative framework that should be used to structure project portfolio methodologies is therefore presented.

To resolve these issues, a scalable generic methodology for visualizing and evaluating optimal future states and to evaluate projects and portfolios of projects in the context of those future states is presented. The methodology described employs Multiscale, Object Oriented Modelling and Simulation with Optimal Design of Experiments to create *n*-dimensional Pareto Frontiers from the set of all feasible production outcomes within given manufacturing configurations and for given strategic scenarios.

The utility of the methodology is demonstrated in three exemplars: a simple manufacturing facility, a more complex manufacturing facility and a multi-site region comprised of thirteen factories across six countries. For each exemplar, we demonstrate the Pareto Frontier, current performance and Pareto Optimal outcomes.

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Abbreviations Used in this Thesis

Abbreviation	Meaning
3NF	Third Normal Form
3ONF	Third Object Normal Form
A3	Refers to the ISO A3 paper size of a plan on a page or problem on a page
AHP	Analytical Hierarchy Process
AICc	Corrected Akaike's Information Criterion
ANZSIC	Australian New Zealand Standard Industrial Classification
API	Application Programming Interface
AU or AUST	Australia
BIC	Bayesian Information Criterion
BOM	Bill Of Materials
BSC	Balanced SCorecard
CCD	Central Composite Design
CoT	Change over Time
Cp	Mallow's Cp criterion
CTQ	Critical To Quality
DES	Discrete Event Simulation
DF	Degrees of Freedom
DFE	Degrees of Freedom
DMU	Decision Making Unit
DoE	Design of Experiment
ERD	Entity Relationship Diagram
ERP	Enterprise Resource Planning

Abbreviation	Meaning
ESAT	Enterprise Strategic Analysis for Transformation
EVSM	Enterprise Value Stream Map
EVSMA	Enterprise Value Stream Mapping and Analysis
FCFS	First Come First Served
FG	Finished Goods (inventory)
FY	Financial Year
GD	General Discipline
GUI	Graphical User Interface
H	Kruskal-Wallis test statistic
HDPE	High Density PolyEthylene
IDEF3	Integrated DEFinition for process description capture
JIT	Just In Time
LAI	Lean Advancement Initiative
MADM	Multiple Attribute Decision Making
MCDM	Multiple Criteria Decision Making
MIT	Massachusetts Institute of Technology
MODM	Multiple Objective Decision Making
MTTF	Mean Time To Fail
MTTR	Mean Time To Repair
n	Sample size
n_1	Sample size one
n_2	Sample size two
OEE	Overall Equipment Effectiveness
OOM	Object Oriented Modelling
p	p value
P&L	Profit & Loss
PE	PolyEthylene
PF	Pareto Frontier
PROMETHEE	Preference Ranking Organization METHod for Enrichment Evaluation
PS	Pareto Set

Abbreviation	Meaning
PVC	Poly Vinyl Chloride
QFD	Quality Function Deployment
R^2	Coefficient of determination
R^2 Adj	Adjusted R2
Redx	Red X also known as Shainin
RM	Raw Materials (inventory)
RMSE	Root Mean Square Error
ROW	Rest Of World
RSD	Response Surface Design
RSM	Response Surface Map
RTY	Rolled Throughput Yield
S	The non-empty feasible set
SCADA	Supervisory Control And Data Acquisition
SKU	Stock Keeping Unit
SME	Small to Medium Enterprise
SMED	Single Minute Exchange of Die
SQL	Structured Query Language
SSE	Sum of Square Error
SSM	Scale Separation Map
TQM	Total Quality Management
UNSW	University of New South Wales
VSM	Value Stream Map
W	Mann-Whitney test statistic
WIP	Work In Process (alternatively Work In Progress) (inventory)

Symbols Used in this Thesis

Symbol	Meaning
	Factory
	Data flow
	Material flow
	Transport (by truck)
	Inventory
	Process
	Process Parameters
—	Process value-added
—	Process non value-added
○	None
◔	Some (qualitative)
◑	Half (qualitative)
◕	Most (qualitative)
●	All (qualitative)
χ^2	Chi-squared
$\forall$	For all
$\exists$	There exists
$\nexists$	There does not exist
$\exists!$	There exists exactly one
$\rightarrow$	From … To Thus: $f: x \rightarrow y$ means the function f maps the set x into the set y.
iff	If and only if
$\wedge$	And

Symbol	Meaning
$\mathbb{R}$	The set of real numbers
$\mathbb{R}_+$	The set of positive real numbers
$\mathbb{R}^n$	*n*-dimensional space in $\mathbb{R}$
$\mathbb{Z}$	The set of integers
$\mathbb{Z}^n$	*n*-dimensional space in $\mathbb{Z}$
$\prec$	Is dominant
	Thus: $x_a \prec x_b$ means that the decision vector x_a is dominant over decision vector x_b
$\succcurlyeq$	Is not dominant or is equivalent
$\subset$	Proper subset
$\in$	Is an element of
$! =$	Not equal
$\neq$	Not equal
x^*	Strict Pareto Optimum

Software Used in this Research

Software	Version
AnyLogic®	AnyLogic® University 6.9.0 Build: 6.9.0.201303151330
Eclipse®	Eclipse® Standard/SDK Version: Kepler Service Release 2 Build id: 20140224-0627
Java®	Java® SE 1.6.0_65-b14-462-11M4609
JMP®	JMP® 11.0.0
Matlab®	Matlab® R2013b
MySQL®	MySQL® Community 5.5.28
MySQL® Workbench	MySQL Workbench 6.1 Version 6.1.4.11773 build 1454 Community
Navicat® for MySQL®	Navicat® for MySQL® non-commercial Version 10.1.2
OS X®	OS X® 10.9.4 (13E28)
SPSS®	Release 21.0.0.0

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בָּרוּךְ אַתָּה יְיָ אֱלֹהֵינוּ מֶלֶךְ הָעוֹלָם, שֶׁהֶחֱיָנוּ וְקִיְּמָנוּ וְהִגִּיעָנוּ לַזְּמַן הַזֶּה.

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Publications

The following publications arose as a result of this research project:

1. Kornfeld, B. J. & Kara, S. (2011) "Project Portfolio Selection in Lean and Six Sigma," *International Journal of Operations & Production Management*, vol. 31, no. 10, pp. 1071–1088, 2011. [1]
   Cited by [2-5]

2. Kornfeld, B. J. & Kara, S. (2013) "Selection of Lean and Six Sigma Projects in Industry," *International Journal of Lean Six Sigma*.[6]
   Cited by [2,7,8]

3. Kornfeld, B. J., & Kara, S. (2013). "A Framework for Developing Portfolios of Improvements Projects in Manufacturing". *Procedia CIRP*. [9]
   Presented at the 46th CIRP Conference on Manufacturing Systems in Setúbal, Portugal.
   Cited by [2]

4. Kornfeld, B. J., & Kara, S. (2014) Generating Pareto Optimal Improvement Portfolios. Submitted for publication.

5. Kornfeld, B. J., & Kara, S. (2014). Pareto Optimal Improvement Portfolios at Factory and Enterprise Scales. Submitted for publication.

Figure 1: “It takes all the running you can do, to keep in the same place.” [10]

Abstract

Manufacturing organisations must routinely deliver efficiencies in order to remain competitive. Many have embraced continuous improvement methodologies, such as Lean manufacturing and Six Sigma in order to achieve these goals. However their ability to realise sustainable competitive advantage from continuous improvement is hampered by the lack of structured objective approaches for optimal project portfolio selection that link strategy to targeted improvement efforts. As a consequence, scarce resources are inappropriately allocated, opportunities are lost and there is sub-optimisation of the system as a whole.

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The utility of the methodology is demonstrated in three exemplars: a simple manufacturing facility, a more complex manufacturing facility and a multi-site region comprised of thirteen factories across six countries. For each exemplar, we demonstrate the Pareto Frontier, current performance and Pareto Optimal outcomes.

1: Introduction

Continuous Improvement

Manufacturing organisations must routinely deliver efficiencies in order to remain competitive. In many cases the fundamental edict of the annual budgeting process is to offset inflation and depreciation growth with productivity improvements, an effort that would require the organisation to improve even to maintain the status quo (Figure 1). To achieve these outcomes, managers often rely upon structured continuous improvement methodologies.

Over the past three decades at least a dozen continuous improvement movements have come and gone with only a few enjoying any degree of longevity in industry practice [11-14]. Those notable exceptions - Six Sigma and Lean Production - have almost certainly survived because they introduced new and simple formalisms to existing principles. In the case of Six Sigma, most of the underlying tools were already present when it was first developed at Motorola in 1986 [12,15]. Since its inception, Six Sigma has been applied broadly in manufacturing, logistics and service industries [12]. One likely contributor to Six Sigma's widespread appeal is it's simple, yet disciplined logical structure, which can be easily followed by the initiate to arrive at an improved process state.

'Lean Production' also encompasses a range of manufacturing concepts with a long heritage [16]. By the time Krafcik [17] and Womack et al [18] popularised the term there was already a wealth of literature on the subject (for example: Just In Time (JIT) manufacturing: [19-22]; Toyota Production System (TPS): [23-25]). Nevertheless Womack's book, along with others from the International Motor Vehicle Program (IMVP) at MIT, "played a key role in disseminating the concept [of JIT] outside of Japan" [26,27] by formalising a number of concepts under one system.

Despite anecdotal support regarding the benefits of individual continuous improvement projects and programmes on firm performance, there are indications that many programmes do not deliver the expected results at an organisational level [11,13,14,28-30]. Most failure presumably goes unreported, however there is some evidence to suggest that many improvement efforts produce local optima, do not deliver expected results, or do not even yield a positive cost benefit [31].

An examination of the root causes for these failures indicates that many organisations have neglected to take a holistic approach towards continuous improvement [32], overcomplicated their approach [33], or inappropriately applied improvement techniques [34]. As a result, they have failed to focus on the right activities and thus have not achieved their strategic intent [35,36]. If we are to realise the full potential of continuous improvement, we must begin by asking 'how are projects selected' and 'how are they linked to business strategy'?

Project Selection in Continuous Improvement

Organisations execute strategy via a process that translates the overall strategic objectives and themes into patterns of action, or portfolios of coherent initiatives, designed so as to preserve the overall strategic intent [37] and thereby maximise the potential outcomes for the organization as a whole. Since it is generally not possible to implement all initiatives simultaneously, organisations must inevitably select a subset of the available options and then manage the resultant portfolio of projects. Zhang et al. suggested that strategic portfolio selection and project management can positively impact organizational performance [38] and thus decisions that are made during this part of the process can have a substantial impact on whether strategic outcomes are realised or not [39].

Continuous improvement is not merely an operational consideration it also fulfils strategic requirements. Operations managers must therefore give appropriate consideration to both in order to create an appropriate set of improvement projects that are not only operationally impactful [40] but also linked to strategy execution. Therefore portfolio selection may also be the most critical activity in an improvement programme [41,42].

Any organisation that is involved in a continuous improvement programme will periodically be faced with the challenge of choosing between an assortment of potential projects. These projects will compete for scarce resources to satisfy numerous stakeholders and accomplish multiple objectives under conditions of uncertainty. This is true even if the organisation opts to ignore the implications of its choices and pursues a random portfolio or resorts to informal decision making techniques. Such an organisation must unavoidably come to some understanding of the nature of portfolios; the metrics that are relevant to structuring the portfolio; and formal decision analysis methodologies that suit the needs and abilities of the organisation and that deliver outcomes in an efficient manner [43,44]. This is necessary to ensure the organisation identifies and prioritizes those projects that will provide the maximum strategic benefits, regardless of whether those are measured as financial outcomes, flexibility, product differentiation and so forth. Too often, however, organizations select projects on the basis of proximate exigencies or resource availability, rather than working back from strategic principles.

Problem Statement

Although many continuous improvement researchers place project selection high on their list of success factors [31,45-48], it seems practitioners generally do not [49-51] and few proponents pay much attention to it in the popular press [12,52-58]. Project or portfolio selection is a complex and multi-faceted decision making activity that becomes increasingly complicated as organisational size and the number of potential projects increases. Since the benefit from structured improvement programmes such as Six Sigma is asserted to reside in their objectivity and consistency, it seems paradoxical that unstructured approaches, which are reliant upon subjective past experience, are frequently used for project selection [59-61]. This surely must lead to frustration [46,56], lost opportunities [62], inefficient allocation of scarce resources and the sub-optimisation of the system as a whole. Kornfeld and Kara [6] and others [2,48,63] have observed that operations managers approach the problem of project selection and prioritisation using naïve methods, which are unlikely to result in optimal outcomes.

Although, prima facie, project portfolio selection may appear to be a zero-one knapsack problem, in practice one must consider the risk and uncertainty of project outcomes [64,65]; the lack of complete or precise information [66]; the time dependence of projects [67,68]; as well as project interdependencies [69] that might result in non-linear portfolio responses [70].

There is, therefore a growing need for research that addresses a broader view of improvement programme implementation, taking into account the factors that are critical for long-term success - key amongst these being project selection and prioritisation.

Research Hypotheses

The hypotheses that motivated this research are:

i. That continuous improvement methodologies, such as Lean Manufacturing and Six Sigma lack structured objective approaches for optimal project portfolio selection that link strategy to targeted improvement efforts.

ii. That, as a consequence of (i), opportunities may be lost, scarce resources would be inappropriately allocated and that improvement activities would result in local optimality with sub-optimal outcomes for the business system as a whole.

iii. That it is possible to develop approaches to bridge the gaps posited in (i) and thereby fulfil the business needs expressed in (ii).

Research Objectives

According to the aforementioned problem statement and hypotheses, the overall objective of this research is to develop a reliable methodology for identifying optimal portfolios of improvement projects within existing design constraints. Such a methodology will require consideration of business strategies, business processes and will involve the preparation of accurate models in order to describe and predict business outcomes that would arise as the result of changes to business process parameters. Therefore such a methodology ought to be:

- Generic: The methodology should be broadly applicable across different processes, across different industries and to companies following different strategies.

- Scalable: The methodology ought to be capable of identifying portfolios of improvement projects at different levels of an organisation – whether this is a manager operating an individual factory or one responsible for many factories.

- Reliable: Since the research objective is to find improvements within an existing process design, our definition will require internally consistent results rather than absolute results that could be compared to external benchmarks.

Thesis Structure

This dissertation begins with an examination of the first hypothesis through a review of the extant literature (Chapter 2). We seek to answer the question 'what is the current state of the art in identifying and prioritising process improvement opportunities?' In this chapter we contribute to the literature by proposing framework for linking strategy to process improvement [1,9].

Chapter 3 then examines the state of practice through a survey of industry. We answer the questions 'What is the current state of practice?' and 'How does the current state of practice differ from the state of the art?' In this chapter we contribute to the literature by providing insight into the state of practice and comparing this to the normative framework described in Chapter 2 [6].

Having firmly identified the need for a new approach, we propose a methodology in Chapter 4 for modelling and simulation that is scalable from processes to factories or enterprises. The methodology includes an approach to modelling firm performance and for identifying the relative desirability of process improvement portfolios.

Chapters 5, 6 and 7 then present the application of the methodology in a simple SME, a complex SME and a regional enterprise respectively.

Unlike many theses, we discuss our results and set out our conclusions at the end of each chapter. In this way, the reader may better grasp the logical progression of the research as the thesis unfolds. We reserve Chapter 8 therefore, for a more global discussion of the research and Chapter 9 to conclude the thesis with the findings, research contributions and suggestions for potential future research.

Figure 2 (below) sets out the logical flow of this thesis, so that the reader, at a glance, may understand how the layout of the chapters relates to the flow of the research. Where a number is provided in superscript, this refers to a publication arising from this research.

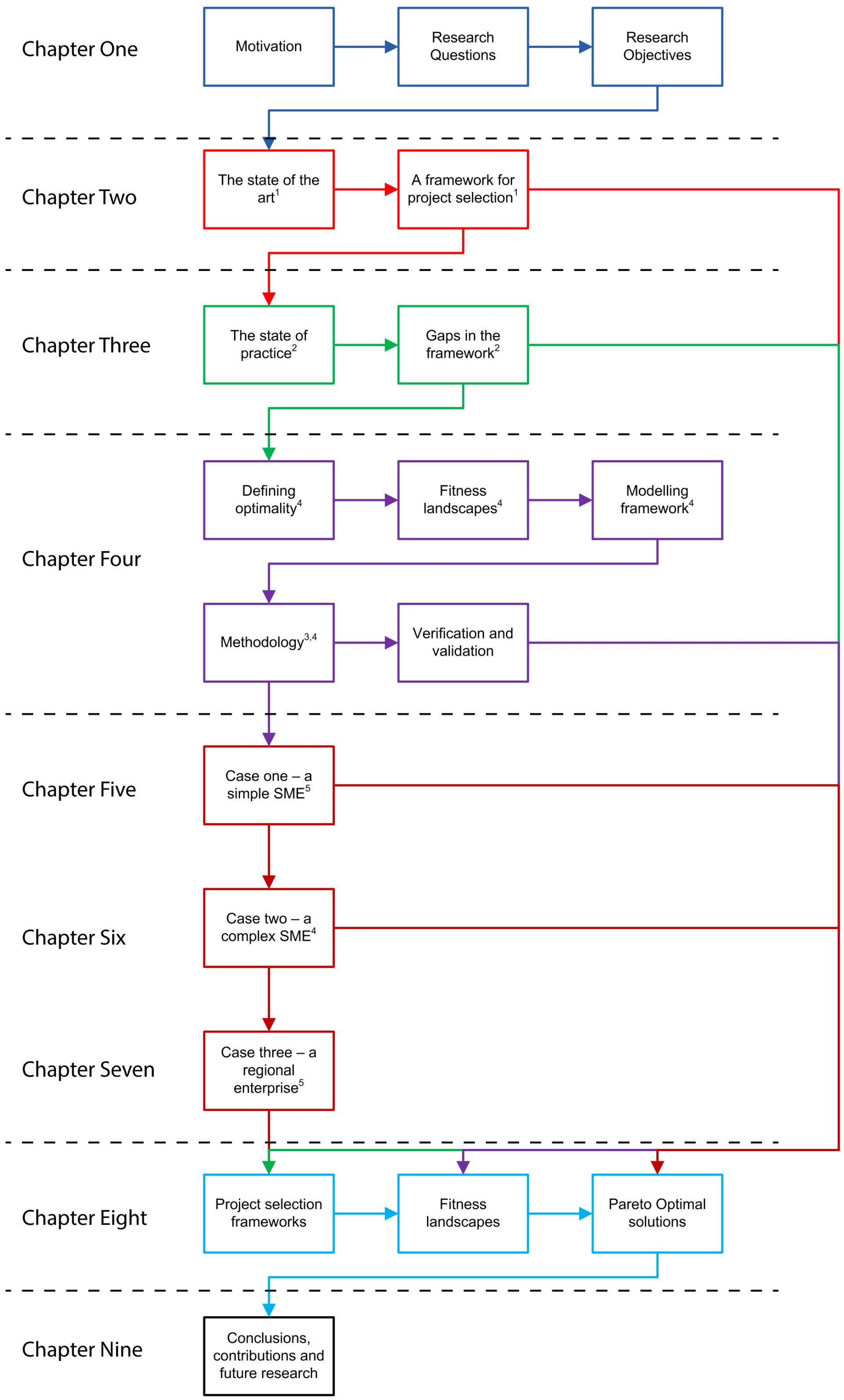


Figure 2: Flowchart Showing Thesis Structure

2: The State of the Art in Project Selection

Structure in Decision Making

People do not act with perfect rationality; instead their decisions are impacted by the systems within which they work. Therefore formal approaches to decision making can be beneficial [71]. Formal methodologies aid communication and also help structure an organisation's thinking by relying on the creation of models and the consideration of alternatives, which may aid in the reduction of subjectivity [72]. Group decision making can suffer from bias and power imbalances [73], yet executives acknowledge the benefits from structured approaches [74] and so it ought to be possible to minimise the impact of these factors. Ultimately the reliability of these methodologies derives not only from their inherent design, but also from the quality of their execution [75], giving consideration to psychological [76] as well as economic matters [77-79]. It is therefore important that the methodology is transparent and understood by those applying it [80] so that misinterpretation and criticism are less likely and so the methodology might be evaluated [81]. Adding structure to decision making can assist the organisation in achieving more objective (though not necessarily rational) decisions. Indeed, deciding *how* decisions are to be made may well have a greater impact than deciding *what* decisions are to be made [82]. We therefore began this research with an exposition of the current state of the art in order to determine to what extent structured and objective approaches for optimal project portfolio selection that link strategy to targeted improvement efforts have been defined.

Decision Analysis

Decision analysis approaches can be broadly grouped into three major categories as shown in Figure 3. These are: single objective decision making methods, decision support systems, and multiple criteria decision making (MCDM) methods [83]. Because continuous improvement projects must contend with many criteria, the multiple criteria decision-making methods are the most relevant to our study. We shall follow this structure and the commonly used names in the ensuing discussion, however we refer to these as decision *analysis* methods as this more accurately reflects the role they should play – that is, a normative approach to assessing decisions on the basis of the "axioms of consistent choice" [84].

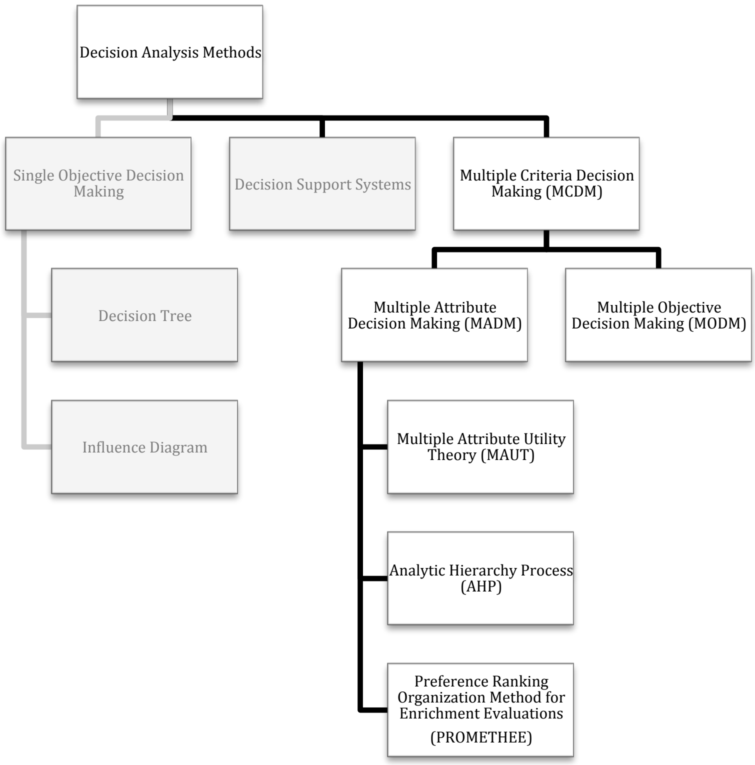


Figure 3: Classification of Decision Analysis Methods [83]

One may approach MCDM by examining the attributes of choices (Multiple Attribute Decision Making or MADM) or by focussing on objectives (Multiple Objective Decision Making or MODM). The major difference between MADM and MODM is that the former begins with a finite set of explicitly defined alternatives and attempts to maximise the portfolio outcomes, whereas the latter explicitly defines objectives and sets out to select from an infinite set of alternatives [85] as set out in Table 1 (below). Thus although both seek to maximise a utility function, MADM leads to an activity-driven portfolio that answers choice questions, that is: 'what is the best subset of actions?' By contrast, MODM asks design questions [86] such as: 'how good can this process be?'

	MODM	**MADM**
Criteria defined by:	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)
Decision maker's control:	Significant	Limited
Decision modelling paradigm:	Process-oriented	Outcome-oriented
Relevant to:	Design/search	Evaluation/choice

Table 1: A Comparison of MODM and MADM Approaches [85].

Project Selection

The extant literature on decision-making is substantial (see Table 2), particularly in regards to project selection in R&D (see for example[87-93]). It describes two broad schools of MADM practice - the American school, which derives from von Neumann and Morgenstern's expected utility theory [94] and the European school of outranking methods. Of the American school, the most commonly encountered is the Analytic Hierarchy Process (AHP), whereas the Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE) methods is perhaps the best known from the European school [95-97].

Although there are vast differences between individual instances, Xu and Yang point to some common characteristics of multiple attribute problems [98]:

- Multiple attributes are often hierarchical;

- Selection criteria are often conflicting;

- Problems are hybrids of qualitative and quantitative, deterministic and probabilistic, and with incommensurable units;

- Problems are subject to uncertainty in data, judgement, and assessment; and

- Problems are frequently of very large scale.

Reference	Methodology	Framework Element
(Lanza et al., 2008)[99]	Simulation	Value Stream Optimization
(Hu et al., 2008) [100]	Goal programming (GP)	Portfolio Generation
(Guiping et al., 2007) [101]	DSS for MODM	Portfolio Generation
(Kumar et al., 2007) [102]	Data envelopment	Portfolio Generation
(Sandanayake et al., 2008) [103]	Simulation	Portfolio Generation
(Ahire and Rana, 1995) [104]	AHP	Project Selection
(Anand and Kodali, 2008a) [105]	ANP	Project Selection
(Anand and Kodali, 2008b) [106]	PROMETHEE	Project Selection
(Chen et al., 2005) [107]	TOPSIS	Project Selection
(Evans and Alexander, 2007) [108]	Simulation & AHP	Project Selection
(Huang et al., 2009) [109]	Fuzzy AHP	Project Selection
(Jung and Lim, 2007) [42]	Categorical	Project Selection
(Kahraman and Buyukozkan, 2008) [110]	Fuzzy AHP, Fuzzy GP	Project Selection
(Kelly, 2002) [111]	Selection Matrix	Project Selection
(Kumar et al., 2008) [31]	LINDO	Project Selection
(Mawby, 2007) [70]	Various	Project Selection
(McDonald et al., 2002) [112]	Simulation	Project Selection
(Rabelo et al., 2007) [113]	AHP Hybrid Simulation	Project Selection
(Su and Chou, 2008) [47]	AHP	Project Selection
(Abdulmalek and Rajgopal, 2007) [114]	Simulation	Project Selection

Table 2: Selection of Approaches Appearing in the Peer-Reviewed Literature

The American School

The AHP was developed by Saaty [115] to compare a finite number of alternatives and to ensure that the participants select only those factors that are essential to making the decision [116]. This obviates the greatest weakness of the simple Multi-Attribute Value Function, which is its failure to include systematic verification of consistency [117].

It achieves these aims by arranging the objective, criteria and alternatives in a hierarchy not dissimilar to a Six Sigma CTQ flow down [118] to provide an overview of the relationships and to allow for a comparison between them [119]. Pair-wise comparisons are then made to quantitatively or qualitatively arrive at a matrix of preference orders. Eigenvectors are computed to produce criteria weights and a final preference order is produced.

The key assumptions of AHP are [120]:

- Reciprocal comparison - decision makers can compare and identify the magnitude of their preferences,
- There is homogeneity of preferences,
- Criteria are independent of the properties of the alternatives,
- The hierarchy is assumed to be complete.

AHP has been demonstrated as a tool for the selection of pilot improvement projects in businesses that are starting out on their continuous improvement journey [32,104] and Mawby [70] and Kahraman [110] present it as a tool for project selection in Six Sigma. Ahire and Rana argue for a pilot approach under such circumstances since the deployment's long term success or failure depends to a large extent on management's initial experiences [104]. In this case the use of an attribute-based selection process makes perfect sense – the organisation is not seeking to improve itself but rather is attempting to identify the project that offers the greatest likelihood of success against a number of attributes. The authors make a final comment, however, which is unsupported in this paper - that AHP could also be applied for ongoing TQM implementation. Yet ranking methods like AHP are not applicable to decisions involving resource constraints, project interdependence [121] or for continuous problems where there is a requirement to optimize [117]. Although the method is best suited to situations in which there is certainty, it has also been applied under stochastic uncertainty.

The AHP has been criticised because of the potential for rank reversal and for its lack of transitivity [119]. Rank reversal means that the sets $\{a_1 \cdots a_n\}$ and $\{a_1 \cdots a_{n+1}\}$ might not result in the same preference order under AHP, even when a_{n+1} is unrelated. The lack of transitivity means than although alternative 1 is preferred to alternative 2 and alternative 2 to alternative 3, alternative 1 might not be preferred to alternative 3. Gass argues that these are irrelevant axiomatic issues [119], but in practical terms they both mean that the alternatives for AHP must be defined a priori.

The European School

PROMETHEE is a family of outranking methods used to rank and select from a finite set of alternatives [122-124] with quantitative input data, although there have been limited application with fuzzy input data sets [125].

PROMETHEE has some advantages over AHP as identified in Macharis et al. [126]:

- Information can be lost using AHP as good and bad scores are aggregated when trade-offs are made

- AHP is artificially limited by its use of a 9 point scale for evaluation;

- It is possible to conduct sensitivity analyses on the results of PROMETHEE;

- The generation of weights in AHP is an unbiased but non-trivial task comprised of a sequence of $\frac{P!}{2(P-2)!}$ pair-wise comparisons followed by the calculation of eigenvectors for the resultant matrices.

Despite its advantages, PROMETHEE appears to have had very little application in the selection of improvement projects with only one specific reference regarding its potential use [124]. Anand and Kodali [106] applied PROMETHEE to the problem of selecting a Lean manufacturing system. The problem was trivial since there were three binary alternatives to select from, yet Anand reported that the methodology was limited as it provided rankings rather than ratings, the methodology and necessary use of software obscured the process and, it did not deal with uncertainty or incommensurate data.

MADM or MODM?

The application of MADM to the selection of continuous improvement portfolios raises a number of fundamental issues. Perhaps the most significant of these is that MADM is applicable to discrete and not continuous problems. That makes it useful for dealing with choice problems but not for design problems. One might argue that continuous improvement is indeed the application of many small changes for the better and thus the problem space is indeed one of maximising outcomes from a group of alternatives.

On any practical scale this argument must fall down, as MADM limits itself to the a priori definition of alternatives identified by a small group of decision makers, and only implicit definition of objectives. Except for small decisions, the implicit definition of objectives could result in poorer outcomes [139]. These options are typically short term; not time phased; and potentially sub-optimising. Since strategy is by its very nature irreversible, tactical decisions made in this fashion can well commit the firm to paths that are irrevocable [31].

By contrast, MODM approaches are not restricted by an a priori set of alternatives but rather they seek to identify these through a design process. Instead of a 'bottom-up' fit of alternatives to strategy, they are suited to strategy-led designs.

To fully appreciate the importance of the dichotomy between choice and design approaches, one must first consider the strategic context for continuous improvement.

The Strategic Context

In addressing the question ‘What is Strategy?’ Porter began by pointing out that it is not the same as operational effectiveness, since effectiveness on its own does not create sustainable differentiation [127]. Yet many forms of strategic differentiation rely upon the implementation of appropriate operational effectiveness activities for their realization. Realized strategy is, in

Mintzberg's terms "a pattern in a stream of decisions" [128] and creating a pattern which is coherent with strategy is therefore of utmost importance to the continued success of a business. Coherence necessitates that clear cause and effect relationships are established between strategy and operational outcomes [129]. Without such coherent patterns, neither activity can make complete its proper contribution to the organization.

Although the literature on strategy is extensive, so too is the record of strategy failure. Kornfeld and Kara have previously written that this is frequently due to the lack of a formal framework for linking strategy to process improvement implementation [1]. Project selection frameworks may be used to map strategy to portfolios and this might help to identify misalignments or gaps in shop-floor execution of strategy.

Project selection frameworks

If one considers projects to be the fundamental expression of business strategy [130] then it follows that an organization must be careful in how it selects them [42,131]. Hoshin Kanri [132] and its precursor Quality Function Deployment (QFD) [133] have been successfully employed by sophisticated enterprises since the 1960s to align strategy to projects and objectives, however smaller and less mature organizations are not always successful in making that link. For example, in the study by Cagliano et al. [134] firms chose projects that aligned with strategy only 43% of the time. This should not come as a great surprise since, although researchers recognize that project selection is critical for the success of continuous improvement programs [46,47], such discussion is generally absent from the popular press [12,52,53,55-58,135] leaving practitioners to develop their own approaches to strategy alignment.

As a result, industry practitioners have often used more or less subjective approaches when selecting and prioritizing improvement projects. Recently we reported on a survey in which we found that only half of the respondent organizations had defined value streams for all strategic value creation activities and less than half explicitly linked their Value Stream Maps (VSMs) to strategy using metrics [6]. In a study of companies in the United Kingdom, Banuelas [48] found that practitioners predominantly used brainstorming to identify projects and, despite recognizing the importance of linking projects to business strategy, used prioritization tools that were, at best, only loosely connected to strategy.

Strategy and Practice Bundles

According to Kotha [136] there are four levels at which strategy is developed: Industry (industry policymaking by Government); Corporate (defining the nature of the business and resource acquisition and allocation); Business (strategic business unit boundaries, scope, direction and the basis of competitive advantage); and Functional (how a function such as manufacturing supports the Business level and other Functional level strategies). Since one determinant of competitive advantage is how well the organization's internal capabilities fit the external environment [137], the concept of portfolio 'completeness' can be defined as the match between the Business level strategy and Functional level actions. This will hold true whether an organization's strategy is market-led or resource-led, since either will necessitate various improvement actions or decisions from within manufacturing that will impact business performance [138-140]. Thus, whereas our interest lies at the Functional level, we must necessarily begin with a brief discussion of business level strategy.

Generic Strategies

The purpose of this chapter is not to enumerate or extend the literature on business strategy; nevertheless we require a reference point from which to explore the strategy–portfolio linkage. Although a number of authors have developed various schemas describing Business Level 'generic strategies', Michael Porter's generic competitive strategy model has made the most significant contribution to business and the literature on business strategy over the past 30 years [141,142]. Although it has not received universal support and has some empirical and methodological issues, its broad application makes it a reasonable as an exemplar from which readers may then choose to apply this approach to other strategy frameworks.

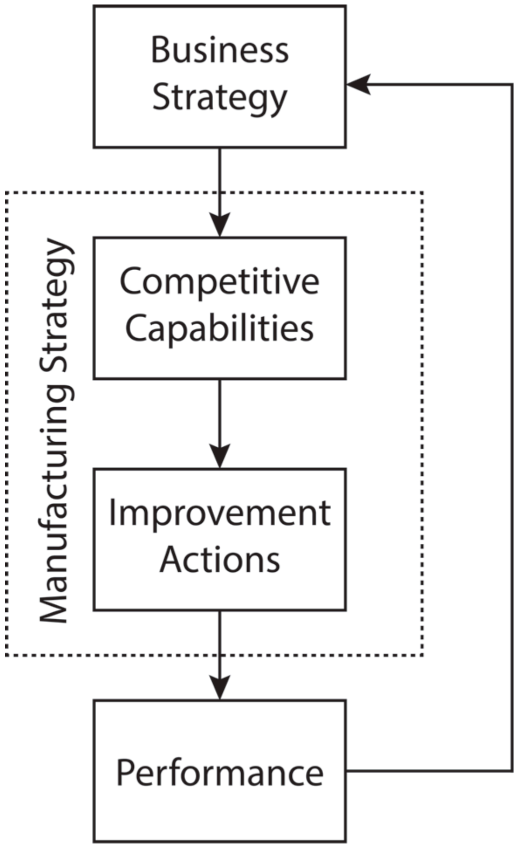


Figure 4: Competitive Capabilities and Strategy [139]

Porter [143] set out three strategic generic stances that an organization might adopt – Differentiation, Cost Leadership and Focus. Although not entirely orthogonal, Porter took the view that an organization must select one or other of these positions lest it be caught 'stuck in the middle' – losing strategic focus. Organizations choosing to position themselves in a differentiation strategy, would seek to provide unique values (either tangible or intangible) in its products or services through innovation, agility, quality or timeliness. Alternatively, an organization could choose to implement a cost leadership strategy, in which it would seek to create competitive advantage through a sustainable cost (and therefore price) advantage, through the pursuit of scale economies in production or distribution, cost saving technologies, product and process design, input cost, capacity utilization of resources, and access to raw materials. Finally in the Focus strategy, a firm will select and target a particular market segment (customer, geography or product) and deliver cost or differentiation.

Ultimately any strategic thrust will depend upon one or more of only five competitive manufacturing capabilities - cost, quality, delivery performance, flexibility and service [139,144].

For example a differentiation strategy might be built on quality and service capabilities. For any particular firm, though, each of these capabilities is composed of unique bundles of manufacturing practices such as Total Quality Management (TQM) or Six Sigma [138,139] driving actions and performance as shown in Figure 4 above.

Practice Bundles

These practice bundles may be broad ranging, overlapping and multidimensional. For example, Six Sigma is a broad ranging practice since, even though it is a methodology that focuses on the reduction of process variation, process variation can improve product quality through tightened production outputs; reduce scrap and therefore production expenses; or improve delivery performance through reduced variation in processing time. Practice bundles that are very different may have overlapping impacts, for example it is possible to reduce WIP through both the scrap reduction impacts of Six Sigma and the implementation of kanbans and pull production in Lean. Finally, projects do not often impact a single dimension of a business - improving product quality, for example, is also likely to reduce scrap (and therefore cost), inspection and rework (and therefore overhead) and WIP (and therefore improve cash-flow).

Whereas strategy is set top-down, improvements are generally identified bottom-up and so although understanding practice bundles can assist practitioners in targeting strategic outcomes, the problem of ensuring that a complete mapping from strategy to performance remains.

Portfolio Generation and Optimization

Many continuous improvement methodologies recognise the link between strategy [132] and improvement [145]. This is evident in Lean Manufacturing, for example, in its Hoshin Kanri ('policy deployment') process. Similarly, the Balanced Scorecard [146,147] and Strategy Map approaches [148,149] provide a generic hierarchical cause and effect structure for an organisation to map its strategy to improvement activities [133,150,151]. However each of these approaches then relies on managerial experience to translate broad strategic concepts directly into project portfolios.

In 1998 Rother & Shook took the Toyota method of Material and Information Flow Mapping and popularised it as the Value Stream Map (VSM) through their book 'Learning to See'

[57,152]. The VSM provides a supplier to customer view of a product value stream. At Toyota the tool had been used to depict current and future process states, whereas elsewhere the tool is used as much as a diagnostic instrument to help practitioners to understand where waste exists and identify project opportunities.

Insofar as the VSM allows practitioners to examine an entire product value stream, it provides a strategic and cross functional approach to portfolio selection [153] and a means of comparing the current state with a future design. Since discussion during a VSM workshop focuses around solving issues identified on the VSM, it also may assist in identifying alternative improvement approaches. Like the strategy deployment approaches, this method also directly yields a discrete set of alternative approaches, which are subsequently ranked.

The VSM approach is not capable of dealing with the dynamic and stochastic nature of processes [154] – something that discrete event simulation (DES) handles well. Yet although a number of researchers have applied DES to design Lean processes [155-157], to ascertain the appropriate parameters for operating Lean processes [155,158-160], or to quantify the benefits from converting a process to a Lean process [161,162], only a few have combined it with the VSM approach.

McDonald et al. demonstrated the use of DES for the complexity of an entire VSM in order to visualise the future state before implementation [112]. They did this, not as a design exercise, but rather as a means of affirming the outcomes from the selected discrete portfolio of projects. Scullin later demonstrated the practical feasibility of implementing this approach [163] and Lian et al. proposed at formal VSM modelling method for it [164].

Utilising a factorial designed experiment, Abdulmalek and Rajgopal ran a series of simulations to study the effect of three factors on production lead-time and WIP [114]. In doing so they demonstrated the possibility of value stream optimisation, though their work was still based on optimising outcomes from a select group of alternative improvements.

Recently Lanza et al. have extended the VSM simulation approach, using simulation to quantify the interdependencies between Lean methods and production outcomes [165-167]. The group then applied this to develop a simulation-based approach to optimisation using Lean methods under different scenarios [99]. This approach integrates the optimisation tool OptiSLang® with the simulation software Plant Simulation® to vary parameters in the simulation using a control loop.

Whereas other approaches discussed are likely to lead to a project portfolio, this group's work is the most promising so far for delivering quantitative goal-directed optimisation of a value stream. It therefore fills an important gap in the literature between strategy and portfolio generation. The shortcoming of this work is that it does not define the possible project portfolio required to achieve this optimal state.

Indeed decision analysis is non-trivial for all but the smallest portfolios due to the combinatorial effect of these characteristics [98]. Although the fundamental approaches may struggle with decision analysis under uncertainty and risk, in recent years fuzzy approaches to Multi Attribute Analyses have also been developed [168].

The Need for Decision Analysis Frameworks

In the foregoing examination of MADM and MODM, it is clear that a tool is not sufficient on its own; it must have a process to give it context in an organisation. In the case of MADM, this process must first provide a set of alternatives from which to choose, whereas for MODM we first must know what the optimal outcome looks like. Archer and Ghasemzadeh [91,169] proposed a generic process for decision analysis to provide this context (Figure 5), however it is clear that this is suited only to MADM approaches as it is driven by available alternatives and seeks to develop an optimal portfolio from within that constraint.

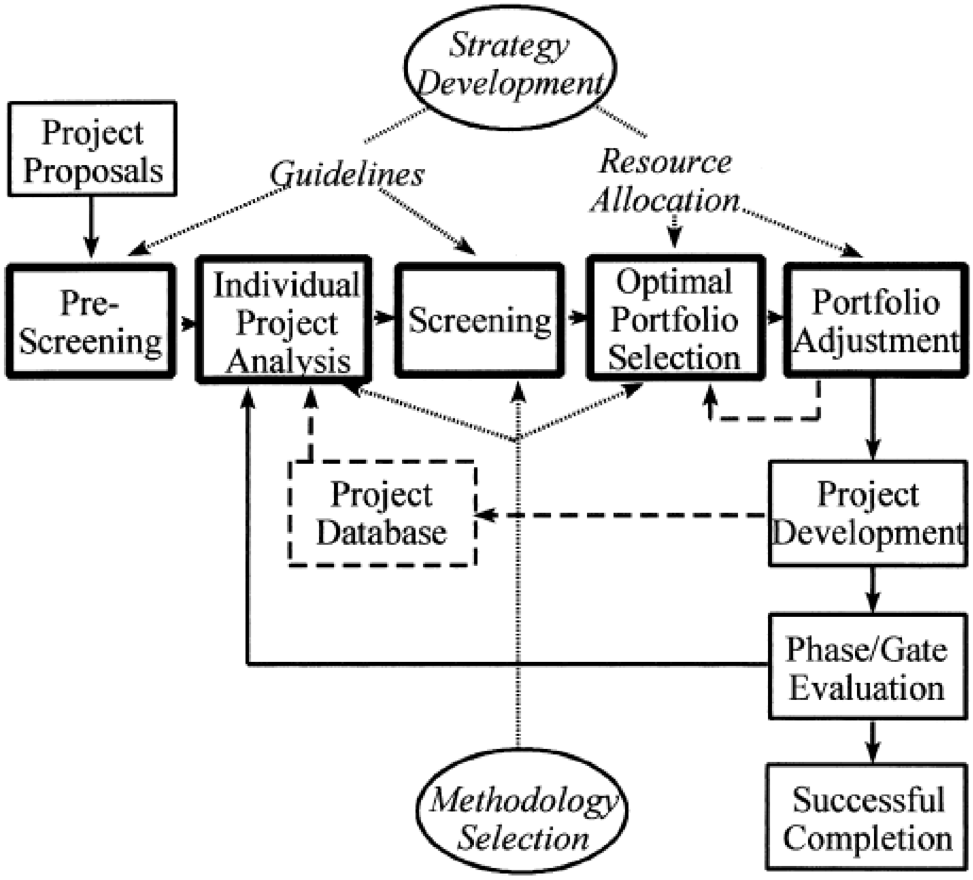


Figure 5: Process for Portfolio Selection using Multiple Attribute Approaches [124]

Discussion

We regard it as axiomatic that there is a positive nexus between strategic alignment and business performance [128,170]. If projects represent the eventual implementation vehicle for strategy [130] then they must also be directed by that strategy [37,149] and thus a mediating process must exist to translate strategy into projects. We therefore proposed a framework, shown in Figure 6, that represents a normative approach to this mediating process – from strategy to portfolio generation, project selection and project management [1].

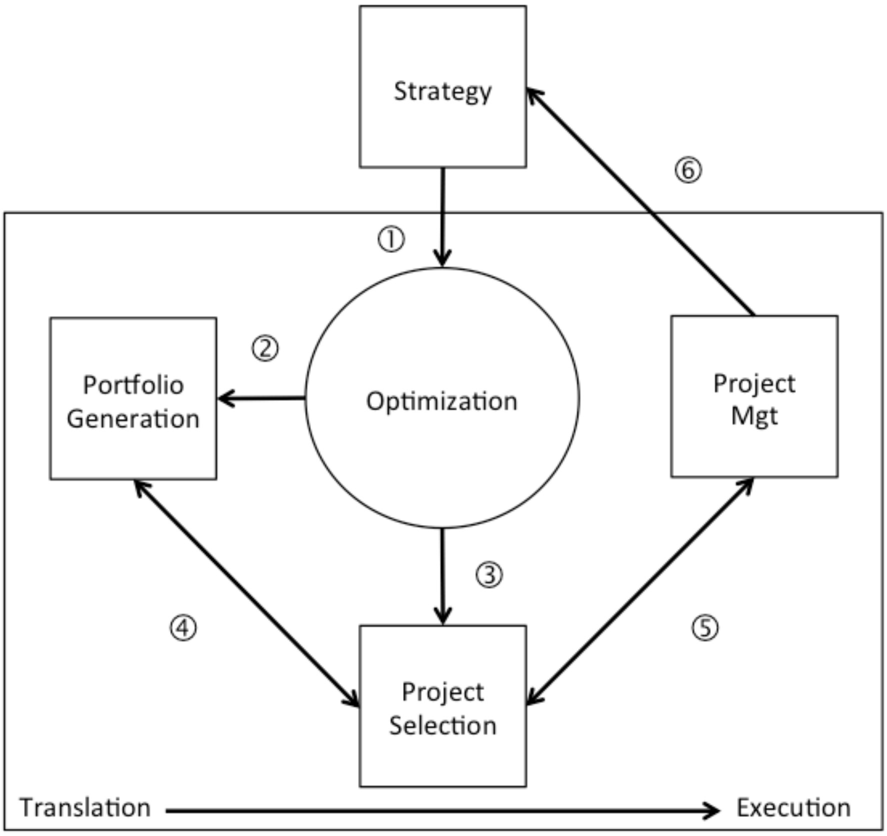


Figure 6: Framework for Linking Strategy to Process Improvement Implementation (Normative Model)[1][1].

Strategy informs a business about what metrics to alter, in what direction, at what rate and by how much. It is up to the business to interpret these instructions into implementable actions [149]. We suggest that there are two reasons why this translation of strategy into projects should not occur in one step. First, although it is possible to directly arrive at a universe of promising alternative actions (and many organisations do) it is not possible to know, a priori, whether these will deliver the best overall outcome for the business. Second, it is also possible that the strategic endpoint differs from what is possible within the current business configuration and constraints. To address these concerns, we propose a two-step process as illustrated in steps 1 and 2 in Figure 6. In the first step, suitable optimization approaches should be used to identify the optimal future state for the business. Examination of the differences between the current state of the business and the optimal state should then drive portfolio creation as depicted in step 2.

[1] In this and subsequent versions of this figure, solid arrows indicate an explicit link, dotted arrows indicate an implicit link and arrowheads indicate the direction of information flow.

The resultant portfolio of projects would compete for scarce resources to satisfy numerous stakeholders and accomplish multiple objectives under conditions of uncertainty [66] time dependence [68,171] and interdependencies that might result in non-linear portfolio responses [70]. As well as resource interdependencies, the projects might also be interdependent upon each other in delivering the desired overall outcomes [172]. These factors would necessitate the use of formal methodologies that select an optimal subset of the strategic portfolio (Figure 6, steps 3 and 4). This selection process would also provide feedback for future iterations of portfolio generation.

In this approach, the optimal future would first be modelled (step 1) and differences between the current state of the business and the optimal state would then drive portfolio creation (step 2) followed by the use of formal methodologies to select an optimal subset of the strategic portfolio (steps 3 and 4).

The ensuing project portfolio would be required to fulfil multiple objectives, which could vary depending upon the organization's chosen strategy. Organizations should therefore attempt to ensure the portfolio is both capable (each project has the potential to successfully address the target issue) and complete (the entire portfolio addresses all dimensions from the multiple objectives of strategy). Since a discussion on capability goes to the heart of improvement methodologies such as Six Sigma or Lean, it is out of the scope of this research. Rather, we were interested in how organizations could determine whether or not a portfolio may be considered to be 'complete'. This necessarily brought us to examine what approaches were used in industry for the selection of continuous improvement projects and this is discussed in Chapter 3.

Conclusions

There is a rich literature covering methods for project selection including their use in process improvement. This chapter has identified that there is, however, surprisingly little structure offered to businesses to assist them in defining an overall portfolio of improvement projects. Much of what is available is ill suited to the complexity of real business. Furthermore, it seems that little of this information transcends the boundaries of academic literature into the popular press.

Where the extant literature has examined project selection in continuous improvement, it has concentrated on the application of MADM techniques. This approach is based on the presumption that an appropriately informed and optimised set of projects already exists [169]. MADM, of itself, cannot create the alternatives and yet it frequently appears as the mediating process from strategy to project, with the portfolio implicitly defined [169,173]. Yet if this portfolio is created on the basis of managerial experience alone it is most likely that it is neither optimal nor complete.

The application of MADM to the selection of continuous improvement portfolios raises a number of fundamental issues. Perhaps the most significant of these is that MADM is applicable to discrete and not continuous problems. That makes it useful for dealing with choice problems but not for design problems. One might argue that continuous improvement is indeed the application of many small changes for the better and thus the problem space is in fact one of maximising outcomes from a group of alternatives. Yet this argument must fall down, as MADM limits itself to the a priori definition of alternatives identified by a small group of decision makers, and only an implicit definition of objectives. Except for small decisions, the implicit definition of objectives could result in poorer outcomes [174]. These options are typically short term, not time phased and potentially sub-optimising. Since strategy is by its very nature difficult to alter, tactical decisions made in this fashion can well commit the firm to paths that are irrevocable [39] and wrong. Moreover, the methodologies presented assume the relationship between attributes to be static and linear and introduce subjectivity through the weightings.

By contrast, MODM approaches are not restricted by an a priori set of alternatives but rather they seek to identify these through a design process. Instead of a 'bottom-up' fit of alternatives to strategy, they are suited to a strategy-led design, though more complex to use [175].

3: A Survey of Industry Practice

Introduction

The foregoing discussion suggested the need to examine the practice of project and portfolio selection in industry to determine if this gap indeed existed. There was, however, a dearth of peer reviewed research into industry practices and what did exist is limited by small data sets [48,63] or did not address the question of project selection [176].

In the study by Banuelas et al. [48], 1 113 companies in the United Kingdom were surveyed to ascertain what criteria and methods they used to select Six Sigma projects. From this sample the researchers received 25 useable responses and these indicated that brainstorming was the predominant method for identifying projects, although 20% to 30% did use structured methods such as CTQ or QFD. Respondents identified that a project's link to business strategy was one of the key factors in the project selection process, yet the prioritization tools they then used were either not connected (e.g. cost-benefit analysis) or only loosely connected to strategy (e.g. cause and effect matrix). The study by Gošnik [63] reveals a similar picture, though with only 8 respondents implementing Six Sigma one cannot draw conclusions from this paper.

This left a number of open questions - how do companies select their portfolios; what metrics are used; with what criteria; and are these approaches considered to be satisfactory? In order to explore these gaps in the literature, we set out to specifically examine the state of practice of improvement project selection by conducting a survey of industry.

Research Questions

These gaps in the literature led us to pose the following research questions;

Research Question 1: What methods are used to select and prioritize continuous improvement projects?

Research Question 2: What criteria are used to select and prioritize continuous improvement projects?

Research Question 3: Are practitioners satisfied with methods and criteria used to select and prioritize continuous improvement projects?

Survey Instrument

This study was conducted via an on-line survey instrument using SurveyMonkey (www.surveymonkey.com) under approval of the University of New South Wales Human Research Ethics Committee. Potential respondents were required to review and accept the consent statement in order to proceed to access the survey. The survey instrument can be found in Appendix 1: Survey Instrument.

A survey format was chosen as it provided a means to obtain a large number of responses from many disparate locations in a short period of time [177]. The advent of on-line services also meant that progress could be monitored and reminders sent, which proved to be advantageous to ensuring a high response rate.

The use of a survey instrument also ensured that questions were posed consistently to all participants, which is an important consideration when study objectives require statistical analysis. Since respondents were unguided when answering survey questions, this format required greater design rigor to minimise variation due to individual interpretation of the questions. Questions must be clear, comprehensive and acceptable to participants [177] and so in this case all questions were posed as either five-point Likert scales or multiple-choice questions with the option of free text answers and were tested among a small group prior to the study. Post hoc analysis of the Likert scale questions showed them to be highly reliable by Cronbach's alpha (74 items, $\alpha = 0.905$).

The survey questionnaire consisted of 4 sections, the first section was designed to obtain basic demographic information about the respondent and their organization. The second section requested details of continuous improvement methodologies used. Section 3 examined the use of Value Stream Maps (VSM) in the business, including the extent to which they are linked to strategy and whether they are used to create 'optimal' portfolios. In the final section of the survey we asked about project selection, prioritization and the tools used. The questions were developed to elicit responses to each of the three research questions and to provide detail on factors identified in our literature review, including use of specific tools such as AHP and PROMETHEE.

Analysis

Survey questions that are posed as Likert scales only provide rank information, which is often mistaken for interval data [178]. Although there are varying views on the statistical treatment of these devices [178,179], we are of the view that the intervals in a Likert scale are not uniform but, rather, governed by individual perceptions despite the implied symmetry between individual Likert items. Non-parametric tests or descriptive statistics (mode, median) are therefore appropriate. In this study, we therefore applied the following statistical tests:

- In assessing the tendency in a single Likert scale, the scale was reduced to a bipolar measure and evaluated using a one-sample Chi-Squared test with a null hypothesis of $x_1 = x_2$.

- When comparing two Likert scales we applied the Mann-Whitney test with a null hypothesis of $x_1 = x_2$.

- In one instance we examined the relationship between a nominal variable and a measurement variable and in this case Kruskal-Wallis was applied in preference to Mann-Whitney.

Yusoff and Janor [8] cited our study and concured with the treatment of the Likert scale results using non-parametric statistical methods.

Sample

We targeted and approached 105 organizations known to employ continuous improvement methods such as Lean or Six Sigma. Since we were particularly interested in industry practice, we sought to exclude companies that do not employ these methods from our study. Organizations were identified for participation by their involvement in continuous improvement groups (such as the Institute of Industrial Engineers) and contacted directly by telephone or email.

Sample Characteristics

A total of 93 unique surveys were received, resulting in 74 useable responses. A response was considered to be unique if it had a unique IP address and useable if any question beyond the informed consent and demographics had been completed.

Respondents were from 15 countries, with 66% (n = 49) from Australia (Aust.). The others are grouped in this paper for comparison to Australian companies and are referred to throughout as 'Global'. The sample characteristics are summarized in Table 3 and the detailed results are presented in Appendix 2: Survey Sample Characteristics and Detail Results

	Sample Characteristic (mode unless otherwise noted)
Organization Size	> 10 000 employees (Aust: 37% n = 18; Global: 52% n = 13)
2009 Revenues	> $1B (Aust: 33% n = 16; Global: 60% n = 15)
Sector	Private (Aust: 45% n = 22; Global: 32% n = 8), Public (Aust: 43%, n = 21; Global: 52% n = 13)
Industry	Manufacturing (Aust: 37% n = 18; Global: 36% n = 9)
Respondent Roles	Manager (Aust: 24% n = 12; Global: 20% n = 5) Master Black Belt (Aust: 20% n = 10; Global: 24% n = 6) Director (Aust: 10% n = 5; Global: 32% n = 8)
Improvement Methodologies Employed	Lean Manufacturing (Aust: 71% n = 35; Global: 96% n = 24) Six Sigma (Aust: 57% n = 28; Global: 92% n = 23)
Number of Methods	2 or more methods (median = 3) applied simultaneously (Aust: 71% n = 35; Global: 96% n = 24)
Deployment Duration (Main Methodology)	Median 6 years for Australian firms and 7 years for Global firms
Prevalence of Primary Improvement Methodology	Many or all sites within the business (Aust. 51% n = 25; Global 72% n = 18) (No significant difference - Mann-Whitney W = 1725.0, n_1 = 49, n_2 = 25, p = 0.1826 two-tailed adjusted for ties)

Table 3: Sample Characteristics

Project Selection Methods

Amongst the respondents, Value Stream Mapping is widely used as a basis for formulating improvement objectives. Firms use VSMs to:

- Direct improvement objectives towards optimizing their value streams (χ^2 (1, n = 49) = 12.76, p = 0.000) with no difference by country (Aust: 71% n = 35; Global: 84% n = 21. Mann-Whitney W = 1706.0, n_1 = 48, n_2 = 25, p = 0.3726 two-tailed adjusted for ties).

- Link improvement objectives to key customer outcomes (χ^2 (1, n = 64) = 30.25, p = 0.000) with no difference by country (Aust: 69% n = 34; Global: 80%. Mann-Whitney W = 1660.0, n_1 = 48, n_2 = 25, p = 0.1480 two-tailed adjusted for ties).

- Determine and align improvement objectives with the organization's strategy (χ^2 (1, n = 72) = 9.39, p = 0.002) with a difference by country (Aust: 63% n = 31; Global: 88% n = 22; Mann-Whitney W = 1547.0, n_1 = 47, n_2 = 25, p = 0.0327 two-tailed adjusted for ties).

However, fewer than half of the Australian respondents explicitly link their VSMs to strategy using metrics ($\chi 2$ (1, n = 47) = 3.60, p = 0.058), whereas the majority of the global organizations do (Aust: 55% n = 27; Global: 88% n = 22. Mann–Whitney W = 1504.5, n_1 = 48, n_2 = 24, p = 0.0017 two-tailed adjusted for ties). Furthermore, only half of all the respondent organizations have defined value streams for all strategic value creation activities ($\chi 2$ (1, n = 64) = 0.06, p = 0.814) with no difference by country (Aust: 51% n = 25; Global: 52% n = 13. Mann-Whitney W = 1718.0, n_1 = 48, n_2 = 24, p = 0.6732 two-tailed adjusted for ties).

Project Selection Criteria

The majority of companies indicated that they either take a ‘whole-of-enterprise’ (Aust: 35% n = 17; Global: 28% n = 7) or ‘whole-of-site’ perspective (Aust: 18% n = 9; Global: 24% n = 6) when selecting projects, although there appears to be a dichotomy between Australian and Global perspectives in project selection with ‘Continuous Improvement’ being the modal response for Australian businesses and 'Optimization within a value stream' the Global modal response.

'Site Management' was the modal response to the question "Who determines the majority of your improvement opportunities?" (Aust: 35% n = 17; Global: 56% n = 14), with only a small minority reporting that opportunities came from the shop floor (Aust: 2% n = 1; Global: 8% n = 2).

Notwithstanding these results, most respondent organizations took a short-term perspective when selecting improvement projects, most commonly a project planning horizon of 6 months or less is used ($\chi 2$ (1, n = 69) = 0.71, p = 0.399).

Brainstorming and cost-benefit analysis were the prioritization methods most commonly used by Australian firms (65% n = 32; 63% n = 31), whereas Global firms used cost-benefit analysis and business benefits analysis (72% n = 18; 68% n = 17). No firms used PROMETHEE and only 3 used AHP, as compared with 2 firms that did not use a prioritization method at all (AHP 4% n = 3; None 3% n = 2. Mann-Whitney W = 5550.0, n_1 = 48, n_2 = 24, p = 0.6732 two-tailed adjusted for ties).

The prioritization metrics most commonly used by Australian firms metrics were project resource availability, project timing and cycle time (61% n = 30; 51% n = 25; 51% n = 25), whereas for Global firms these were cycle-time and throughput (84% n = 21; 76% n = 19).

Most companies assess project outcomes and make corrections to the portfolio to deliver the intended outcomes ($\chi 2$ (1, n = 72) = 20.06, p = 0.000) with no difference by country (Aust: 67% n = 33; Global: 88% n = 22. Mann-Whitney W = 1647.5, n_1 = 47, n_2 = 25, p = 0.3769 two-tailed adjusted for ties).

Respondent Attitudes and Sources of Improvement Methodology

Only half of respondents indicated that they were satisfied or very satisfied with their current project selection methods ($\chi 2$ (1, n = 70) = 0.30, p = 0.633) with no difference by country (Aust: 47% n = 23; Global: 56% n = 14. Mann-Whitney W = 1577.5, n_1 = 46, n_2 = 24, p = 0.4684 two-tailed adjusted for ties). Australian organizations used a median of 4 prioritization methods and 4 measures, whereas Global firms reported 4 prioritization methods and 5 measures.

Respondents reported that their methodologies were predominantly developed internally (Aust: 59% n = 29; Global: 68% n = 17) or by consultants (Aust: 37% n = 18; Global: 56% n = 14). The primary driver for implementing the methodology was perceived benefits (Aust: 53% n = 26; Global: 80% n = 20); external pressures (Aust: 51% n = 25; Global: 48% n = 12) or management support (Aust: 39% n = 19; Global: 68% n = 17).

Most respondents indicated that they rely on books (Aust: 65% n = 32; Global: 76% n = 19), business forums (Aust: 55% n = 27; Global: 68% n = 17) or conferences (Aust: 53% n = 26; Global: 68% n = 17) as their source for information about continuous improvement. Fewer indicated that they turn to journals (Aust: 49% n = 24; Global: 24% n = 6) or universities (Aust: 24% n = 12; Global: 28% n = 7).

Discussion

We were able to capture a relatively high proportion of responses (71%) by directly contacting potential respondents and using an internet-based survey instrument. This compares very favourably with the 2.2% return reported by Banuelas et al. [48]. There is, of course, the risk of sample bias in taking this approach, though possibly no more than exists with other surveys, where respondents self-select or opt-in to the survey [180]. This specificity was important in that it helped us to focus on organizations that currently implement continuous improvement, whereas earlier studies have captured a high percentage of extraneous respondents [48,63]. Since the authors are based in Australia, the sample also incidentally shows a bias towards Australian respondents, making this the only such paper that we are aware of but also leaving open the opportunity to gather a more globally representative sample.

Research Question 1: What methods are used to select and prioritize continuous improvement projects?

The results indicated that there is a gap between strategy and project selection in practice. Although 71% of Australian respondents implemented Lean and the same proportion sought to 'optimize' their value streams, there appear to be disparities in the way they went about this.

Although 63% employed VSMs to determine improvement objectives (Mann-Whitney W = 2464.0, n_1 = 49, n_2 = 47, p = 0.4311 two-tailed adjusted for ties), only 55% had metrics that were linked to strategy (Mann-Whitney W = 2579.5, n_1 = 49, n_2 = 48, p = 0.1226 two-tailed adjusted for ties) and just 51% had VSMs for all strategic value creation activities (Mann-Whitney W = 2562.0, n_1 = 49, n_2 = 47, p = 0.1039 two-tailed adjusted for ties). These latter two responses were consistent with the proportion of respondents who indicated they take a 'whole-of-site' or 'whole-of-enterprise' perspective, but they were inconsistent with the operationalization of strategy.

Furthermore, when management and practitioners identified and prioritized projects, they most commonly reported the use of semi-quantitative or subjective approaches. For example, 'brainstorming' was the most commonly referenced method for project selection and prioritization amongst Australian companies. This concurs with the study by Banuelas (Banuelas et al., 2006) and Gošnik found it to be the second most widely used technique for identifying projects [63]. However, this is a technique that is generally used to assist groups to generate a large number of ideas. It has neither the explicit links to strategy, nor the quantitative element required for project prioritization. It is therefore not an appropriate method for project prioritization.

By contrast, the published literature suggested that AHP (Ahire and Rana, 1995) or PROMETHEE (Anand and Kodali, 2008) are more appropriate for project prioritization. Yet since survey respondents placed 'Journals' (Aust: 49% n = 24; Global: 24% n = 6) and Universities (Aust: 24% n = 12; Global: 28% n = 7) low on their list of sources used to learn about continuous improvement, it is possible respondents were unaware of these methods. The popular press (which ranked highest in this list) recommended that practitioners use tools such as cost benefit analysis; cause and effect matrix; brainstorming and Pareto analysis to identify and prioritize projects. These approaches have the benefits of simplicity and buy-in, but they create an undeserved sense of objectivity in practitioners' minds. They do not provide any means for identifying alternative projects; evaluating project interactions; evaluating the overall impact of the portfolio on an organization's goals; nor can these approaches differentiate between local and global optima. Instead they are more of a means to filter down a large group of opportunities into a handful of actions. Of particular importance is that these approaches lack both a viewpoint from which to examine the entire organization and an explicit strategic context.

Research Question 2: What criteria are used to select and prioritize continuous improvement projects?

Study respondents reported an equal application of process measures (such as throughput or cycle time) and project measures (such as current workload or resource availability) when selecting projects (no significant differences at the $p < 0.10$ level for Australian firms by test for equal proportions). This is not surprising, given the selection and prioritization methodologies employed and it suggested that organizations are as likely to construct their portfolios on current workload and resource availability as they are on process outcomes.

It also corresponded with the guidance found in the popular press, which recommends that organizations evaluate projects against three generic categories - business benefits; feasibility; and organizational impact [46].

Research Question 3: Are practitioners satisfied with methods and criteria used to select and prioritize continuous improvement projects?

The survey respondents were predominantly large manufacturing firms with 6 to 7 years experience implementing their key continuous improvement methodology. Yet, despite this level of experience, only half indicated that they were satisfied with their approach to project and portfolio selection. Although the satisfied organizations tended somewhat towards longer horizons and more impactful outcomes (Figure 7 and Figure 8), there was a clear link between the number of metrics or the number of methods applied for prioritization and satisfaction with the approach (Figure 9 and Figure 10). There was a significant relationship between the number of prioritization methods applied and reported satisfaction at the $p < 0.10$ level for Australian firms by Kruskal-Wallis ($H = 15.78$, $DF = 9$, $p = 0.072$ adjusted for ties), supporting the view that more thorough prioritization led to better outcomes.

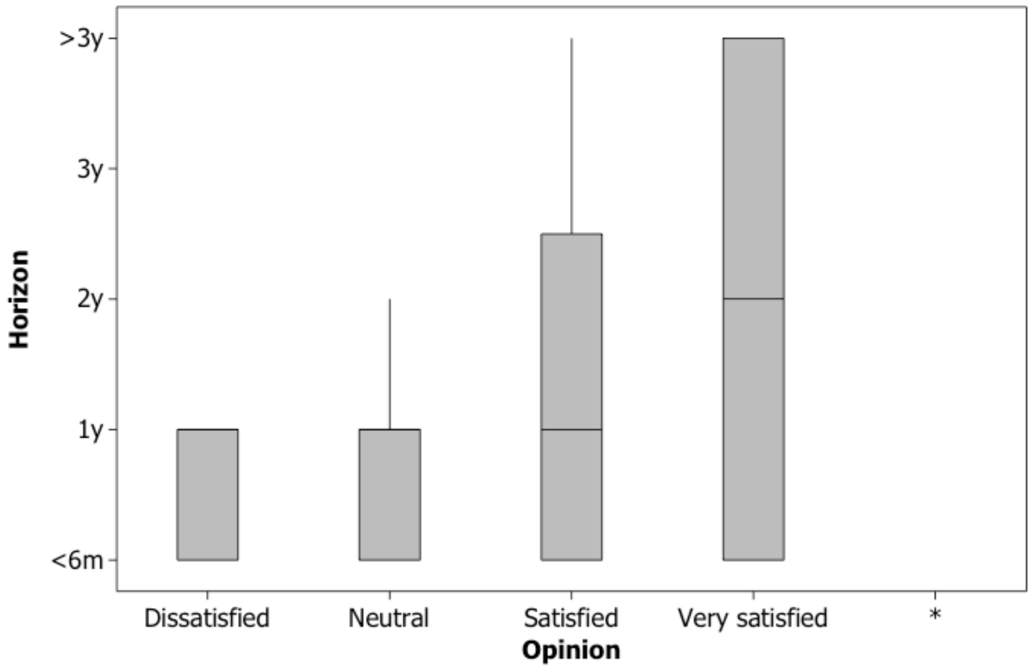


Figure 7: Opinion of Prioritization Approach versus Portfolio Horizon

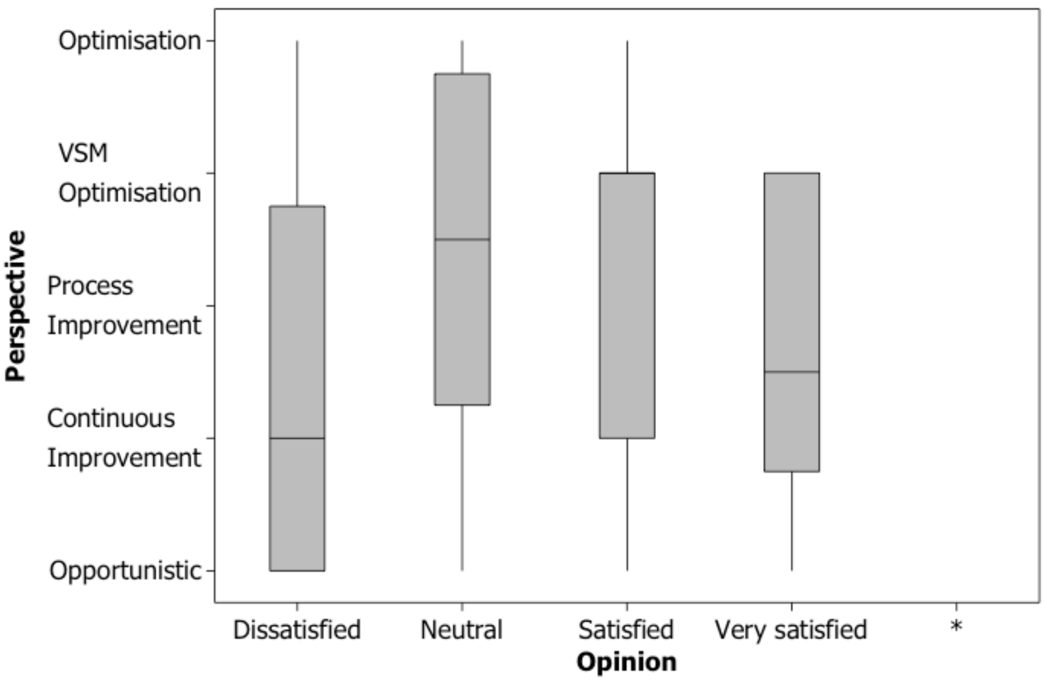


Figure 8: Opinion of Prioritization Approach versus Opportunity Scope

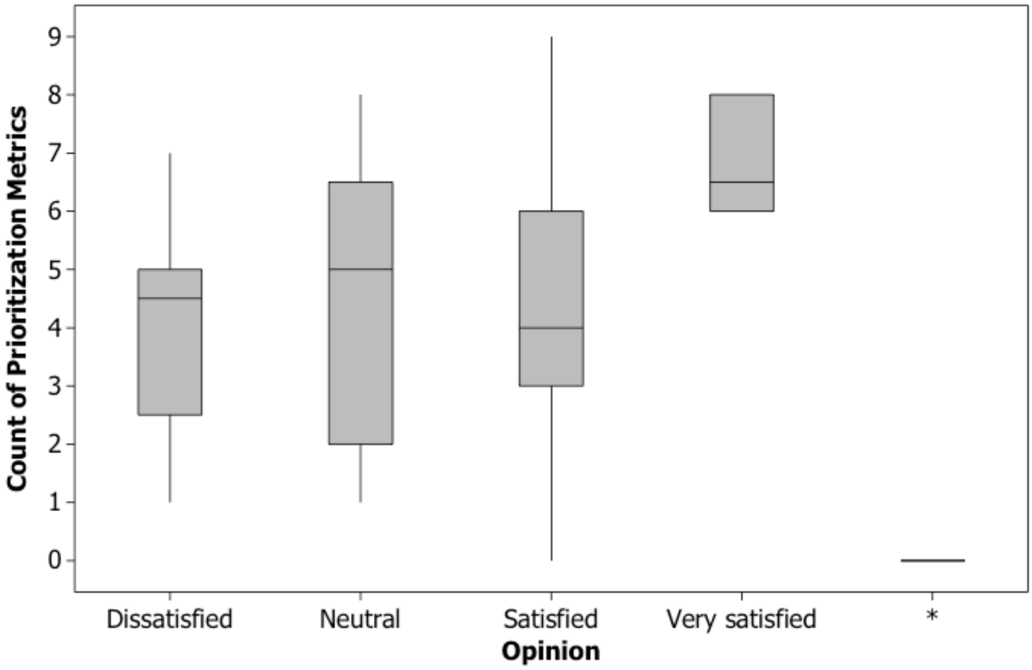


Figure 9: Opinion of Prioritization Approach versus Number of Metrics Used

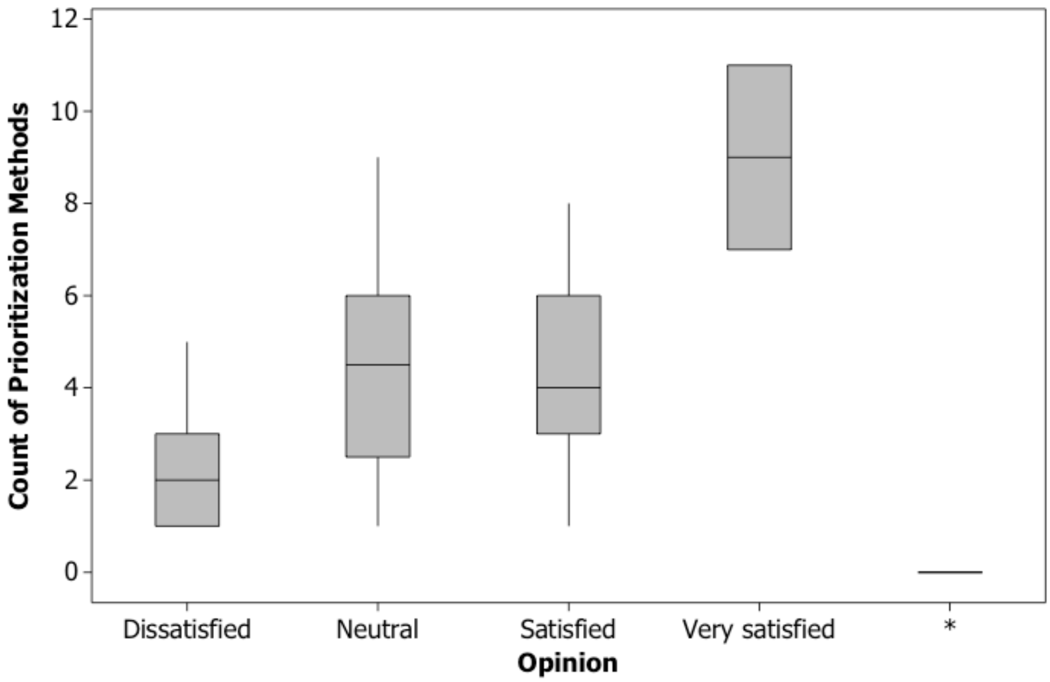


Figure 10: Opinion of Prioritization Approach and Number of Prioritization Methods Used

Organizations also reported that they employ a median of 3 improvement methodologies, which is in contrast to Zhang [38] who suggested that most firms apply one methodology at a time. It is not clear, however, whether this is due to dissatisfaction with the methodologies or recognition that each method serves a different purpose.

What is most striking, however, is that those firms that linked value stream metrics to strategy reported greater satisfaction than those that did not (Figure 11 and Figure 12). In the case of organizations that reported that value stream improvement objectives are determined from and aligned with the organization's strategy, this result was significant for all firms (Mann-Whitney W = 7207.0, $n_1 = 70$, $n_2 = 72$, $p = 0.0000$ two-tailed adjusted for ties). Where organizations reported that value streams include metrics that are linked to the outcomes determined in the organization's strategy, the relationship was significant for all firms (Mann-Whitney W = 7231.0, $n_1 = 70$, $n_2 = 72$, $p = 0.0000$ two-tailed adjusted for ties). These results give credence to our view that a strong link to strategy is important for business outcomes.

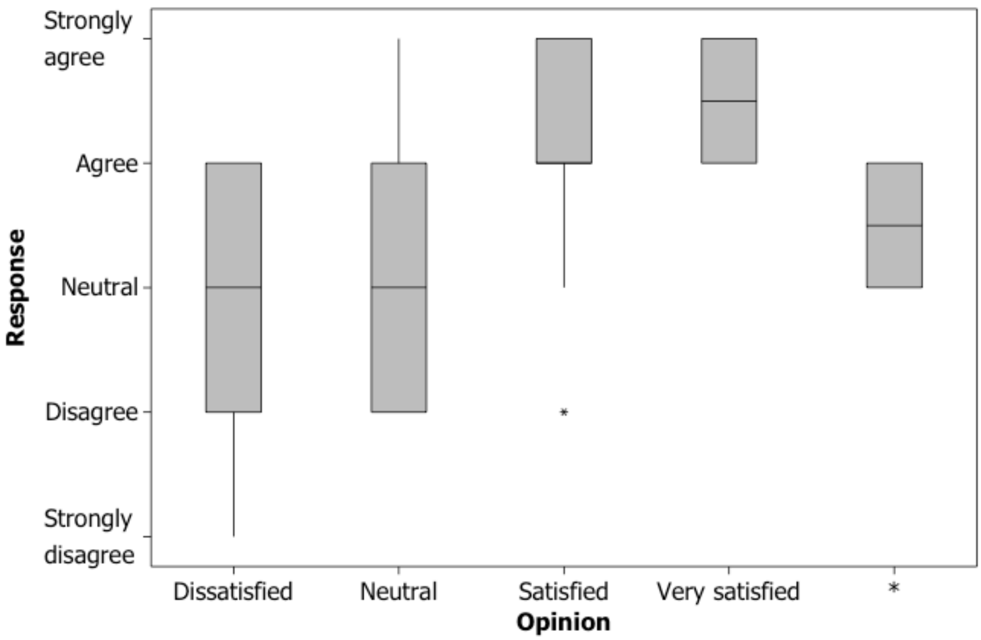


Figure 11: Opinion of Prioritization Approach versus Alignment to Strategy

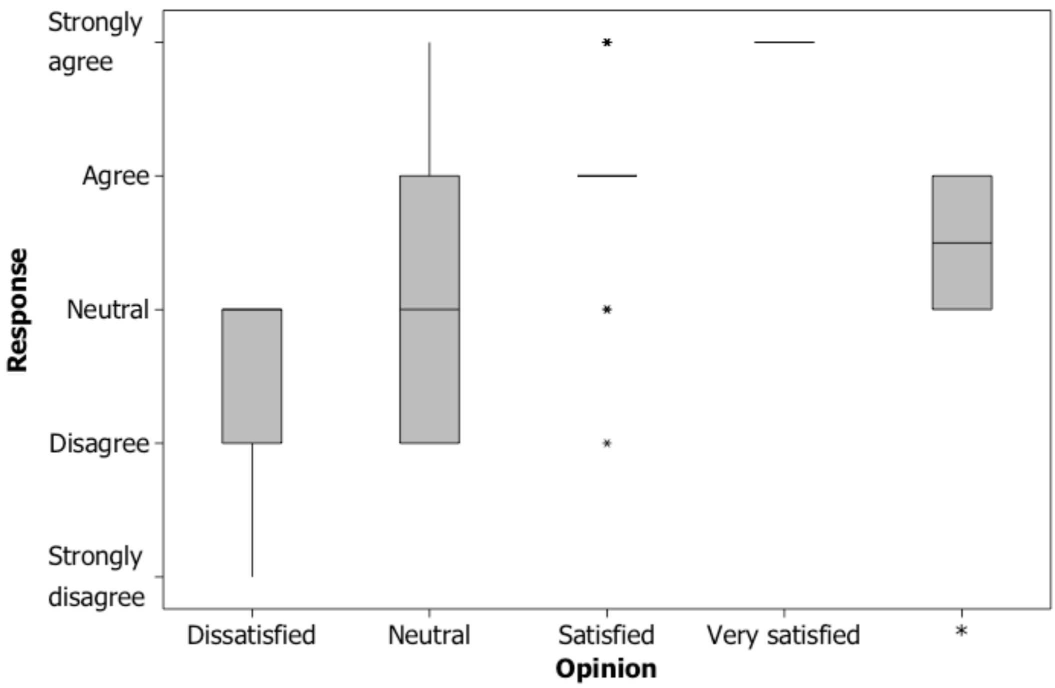


Figure 12: Opinion of Prioritization Approach versus Alignment to Strategic Metrics

Conclusions

Portfolio generation may be tightly linked to strategic priorities and future states (as is the case in strategy mapping), or only loosely linked (as is the case in VSM). However neither case makes an explicit attempt to drive the business towards an optimum end state. Therefore any portfolio so derived is unlikely to be the best possible set of options.

Organizations do not use the most appropriate structured tools to select their project portfolios. Tools such as brainstorming, which are advocated by the popular press, are not appropriate for project selection and prioritization. Instead, there are a number of multi-attribute decision making tools, such as AHP, which are better suited and their application is well described in the literature. Our results showed that there was considerable dissatisfaction with project and portfolio selection amongst practitioners, which suggests that practitioners are likely to be receptive to new approaches.

Our study indicated that practitioners made only an implicit connection (sometimes even no connection) between business strategy and project selection. This is illustrated by the dotted line

2 in Figure 13 (below). Even though an attempt might be made to optimise the project selection (for example by using a MADM technique), this would be made on the basis of a non-optimal project portfolio and would therefore reduce the likelihood that project outcomes would have the desired impact on the business and that improvement resources would not be efficiently deployed.

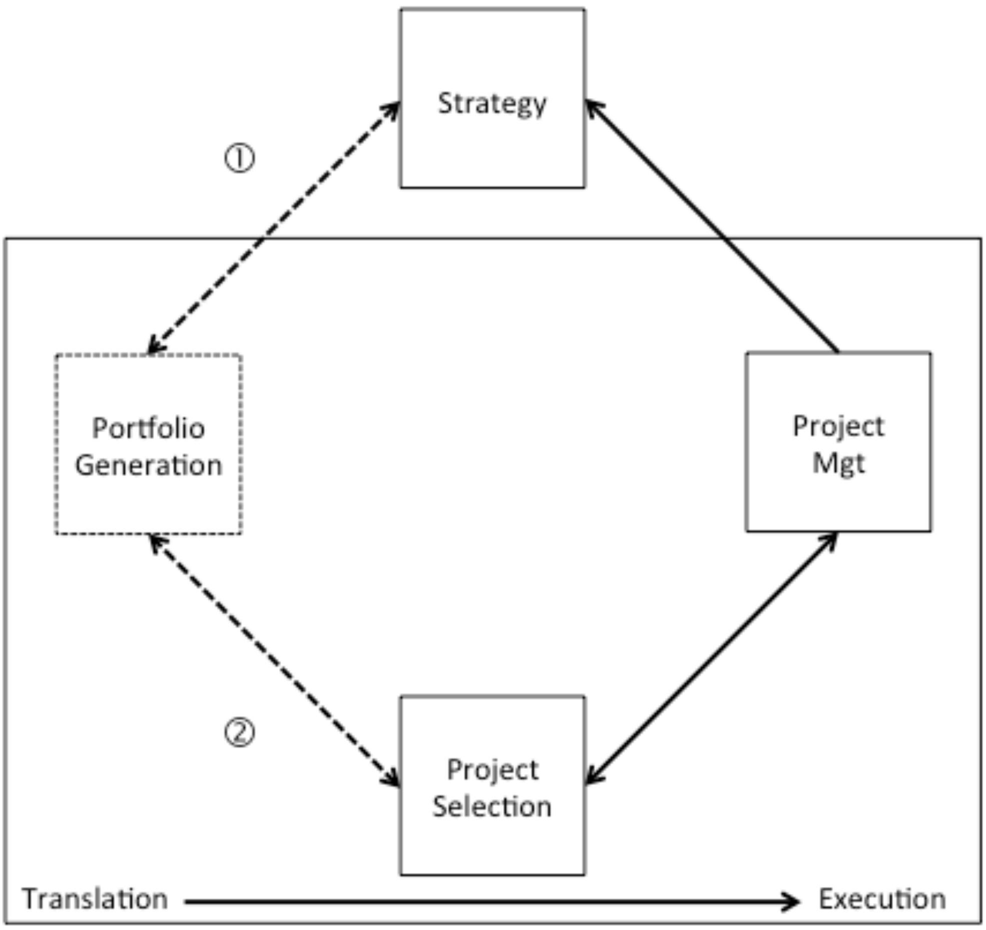


Figure 13: Descriptive Model of Strategy Linkage to Process Improvement Implementation.

It is, however, difficult to measure the real efficacy of these approaches for there is a "confusion and inconsistency" around the definition of Lean Production [181] and it is clear that neither Six Sigma [182] nor Lean have provided enough direction to business in this regard [183,184]. Moreover, in evaluating the utility of various decision-making approaches, the literature generally fails to quantify and evaluate comparative outcomes (i.e. whether the approach led to a quantifiably better outcome). Instead, authors tend to resort to qualitative considerations regarding the approach itself, such as ease of use.

Can we measure outcomes? Traditional financial measures can prove problematic and even drive aberrant behaviours [16] – for example a focus on overhead absorption can drive local optimisation, whereas the excess inventory created is valued as an asset. Fullerton [185,186] pointed out that non-financial performance measures help organisations to make the link between Lean manufacturing and global financial outcomes and this is an important precursor for the application of decision analyses [181,187-189]. Such measures are often used in operations management literature and, though problematic, have validity if bias and sampling are understood and properly addressed [190].

In the previous chapter we proposed a normative framework to link business strategy to process improvement implementation. In this framework the strategic direction and an optimal future state would be used to direct the creation of the project portfolios. We suggest that practitioners should use a structured framework such as this along with appropriate metrics to ensure optimal outcomes and resource deployment are achieved.

Projects may well be the ultimate expression of business strategy but there appear to be gaps in industry practice, which would mean strategy is not ultimately executed. A critical step - linking the strategy to projects – is skipped and instead practitioners try to find implicit links using informal and subjective methods focused on near term and activity based requirements. This gap is most likely the reason that projects fail to deliver and why practitioners are so often dissatisfied with their selection methods.

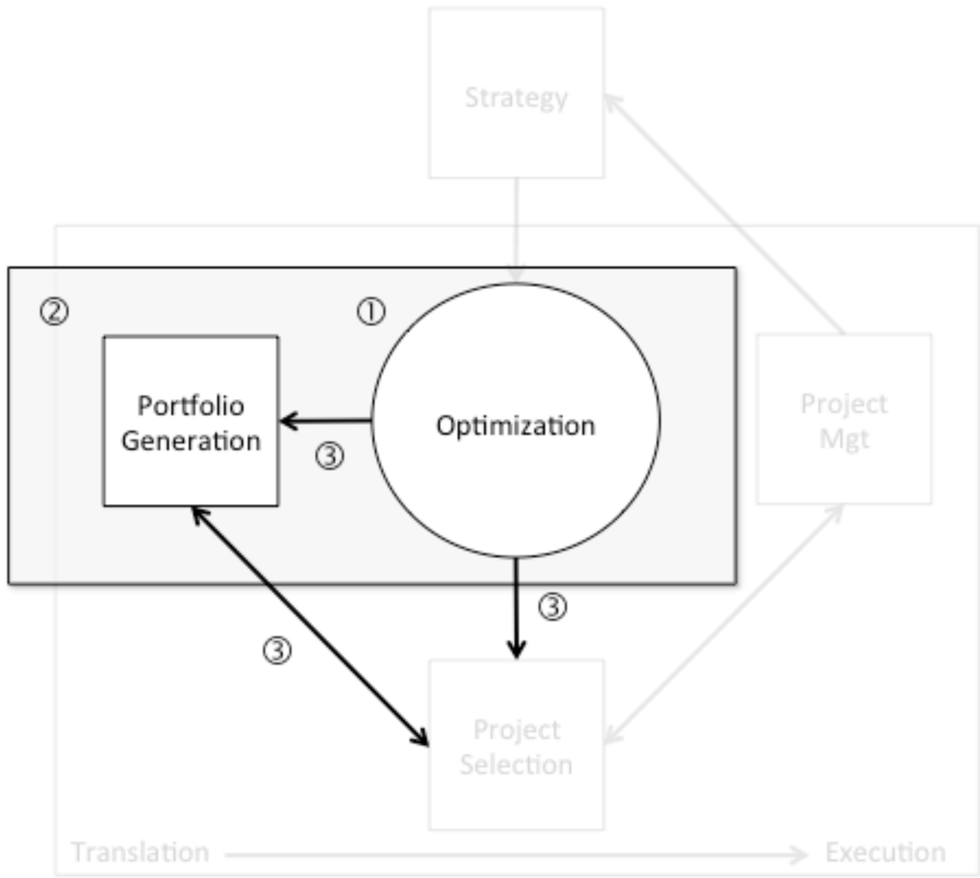


Figure 14: Gaps Between the Normative and Descriptive Models.

It is clear, then, that there are three gaps in the current state of the art. – (1) optimization of the future state, (2) portfolio generation and (3) the appropriate measurement to judge outcomes (Figure 14 above). The remainder of this research examines whether it is possible to design optimal future states that yield quantifiably better global outcomes than subjectively designed or implicitly defined future states and if it is possible to prepare project portfolios from such future states that yield quantifiably better global outcomes than subjectively designed or implicitly defined portfolios (shown as the shaded box in Figure 14 above).

An improvement cycle based on these methods and the framework ought to help managers to make better choices in selecting project portfolios, choices that will ultimately help them to realise the true promise of their improvement approach.

4: Methodology

Introduction

Modern factories are complex multiscale systems comprised of interconnected and interdependent machines and production lines. Each element in these systems is characterized by distinctive constraints and transfer functions that vary stochastically and dynamically in relation to production demands. Within this complex operating environment, managers must simultaneously deliver operational performance, whilst driving towards strategic business outcomes.

Given the immediacy of day-to-day production issues, however, it is not surprising that the focus of management tends to be asymmetric towards operational concerns, potentially to the detriment of the strategic goal. This tendency is further encouraged by many improvement approaches (for example the Kaizen philosophy of Lean Manufacturing) as well as traditional accounting systems (for example maximising departmental overhead absorption whilst simultaneously valuing inventory as an asset in a full-absorption costing environment). Notwithstanding these influences, even a motivated manager will not have a priori knowledge of whether an improvement action or set of actions represents the most efficient contribution to overall factory optimization.

Defining Optimality

In previous chapters we have noted that all operations managers are faced with the challenge of driving continuous improvement to achieve strategic and operational goals through the application of a finite pool of resources. Moreover, it is not unusual to find that this requires trade-off decisions across a portfolio of potential improvement projects. Previously it has been observed that operations managers approach the problem using naïve methods that are unlikely to result in optimal outcomes [6,48].

Since the operational performance construct may include many outcome dimensions (for example cost, scrap, WIP, throughput, energy consumption, response time and so on), the challenge facing managers is a multiobjective optimization problem, the general form for which is set out in Miettinen [191]:

$$\text{Minimize (or maximize)} \qquad \{f_1(x), f_2(x), \dots, f_k(x)\}$$

$$\text{Subject to} \qquad x \in S,$$

Where there are $k \geq 2$ objective functions $f_i: \mathbb{R}^n \rightarrow \mathbb{R}$ and the decision vectors $x = (x_1, x_2, \dots, x_n)^T$ belong to the nonempty feasible space $S \subset \mathbb{R}^n$ (the decision variable space).

In a factory, however, there are often conflicts between objective functions and indeed objective functions may be incommensurate with one another. For example, flexibility may be measured in time or customer service level, whereas the conflicting goal of efficiency of large batch sizes may be measured in dollars of overhead absorbed.

Moreover, it would be unusual to find a situation in manufacturing where a single solution optimizes every objective function. We must therefore define success in terms of the dominance or management preference of decision vectors over one another (represented as $x \prec u$), such that one decision vector $x = (x_1, x_2, \dots, x_n)^T$ dominates another decision vector $u = (u_1, u_2, \dots, u_n)^T$, which is the case iff $\forall i \in \{1 \dots n\}, x_i \leq u_i \ \wedge x \neq u$ for the minimization case [192,193].

Although a feasible solution, $x \in S$, is a strict Pareto-Optimal solution (x^*) $\text{iff} \nexists u \in S: f(u) \prec f(x)$, any improvement journey will involve traversing the set of Pareto optimal solutions (the Pareto Set or $PS = \{x \in S: \nexists u \in S, f(u) \prec f(x)\}$.

In practice, knowing that feasible solutions exist is important but not sufficient; one must also find an efficient path from the current state to a chosen solution. Constructing that path ought to involve sequencing interdependent improvement projects into a project portfolio that may span months or years. However we have found that managers often approach the problem as a random walk, with a short-term view and without foreknowledge of whether $\exists u \in S: f(u) \prec f(x)$ - that is, a given solution is Pareto-Optimal [6]. Moreover, there is little in the technical literature to alleviate this situation [1].

Yet, without such a reference frame, it is not possible to know a priori whether a project or projects satisfy the conditions of Pareto Optimality. It is even more difficult to assemble a coherent multi-period portfolio of projects.

Fitness Landscapes

To resolve this issue, we propose to borrow an idea from biology and create an n-dimensional 'Fitness Landscape' - a reference frame that would also help visualisation, allowing managers to easily judge current and future performance.

In biology, 'fitness' refers to an entity's ability to achieve biological and reproductive success in a given environment [194]. For example, adaptive fitness of the organism may be visualized as a continuous landscape whose dimensionality is allele frequency, as shown in Figure 15 [195]. In this diagram, different genetic combinations (x- and y-axes) give rise to varying degrees of biological success or 'fitness', which is denoted by the height of the surface in the z-axis. It can be readily observed that some combinations lead to better outcomes than others and also that local and global optima exist.

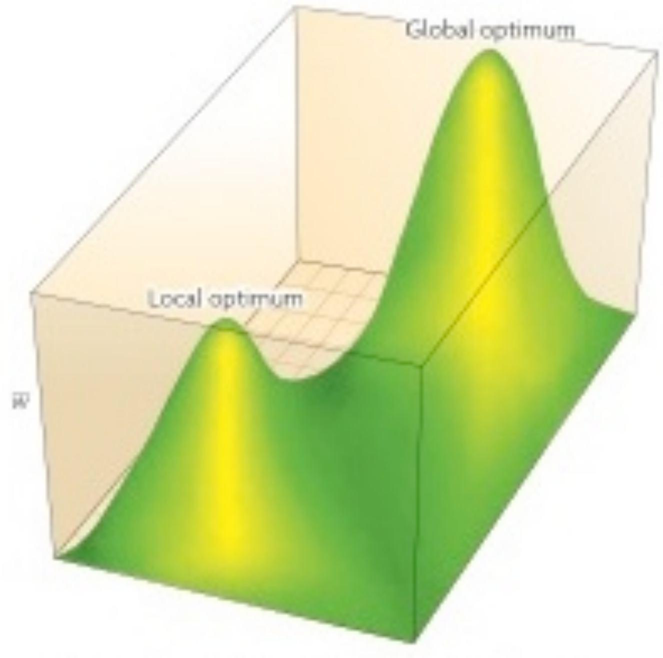


Figure 15: A Three-Dimensional Fitness Landscape from [195]

Applied to manufacturing, the Fitness Landscape becomes a visualization of productivity performance dimensioned by the company's strategy, for example - maximizing throughput whilst minimizing work in progress and scrap as shown in Figure 16. In this manifestation, the figure shows varying degrees of operational success as the relative height of the z surface 'throughput', although in practice this could be any of a number of strategic outcomes.

This *n*-dimensional Fitness Landscape (FL) is the image of the PS in the objective space [196] $FL = \{f(x): x \in PS\}$ and our approach places current and potential future performance outcomes into its context, allowing decision makers to visualize the paths of competing portfolios in the context of the potential performance space.

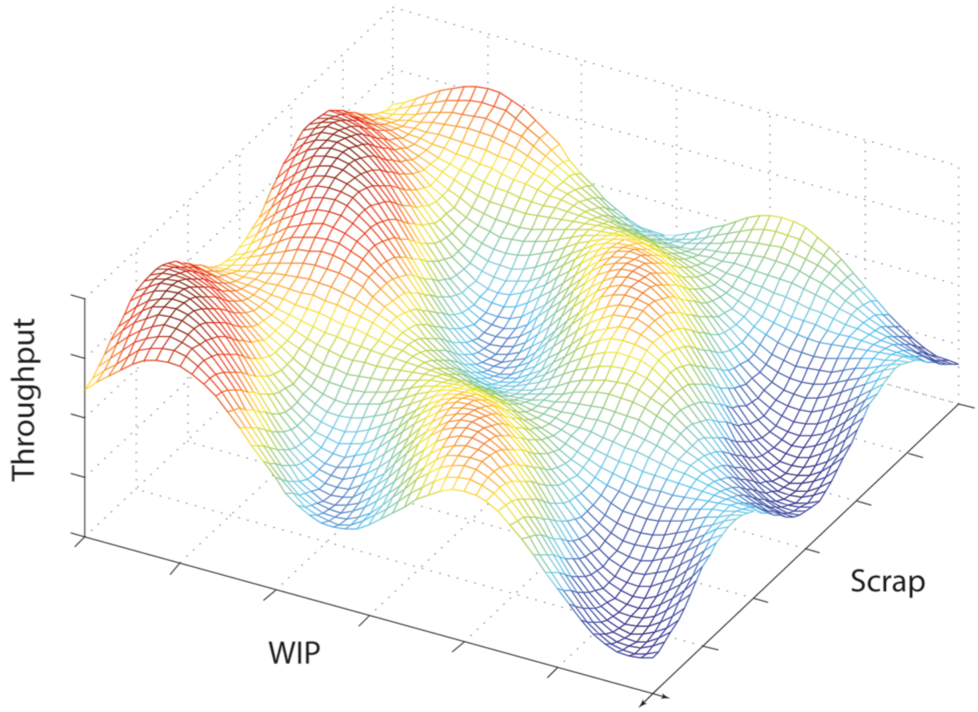


Figure 16: Depiction of a Simple Fitness Landscape

Once the landscape is defined, a strict Pareto Optimal solution on the landscape may be selected. Competing alternative improvement options can then be mapped as a path from the current state to a strict Pareto Optimal state in order to formulate an efficient improvement portfolio (Figure 17).

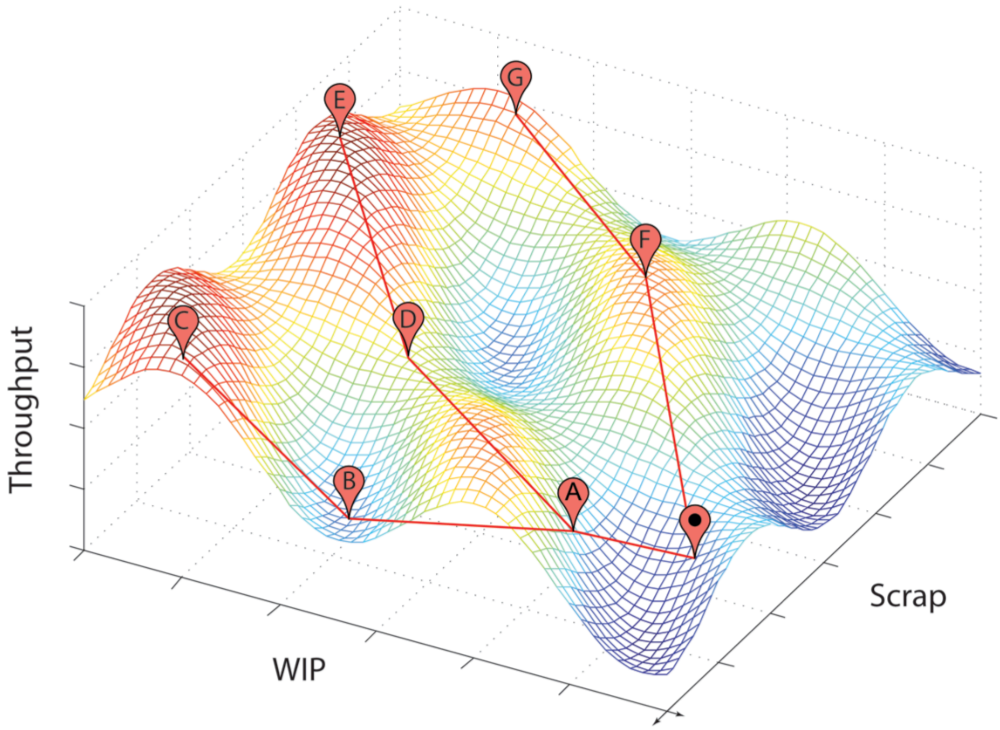


Figure 17: Depiction of a Fitness Landscape with Search Paths

For the purpose of illustration, we have identified the x-axis as WIP, the y-axis as scrap and the z-axis as throughput in Figure 17. We have also indicated the current state on the Fitness Landscape with a map location pin marked with a filled circle. At this point the factory is in a valley of low throughput in a region marked by high WIP and high scrap losses. A manager seeking to improve performance has two immediate options, marked by the pins 'A' and 'F'. These might be, for example, to reduce changeover time on one machine (A) or to focus on reducing the amount of scrap on another (F). At first it would seem that reducing scrap is the more favourable of the two, since it sits high on a ridge with lower scrap, whereas reducing changeover time (A) does not quite bring the factory out of the throughput valley. However the manager must consider each of these in the context of multistep paths. Having chosen to reduce scrap, it now becomes difficult to maximize throughput without increasing scrap (E). The result is good, but not optimal in terms of throughput or WIP.

Alternatively, choosing to reduce changeover time (A) leads to the possibility of reducing batch sizes, which results in slightly more throughput but less WIP and scrap (D). From here it is possible to improve batch sizes and changeovers leading to a Pareto optimal position for throughput, WIP and scrap (E).

It should be noted that these paths reflect the fitness of the outcomes and not the difficulty of achieving them. For example, the steep path between (D) and (E) is a reflection of the increased throughput, not of the difficulty in attaining it. Results from the response surface must be combined with information about cost and resource requirements to determine the most acceptable result set.

Production System Definition

The problem domain for enterprise improvement has many levels, since factory outcomes are the net result of effects (whose algebra may be non-linear and not commutative) of the operation of lines and machines. Moreover at a machine level, components may be produced at sub-second frequency, whereas production schedules are set for intervals of hours or days at a factory level. Finally, the behaviours of process elements vary through these different organizational levels. For example, a line produces parts in discrete units but a milling machine consumes lubricants and energy continuously. Some aspects of scale and dimensionality of manufacturing systems are shown in Table 4.

Aspect	From	To
Time	Seconds	Months, Years
Data	Discrete	Continuous
Focus	Machine, tool	Factory, Enterprise
Improvement activity	Single step, single project	Multi-step, portfolio
Process variation	Deterministic	Stochastic
Uncertainty	Common cause variation	Long run uncertainty, risk
Dimensionality	Multiple	Multiple

Table 4: Scale and Dimensionality of Systematic Improvement

A suitable systems model will therefore be multiscale and will require the use of multiple methods and yet permit the integration of all the diverse aspects of the system elements.

Scale selection is a modelling decision and typically modellers will choose a single scale, abstracting away superstructures and substructures to facilitate ease of modelling. This is a very useful approach when searching for point solutions, however organizations do not operate at just one level. Thus, the modelling challenge is to understand the fundamental processes, the scales at which they operate, their interaction and the emergent behaviours that arise in order to understand the system as a whole.

We approach this problem by (i) decomposition and categorization, (ii) abstraction and implementation and (iii) case modelling and simulation.

Decomposition and Categorization

As with biological systems, manufacturing organizations may be decomposed into a hierarchy of meronyms for which characteristic scales (temporal and organizational) may also be defined. Meronyms are constituent parts of a whole as an archetype [197], but more specifically in our application, they represent problem domains that have more or less homogenous solution spaces and which may be modelled independently. They have the characteristics of being transitive $(\text{if } A \in B \wedge B \in C \rightarrow A \in C)$, reflexive $(A \in A)$ and antisymmetric $(\text{if } A \in B \wedge A \mathrel{!=} B \rightarrow B \notin A)$ [198,199]. Temporal scales can be defined by typical intervals of the meronym's takt time or rhythm. For example a unit operation might typically repeat on a scale of seconds, whereas a plant plans in months or years. Organizational scales are reflective of managerial oversight but they also suggest spatial or geographic dimensions.

Considering a typical enterprise, a meronymy arises thus: a global plant network can be decomposed into regions (for example Asia Pacific) or value chain stages (for example component manufacturing), which are themselves composed of individual plants. Each plant is made up of value streams or production lines and also inventories of Raw Materials (RM) and Finished Goods (FG). Those value streams are assemblies of machines, each of which is the sum of one or more unit operations, and work in process (WIP) inventories.

This meronymy further suggests the following temporal scale: unit operations occur in divisions of seconds, machines produce subassemblies in minutes, lines complete batches in hours or days, factories are managed over weeks or months and regional and enterprise strategies are marked off over months and years. Finally, we also define an organizational scale in terms of

Decision Making Units (DMU) [43], thus a factory manager planning improvements for their plant looks at production lines and the entire factory as the DMU. Machines and unit operations are thus sub-systems of the DMU, whereas the region and enterprise sit above it as an overarching supersystem [200,201].

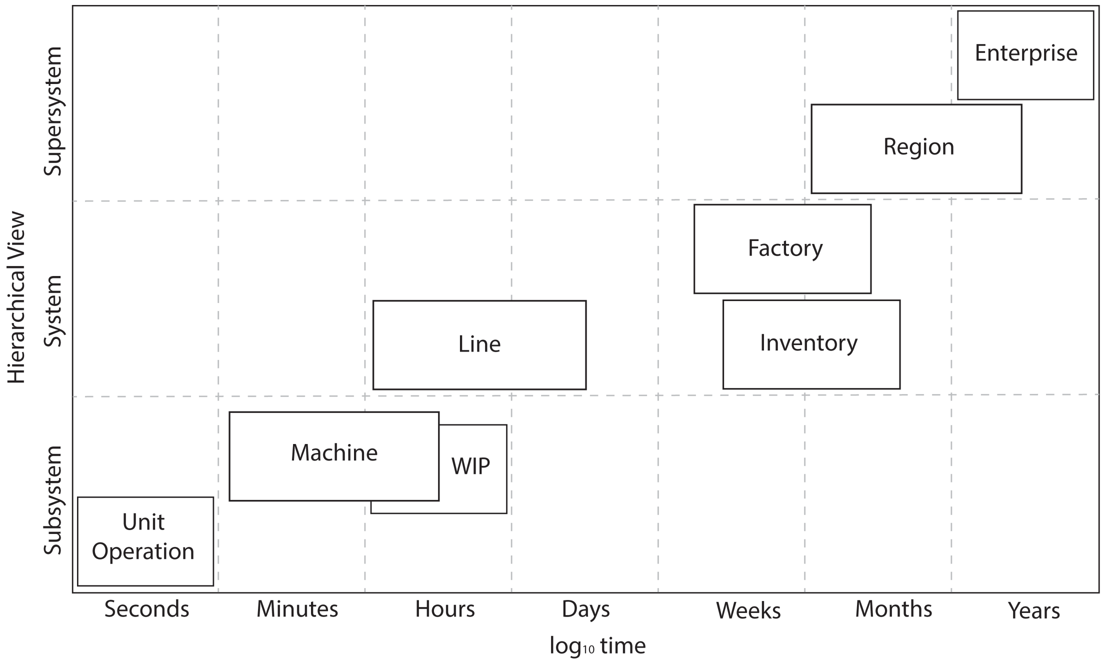


Figure 18: Factory System Meronymy (after [200,201])

Based on this meronymy, it is possible to construct a Scale Separation Map (SSM) as shown in Figure 19. A SSM is a graphical representation of the meronymy of single-scale subsystems in relation to their spatial and temporal scales [202-204].

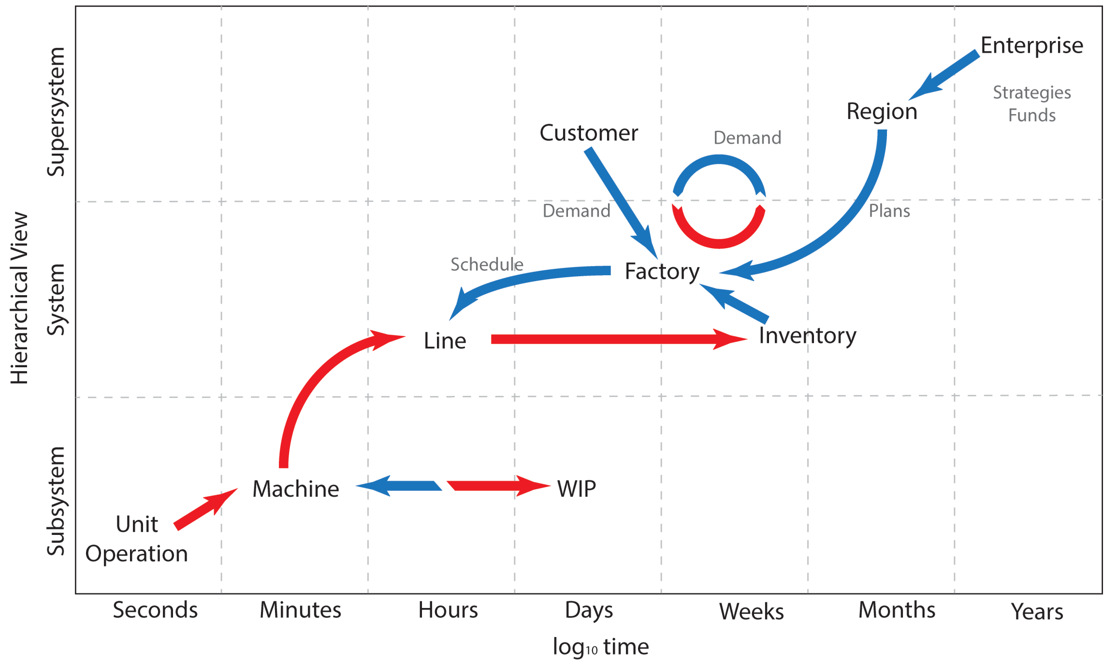


Figure 19: Scale Separation Map for a Generic Factory Model

Within this SSM we identified the interactions between meronyms and across spatial and temporal scales of the system, as shown in Figure 19. Interactions in this model can be either physical, such as the flow of material or parts (shown in red) or logical (shown in blue) as may occur when schedules are used to drive the production of physical batches. Logical and physical flows are fundamentally incommensurate and therefore require a proxy metric to facilitate modelling. Generally we achieved this by monetizing these disparate elements so that parts are costed by the value of direct components and labour, time is valued by overhead, strategy by program funding and so on.

In this generic factory model, unit operations accumulate into assembly operations that produce batches in hours and create hours or days of work in process (WIP). Considering the factory as the system, these activities occur at the subsystem level. They aggregate to batches at the system level, controlled by the counterbalancing forces of demand and inventory in the form of the production schedule. In addition, plants interact with other plants through the supersystem via shared demand and supply. Lastly, planning occurs on a monthly rhythm at the plant level and as yearly strategy at the super-system level.

Although at first glance it may appear that the elements of this SSM are undifferentiated, this is unlikely to be the case. Indeed it is possible that many elements will behave differently across the organization – consider, for example, each factory in a region. Each will make different products, utilize different equipment and operate with different shifts and schedules.

Organisational Context

Within its highly structured approach, Six Sigma directs most of its attention to delivering point solutions to problems and provides no general organisational context. This may be one reason that so little is written on project selection from an organisational perspective. By contrast, Lean Manufacturing relies heavily on the Value Stream Map to identify and select improvement opportunities.

Rother & Shook described a value stream as "all the actions (both value added and non-value added) currently required to bring a product through the main flows essential to every product" [65]. That is, it is a door-to-door process map rather than a detail process map as might be inferred. There is a degree of inherent aggregation as process steps are identified at an assembly stage level as shown in Figure 20.

The VSM is essentially a digraph of process flow (Figure 20) with the key characteristics set out in Figure 21. This VSM begins with the customer, State Street Assembly (), in the top right corner transmitting orders or forecasts () to the factory production control system (). Production control sends forecasts or places orders () on supplier Michigan Steel Co. (), which deliver by road () into Raw Material (RM) inventory (). The main body of the VSM represents the value stream in the factory, showing Work In Process (WIP) as and process steps as , with process parameters below each step () and the process value-added () and non value-added () times tracked on a timeline underneath.

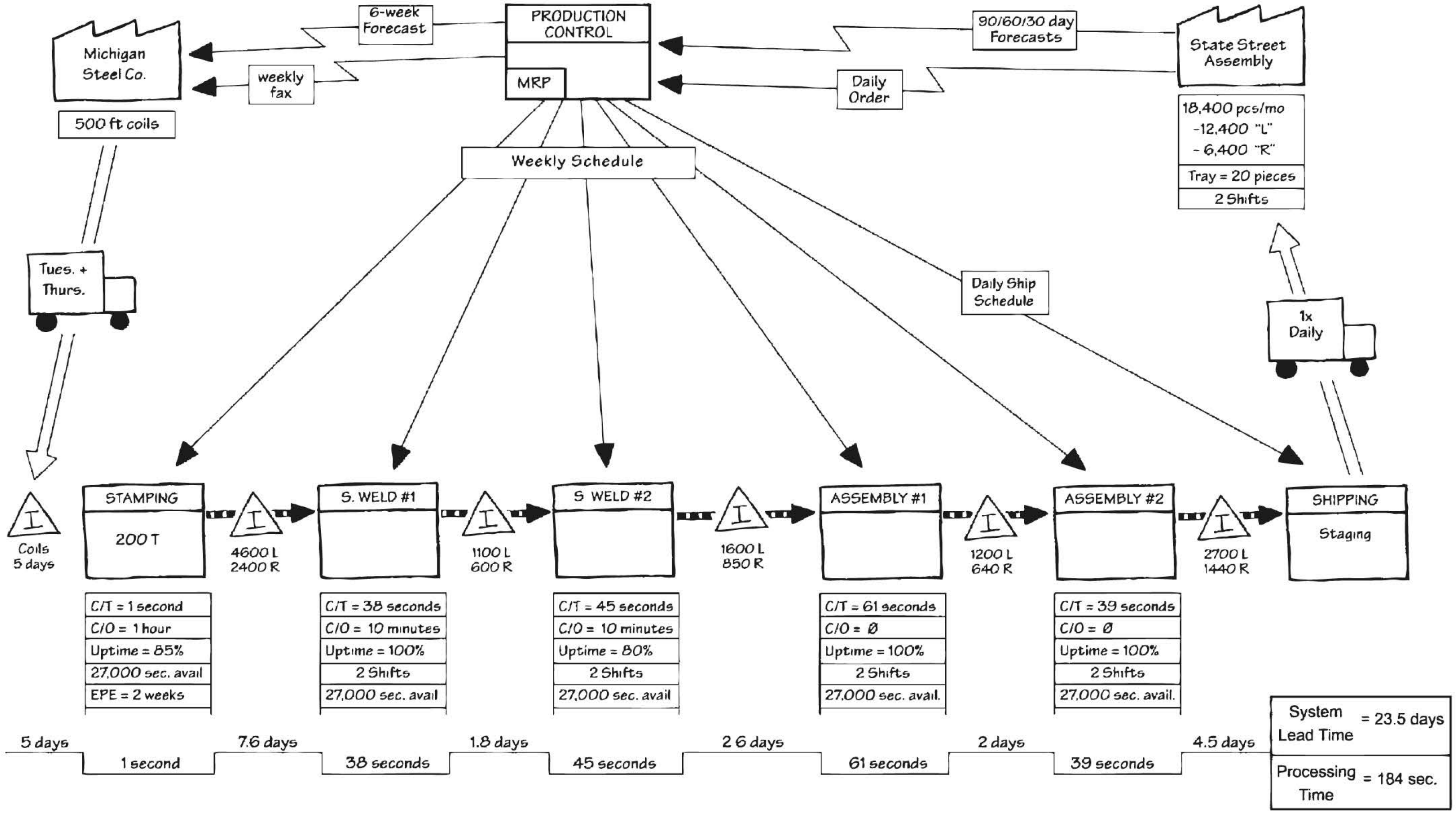


Figure 20: Value Stream Map [57,205]

This VSM therefore provides one with an overall context for material flows and production, albeit for a single product family and factory.

Practitioners exploit this end-to-end context to identify new areas of opportunity for improvement and organisations will usually review their VSMs every 3 to 6 months to drive new activity. Typically these reviews involve brainstorming improvement ideas and then selecting a subset for implementation [6].

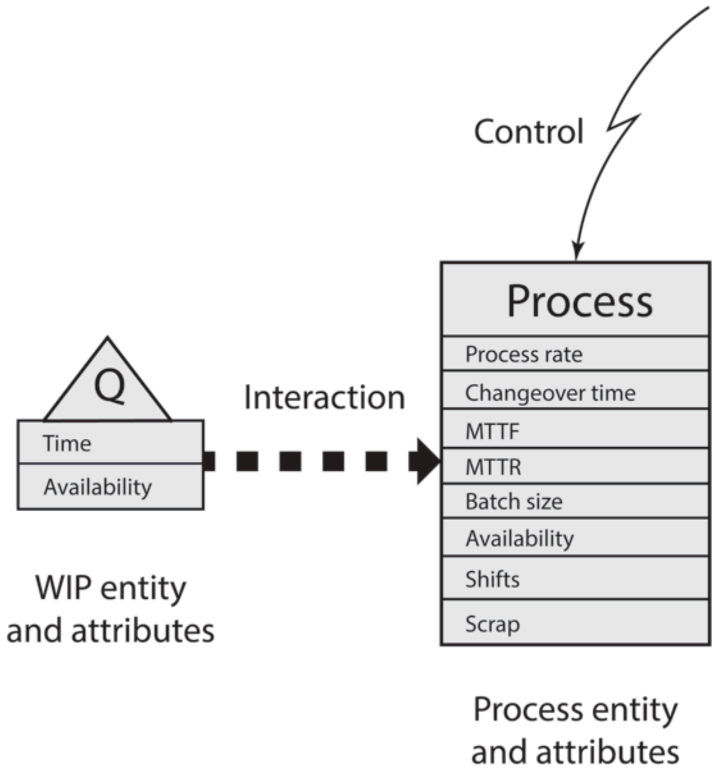


Figure 21: Fundamental Elements of the VSM

In addition to its ability to depict an entire value stream, the basic VSM has the feature of being constructed predominantly by two simple entities – inventory ( ) and process ( ) – making VSM modelling simpler than many other process modelling methodologies. Yet there is still considerable depth to what it can capture. The process attributes, connections and control functions can be varied within constraints to alter its output characteristics and thus also the input characteristics for the next process step. The constraints may be fixed (such as customer specifications) or variable (such as changeover time). Furthermore, the variable constraints may be defined in such a way as to allow for short term feasible versus long term (for example procedural versus capital changes).

Rother & Shook stated that, in their view, the VSM is a "pencil and paper" sketch of the process within a factory [65]. It may lack the methodological rigour of, say IDEF3, but it has sufficient formality and requirements for process data to make it a useful tool for value stream analyses and a good VSM will at least include cycle time, availability, process rate, changeover and inventory data and many practitioners will augment mean data with standard deviations.

The VSM is widely used and understood and has a level of abstraction that makes the notion of an entity improvement portfolio conceivable. Even though it may lack some methodological rigour [178-179], it represents a good starting point for our research.

Even as they were preparing 'Learning to See', Shook was aware of the need to extend the VSM across facilities [177]. Surely, if there was waste in a single value stream, that would be dwarfed by the opportunities across multiple value streams, plants and even companies. Shook, however, determined to limit 'Learning to See' to a single plant focus and it was in 2003 that Jones and Womack released the follow-up 'Seeing the Whole', which laid out the process for enterprise mapping as shown in Figure 22 [177].

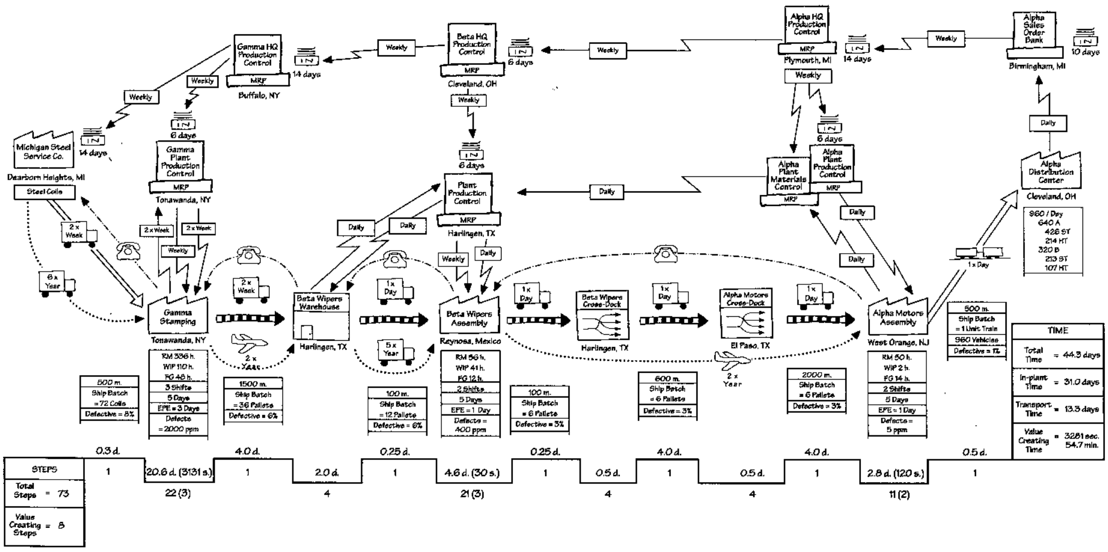


Figure 22: Enterprise Value Stream Map [177]

Examining an EVSM, one begins to recognise that it represents the enterprise as a system as distinct from the VSM's linear process treatment. What also becomes clear is that the scale and complexity of enterprise mapping present considerable challenges - the logistics of the exercise; the combinatorial nature of inter-firm interactions; what vantage point to use; how to deal with a supplier that deals with multiple sites; whether a single approach can capture a useful level of detail and; whether meaningful decisions can even be made.

It is also evident that an enterprise is composed of many value streams operating as a dynamic open system, as suggested in Figure 23 below. Although in an entity a manager will want to optimise a value stream or portfolio of value streams, at an enterprise level one must take into account a broader set of interactions and configurations. It is therefore important to define clear boundaries to limit the extent of the value stream whilst providing sufficient scale to recognise potentially important interactions. In this dissertation we shall assume the boundaries to be those of the enterprise, treating it as a closed system with suppliers and customers considered as externalities.

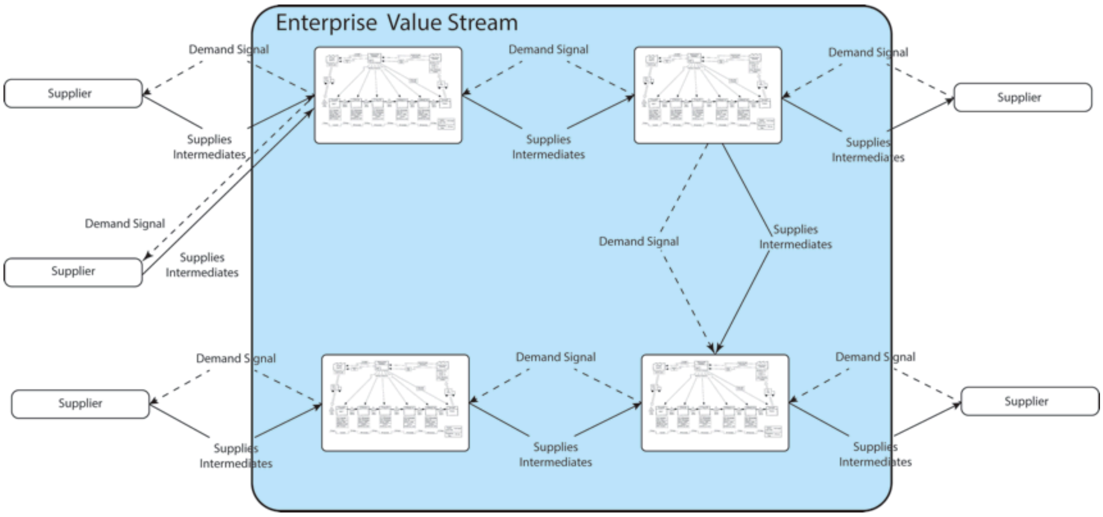


Figure 23: The Enterprise Value Stream as a System of Value Streams

There is scant literature about the use of EVSMs in practice, though the Lean Advancement Initiative (LAI) at MIT has been very active with consortium members from the aerospace industry in delivering facilitated outcomes using Enterprise Value Stream Mapping and Analysis (EVSMA) alongside a strategy analysis framework (Enterprise Strategic Analysis for Transformation or ESAT) [180]. Instead, much of the Lean manufacturing literature focuses on improvement within an existing, static network design. Although network design is an important and legitimate consideration that might arise from an EVSM, it will be outside of the scope of this dissertation, which will address optimisation within an existing network design.

Abstraction and implementation

Such complex systems behave in ways that may be emergent, that is to say that their behaviour cannot be predicted mathematically by the sum of activities but only by means of numerical simulation because of the complex stochastic interaction of their parts. Understanding this complex behaviour required that we build models that incorporate these disparate temporal and spatial activities. Since our goal was to develop a scalable methodology, allowing one to model a VSM of a product family or an enterprise of factories with the same toolset, we identified a consistent approach as the basis for our toolset Table 5.

	Graph theory	Petri net	DES	System dynamics	OOM
Dynamic	○	◔	◕	●	●
Discrete	●	●	●	◔	●
Continuous	◔	◑ Hybrid	○	●	●
Stochastic	◑	◑ Stochastic	●	◑	●
Hierarchical	◑	◑	◕	◕	●
Multidimensional	◑	◕	●	●	●

Table 5: Modelling Approaches Considered

In principle, this problem may be approached by either analytical or numerical approaches. However, simulation modelling was considered to be more relevant in that (i) it affords a more adaptable set of building blocks than analytical models and (ii) relevant transfer functions might not be readily available, whereas it is should always be possible to collect sufficient empirical data and thereby estimate probability distributions.

Whereas much work has been done using multiscale modelling and simulation in materials science [206] and systems biology [207], little has been done to date in manufacturing [208]. We therefore identified that the modelling approach needed to accommodate the following characteristics of our problem domain:

Dynamic: Processes may behave differently depending on certain starting or contributing factors and therefore should be defined parametrically.

Discrete: Certain process elements are defined in $\mathbb{Z}^n$, such as one clock tick or one batch of product.

Continuous: Process elements also are defined in $\mathbb{R}^n$ and may appear as continuous flow. This can be the case for example with liquid materials or energy but is also the case when models are abstracted to higher levels. Here the increments become small relative to the magnitude of the number and so $\mathbb{Z}^n$ approximates $\mathbb{R}^n$. This can also be seen as *n* becomes large for the Bernoulli function and a reasonable approximation can be obtained with a Poisson or even a Normal distribution.

Stochastic: production processes are not deterministic but rather are the result of probabilistic functions. Their probabilistic nature may therefore be described by the Binomial or Bernoulli discrete probability distributions for variables in $\mathbb{Z}^n$ or as a continuous probability distribution such as a Gaussian or Erlang and so forth for variables in $\mathbb{R}^n$.

Hierarchical (or Multiscale): The foregoing description of meronomies indicates that there are similarities that must be captured in our modelling approach. For example, Raw Materials is to factory as WIP is to process. Ideally the modelling approach would take a parsimonious approach to modelling elements.

Multidimensional: An organisation's strategic goals may be incommensurate with one another, for example cost or profit being measured as dollars and flexibility as number of SKUs.

We subjectively assessed a number of methodologies against these criteria and chose to use an Object Oriented Modelling (OOM) approach implemented in Java® to design our simulation framework. OOM allows for construction of well-defined replicable building blocks and also opens up the possibility of creating a great variety of new components through object inheritance and polymorphism. We anticipated that this would allow us to build a library of components and behaviours over time. In this chapter we will only define the major generic classes, however the reader will observe the potential for elaboration upon these generics.

With the ontology described above, we were able to define a generic abstraction in the Unified Modelling Language (UML), where distinct classes represent each meronym. The model is further simplified through normalization [209,210] and the resultant Third Object Normal Form (3ONF) class diagram is shown in Figure 24.

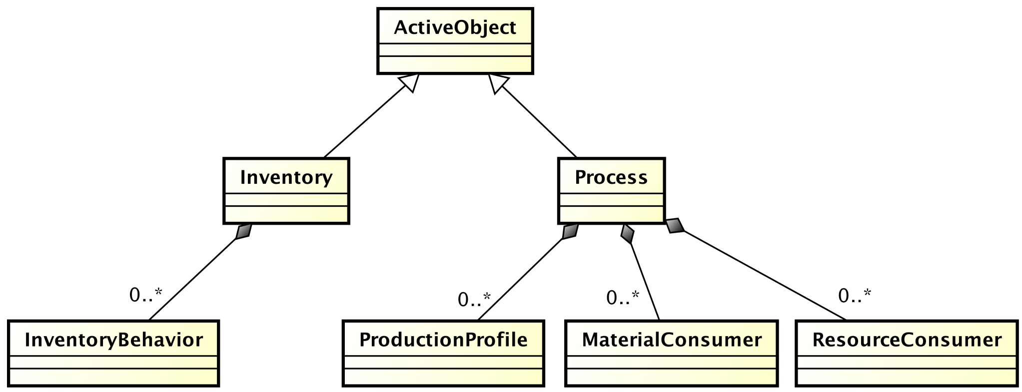


Figure 24: Third Object Normal Form (3ONF) Class Diagram

Although the abstract level described a complete system ontology, implementation required that we create a parsimonious model of entities and their relationships. Thus machines, production lines and factories were all implementations of the abstract class ‘process’, whereas WIP, RM and FG were implementations of the abstract class ‘inventory’. Apart from the variety created when instantiating objects from these classes, these classes may also have specific behavioural models (how they consume resources and materials and how they produce outputs) associated with them and these were defined in our model by using plug-in classes. Since the Application Programming Interface (API) of these behavioural classes is defined by Java® interfaces, it was possible to develop our generics without foreknowledge of what sorts of behaviours one may encounter when modelling specific manufacturing facilities. This also afforded a great deal of flexibility to define and even improve our models. For example it was possible to build a simulation to examine production and later rerun the same simulation with attached energy consumption models to determine energy use. It was also possible to run a simulation with a basic interpolated model of energy consumption and later refine the simulation to a more complex mathematical model.

Although normalization was beneficial from a programming perspective, it was in conflict with the range of time frames and data types that we needed to simulate and this had to be considered in the design of each class and interface.

All models began with an encapsulating class, which we called VSM (for Value Stream Map). This class provides the Graphical User Interface (GUI) within which the modeller could create process maps as shown in Figure 25. It also included procedures to determine what objects were in the model and to capture summary statistics from these objects.

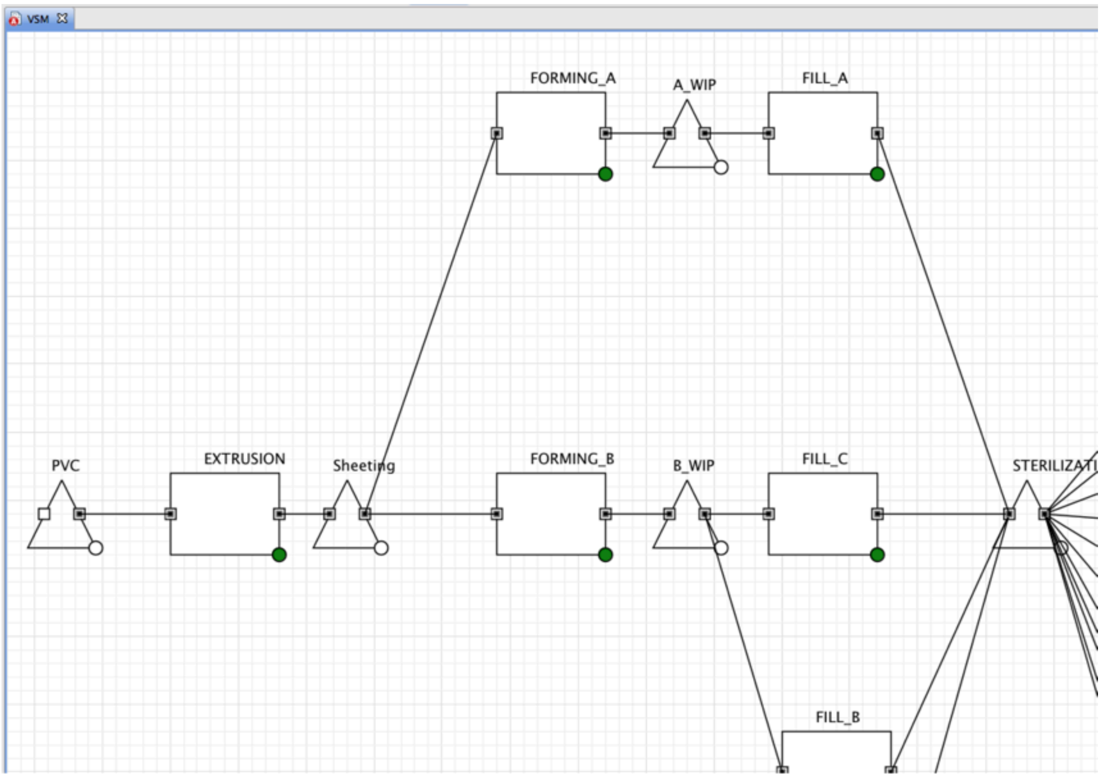


Figure 25: Exemplar VSM Diagram in AnyLogic® (process details redacted for confidentiality).

Finally, the VSM class was also the collection of objects that would be simulated to create each data point on our Fitness Landscape and as such it had access to setter and getter functions of all encapsulated objects. It utilized this access to initialize the parameters of all objects as defined by each experiment and to determine intermediate and final parameters of those objects. During experiments, a VSM object would load a set of parameters from a MySQL® database in accordance with the run number and experimental design. This allowed us to run experiments with over twenty parameters over more than three thousand runs plus replicates.

Unit operations, machines, lines and factories were all derived from the generic class 'Process' (Figure 26). Defining their organizational level and timescale also would also define what other objects they could interact with directly and how they would be decomposed or rolled up in relation to the abovementioned meronymy. For example a Process object could define a machine and operate on a scale of minutes yet interact with a group of Process objects modelling unit operations. Although the inputs and outputs of objects at different levels differed, all objects also monetized their consumption, losses and outputs so that results would be commensurate both along a process as well as up and down through organizational levels.

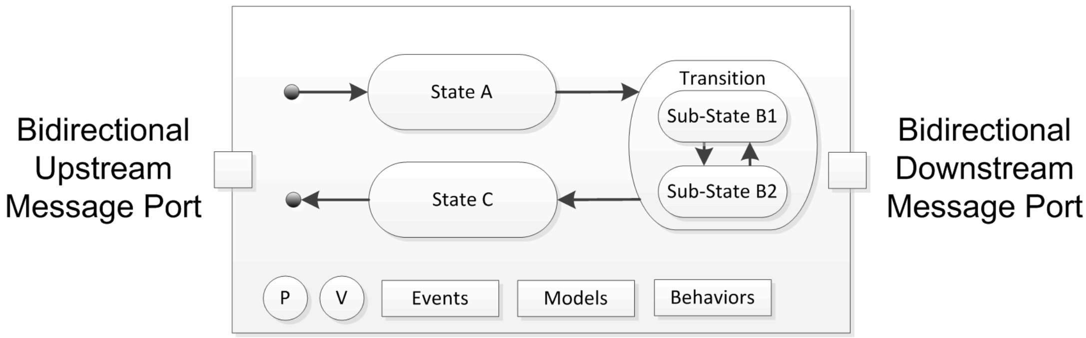


Figure 26: Simplified Process Model

Unlike pure discrete event simulation, where entities are passive objects, Process was an agent class that could communicate bidirectionally with any other objects to which it was connected and act appropriately. For example, it would ask inventory locations how much input materials were available, how much space was available and what state the locations were in and produce outputs accordingly (Figure 27).

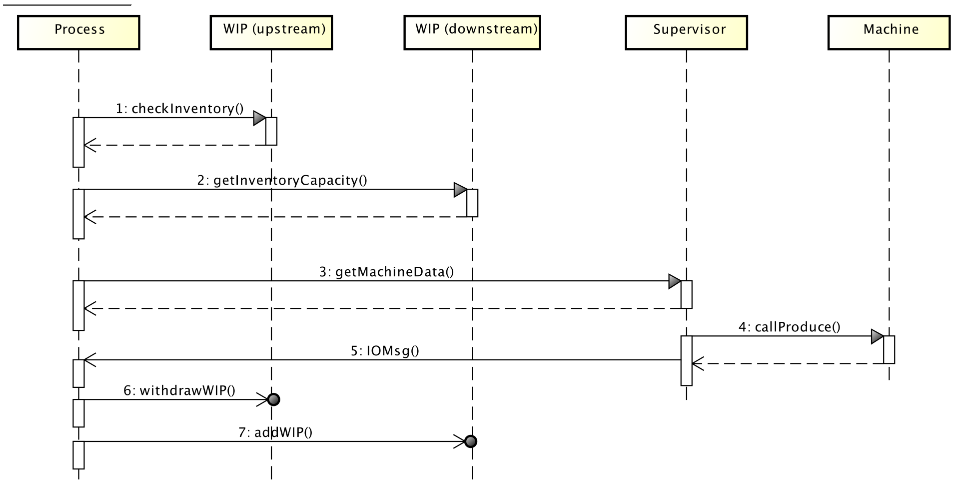


Figure 27: Extract from Process – WIP Sequence Diagram

Class Process also defined complex transitions between possible process states in a transition map. For example, when a machine was started it may pass from OFF to IDLE to RAMPUP to RUN. In this way, complex transition patterns could be defined from a finite number of states depending on the machine as shown in Figure 28. The behaviour of states could further be defined either in a Process object or overridden by behaviours in a plug in object. Thus, for example, the energy consumption during IDLE need not be fixed, it may be a stochastic parametric model taking into account various machine settings and increase in relation to the load placed on the machine during RAMPUP.

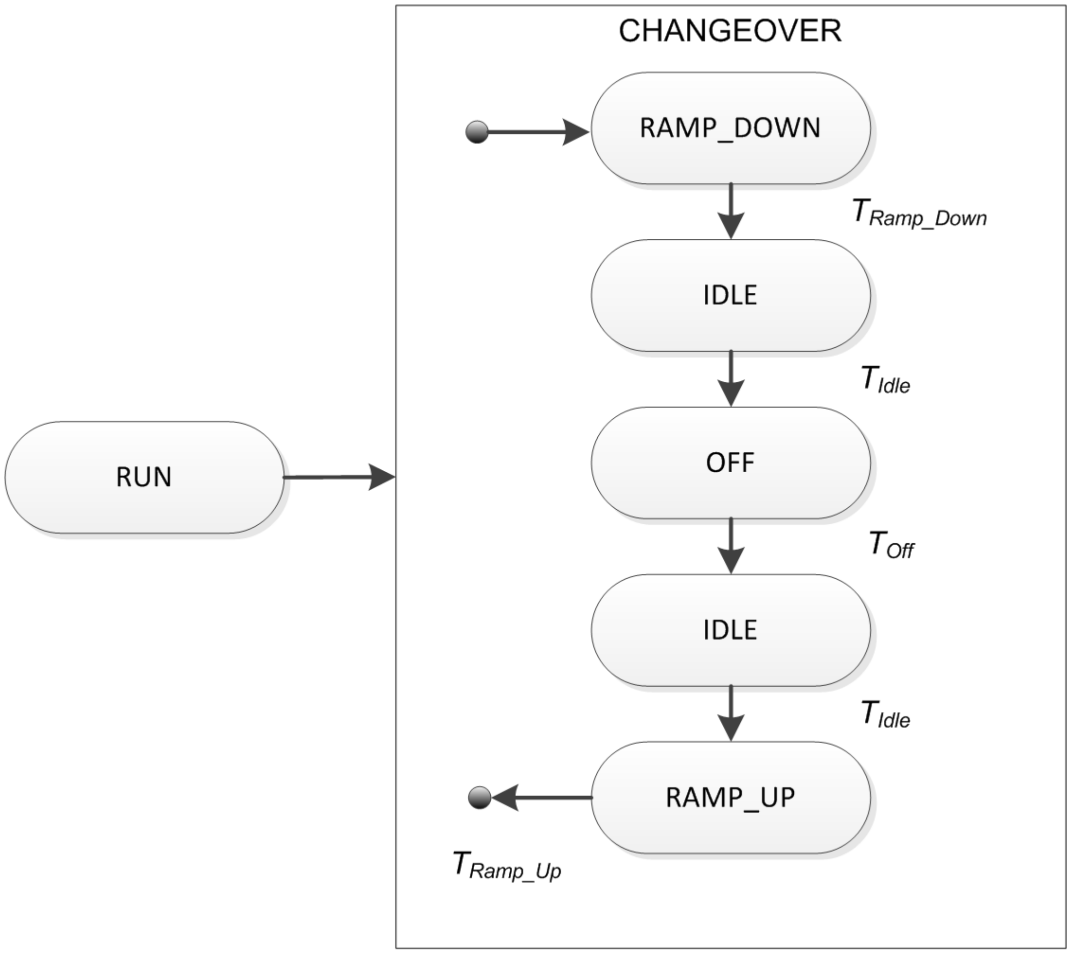


Figure 28: Example of a Complex State Transition

When initialized, each Process object would communicate with a MySQL® database to set its own variables (including production and scrap rates, Mean Time To Fail (MTTF) and Mean Time To Repair (MTTR), Changeover Time (CoT), products produced, schedule, costs and so on). Since this process also took into account start-up parameters, it was possible to create complex Design of Experiments (DoE) needed to create a fitness landscape. Once again, all of these behaviours could be programmed into the Process object or overridden by behavioural plug-in objects at runtime.

The object provided statistics of utilization, output, scrap and so on required by the encapsulating VSM object. In our experiments we monetized these statistics to allow us to rollup total product produced, total WIP, total scrap and so forth.

Like Process, the Inventory class was an agent that can communicate bidirectionally (for example it might need to communicate that it is full) though it was generally more passive in practice than the Process class. It could also be configured at runtime for things such as minimum and maximum size, products taken, whether it was a kanban and so forth.

We created four Behavioural Interfaces: InventoryBehaviour, ResourceConsumer, MaterialConsumer and ProductionProfile. These specified the API that must be implemented by plug-in objects in order to override (and thereby extend) the behaviour of Process and Inventory objects. For example, a MaterialConsumer plug-in object must be told what state and transition pattern the Process object was in and it has Consume and Produce methods that would return input and output results.

Although we used Java® for its flexibility, we implemented our models and experiments in the proprietary simulation software AnyLogic® [211] for its simulation engine and Graphical User Interface (GUI) and we managed our data sets and experimental parameters in MySQL®.

An Entity Relationship Diagram (ERD) in Third Normal Form (3NF) for one of our experimental cases is shown in Figure 29. Product information (here name and size) was captured in one table, machine specific information (such as Mean Time To Failure or MTTF) in another and the schedule in a third. The normalisation process required many-to-many relationships be resolved and this was achieved through the implementation of the MACHINE_has_PRODUCT table. Externalising production parameters in this way allowed experimental control over the simulation. A separate table for experimental designs was also prepared (not shown), this was used to store index values (that also represented to the DoE simulation run number) as well as the design matrix. The AnyLogic® simulation would use its index value to query this table and then query the main database for all parameters needed for the simulation run.

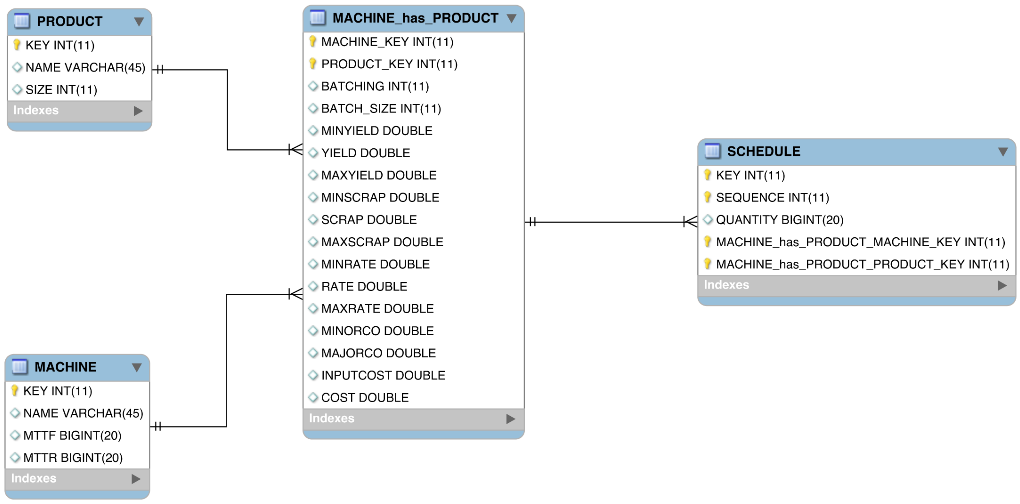


Figure 29: Example 3NF ERD for Managing Production Data

The overall system is depicted in Figure 30, showing the relationships between simulation elements and software platforms.

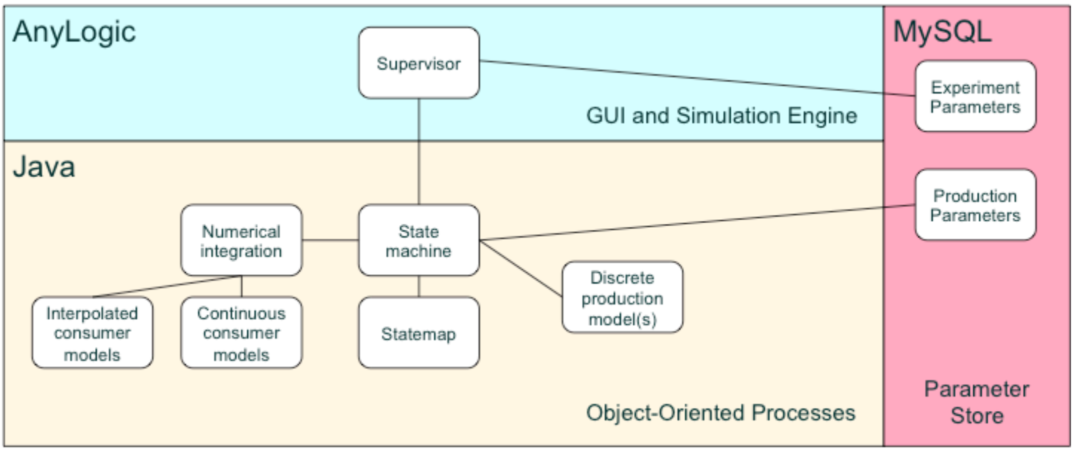


Figure 30: Complete Modelling Engine

Optimal Design of Experiments

Having defined our modelling approach we now return to the reference frame. Since any individual run of our model would only represent the production performance outcomes for one set of production parameters, $u = (u_1, u_2, \dots, u_k)^T$, it was necessary to repeat the simulation many times to create a Fitness Landscape with sufficient granularity to be continuous for our purposes. Indeed, given the large number of process elements and the many possible control points, this number could become exponentially large – for example in one firm, we identified 9 machines as potential sources of improvement. If we simulate run rate, changeover times and scrap and establish outputs for all of these at three levels, we would need at least 2.6×10^9 experiments to create a response surface.

Of course one-factor-at-a-time approaches are neither parsimonious, nor do they take into account potential interactions between variables. Only statistically designed experiments (DoE) can achieve these outcomes simultaneously and even then one must be cautious in selecting an experimental design. When examining individual processes or machines we might typically prepare a response surface using second-order designs such as a 3^k factorial or Central Composite Design (CCD) experiment [212], however the number of experiments required by a full factorial grows by 3^k and, whereas CCDs grow at a rate of only $3^k + 2k + 1$, even CCD designs become unwieldy above 12 or so factors.

These designs are commonly used, since their orthogonal nature simplifies both experimental design and regression estimation [213]. However, in addition to such practical considerations, it is important to consider the design optimality of the proposed experiment [214]. Whereas such designs are generally suited for parameter estimation (since they attempt to separately estimate regression coefficients to have the minimum variance), they are not always suitable for response prediction where we seek to minimize the integral prediction variance over the design space - that is I optimality [215].

Optimal designs are ideal experimental designs with respect to a statistical condition of the resultant model, such as variance reduction [216]. In this case, we seek to minimize the average variance over the design space in order to maximize the predictive power of our response surface, thus given the polynomial:

$$f(x) = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \sum_{j=i+1}^{k} \sum_{i=1}^{k-1} \beta_{ij} x_i x_j + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \epsilon$$

(where β is a production parameter and ϵ is an error term), we define an I-optimal DoE as one that maximise the design optimality criterion I where:

$$\mathrm{I} = \int_{\mathrm{R}} \mathrm{f}^{\mathrm{T}}(\mathrm{x}) \left(\mathrm{X}^{\mathrm{T}}\mathrm{X}\right)^{-1} \mathrm{f}(\mathrm{x}) dx = \mathrm{tr}[\left(\mathrm{X}^{\mathrm{T}}\mathrm{X}^{-1}\right) \int_{\mathrm{R}} \mathrm{f}(\mathrm{x})\, \mathrm{f}(\mathrm{x})^{\mathrm{T}} dx]$$

and where $[\mathrm{X}^{\mathrm{T}}\mathrm{X}]$ is the design matrix.

Such models are developed algorithmically taking into account the number of variables, the level of interaction and so forth in software packages such as R and JMP® [217,218]. For our experiments we used JMP®, which utilizes the iterative coordinate exchange algorithm [217,219]. Returning to our earlier 3^{27} example, JMP® was able to create a design requiring only 3 336 runs, although the design itself took several hours to generate on a standard quad-core Intel PC. The resultant coded design was then loaded into a MySQL® database to drive the parameter changes across each simulation run of the experiment as described above.

Portfolio Selection on the PF

It is now possible to place the organization's current performance on or below the PF. Given any set of decision vectors, $\{A: x_a = (x_1, x_2 \dots x_k)^{\mathrm{T}}\}$ where $\mathrm{A} \subset \mathrm{S}$ and S is the nonempty feasible space $\mathrm{S} \subset \mathbb{R}^{\mathrm{n}}$ (the decision variable space), we can prepare a directed graph of decision vectors whose order ought to flow such that there is a sequential preference $\mathrm{x}_a \preccurlyeq \mathrm{x}_b$. We expressly used the word 'ought', since individual search paths may indeed require a step whereby $\mathrm{x}_a \succcurlyeq \mathrm{x}_b \rightarrow \mathrm{x}_b \prec \mathrm{x}_c : \mathrm{x}_a \prec \mathrm{x}_c$.

Each of these decision vectors represents the production output for a given set of production parameters and so may be estimated from the prediction function derived as a result of the DoE. In addition, one must consider the time and cost of each vector in developing an overall ROI within the time constraint of the firm's planning period. Given these data, one may then apply discrete optimization to find the best search path on the graph of decision vectors.

Case Modelling and Simulation Procedure

Our methodology for case modelling and simulation is set out in Figure 32 as follows:

System Definition and Process Mapping: The boundaries of the system were defined, for example a single VSM, a factory of multiple VSMs but not including its suppliers. The Decision Making Unit (DMU) would also be defined in order to then circumscribe the relevant strategic metrics and therefore the dimensionality of the Fitness Landscape. Based on these decisions, a VSM would prepared by the method set out in By Rother and Shook [57] or Jones and Womack [205] in the AnyLogic®/ Java® tool described earlier.

Data Collection: For each element of the VSM, detail process parameters were collected such as production rate, changeover time and scrap. In addition, the Bill of Materials (BOM) was used to gather relevant financial measures such as component costs wherever possible. The collected data would be stored in a MySQL® database prepared for the study.

Modelling and Simulation: Detailed process modelling was conducted using the Java® components, where appropriate. The production factors for the DoE were defined and managed in a MySQL® database and an I Optimal DoE would be defined using JMP®. Depending upon the complexity of the DoE, this could first be conducted as a screening DoE in order to limit the number of factors for later experiments. It is possible to over-parameterise a model and this can both complicate the simulation and result in a model with a misleading high coefficient of determination (R^2). To minimise this risk, we conducted stepwise parameter selection of regression by forward selection [220] using JMP®.

Portfolio Mapping: The resultant regression model was then plotted as a surface using Matlab®. The outcome from the organisation's extant improvement portfolio would be estimated, stepwise if possible, using the regression model and these would then also be plotted on the Fitness Landscape along with the organisation's current state. The top Pareto Optimal and local Pareto Optimal points were then identified using a simple greedy sort algorithm (Figure 31) and plotted on the surface as well. At this point our method makes use of a simple heuristic to the regression model to identify a path from the current state to a local Pareto Optimum as follows:

- Identify base case parameter set $b = (\mathrm{x}_1, \mathrm{x}_2, \dots, \mathrm{x}_\mathrm{n})^\mathrm{T}$
- Select a Pareto Optimum
- Identify Pareto Optimum parameter set $p = (\mathrm{x}_1, \mathrm{x}_2, \dots, \mathrm{x}_\mathrm{n})^\mathrm{T}$

- Compare $b \rightarrow p$ and derive a requisite parameter shift set $s \subset p$.
- Determine $\{f_1(x), f_2(x), \ldots, f_k(x)\}$ for s
- Select project portfolio subset

```
Quicksort(A,x,y):
        If x < y;
        p := Partition(A,x,y)
        Quicksort(A,x,p-1)
        Quicksort(A,p+1,y)

    Partition(A,x,y)
        n = A[y]
        i ← x - 1
        for j ← x to y – 1 do
            if A[j] ≤ n then {
                i ← i + 1
                Exchange A[i] and A[j]
            Exchange A[i+1] and A[x]
        return i + 1
```

Figure 31: Sort Algorithm

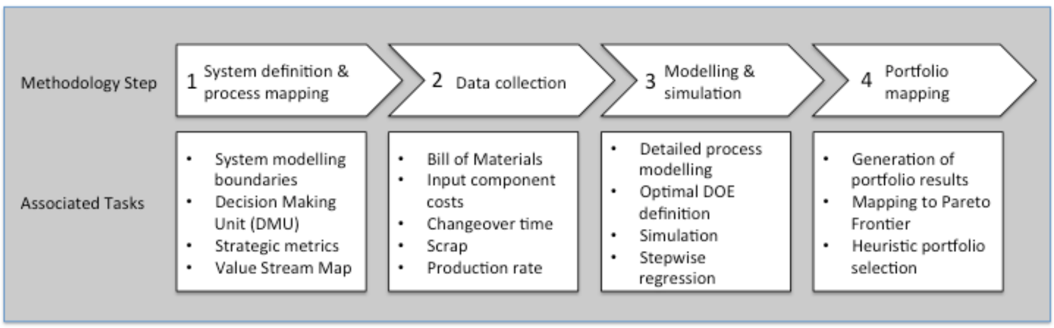


Figure 32: Case Modelling and Simulation Methodology

Operational Validation

Models are simplified representations of real work systems that are created via a process that relies upon abstractions, assumptions and exclusions. Modellers will make choices that translate real world detail into conceptual and computational models. As a consequence, models are at risk of conveying inaccuracies and therefore must be subject to a process of verification and validation prior to use [221]. Verification is defined by Kleijnen as the process that ensures that simulation software performs as intended [222], whereas validation "is the process of determining whether a simulation model is an accurate representation of the system, for the particular objectives of the study" [223]. Any given system may be modelled in a variety of ways with any number of levels of sophistication and detail, however the end result should be fit for the particular study purpose and therefore the validation process must give due reference to that specified purpose.

To this end, some researchers (for example Leal [221] and Kleijnen [222]) recommend that a statistical operational validation of the model in use is conducted in order to demonstrate that the model's variance and mean are similar to historical reference data (as shown below in Figure 33). Although we agree that statistical operational validation is necessary, we contend that the process outlined in Figure 33 [221] is not necessarily valid for four reasons:

i. Models are parametrically controlled representations of real world situations. When the model is run it is provided with a certain fixed set of parameters. However we have no parametric control over the historical reference data set and thus we cannot have any certainty that we are comparing similar states.
ii. Following on from (i) it is generally the case that the available data will not include parametric details.
iii. Any individual run or set of runs will be conducted at a specific treatment level, whereas the resultant behaviour would be compared to a broader set of conditions.
iv. Finally, in this specific case, the particular objectives of the study require that we demonstrate the relative effect of parametric changes, not an absolute effect. We therefore suggest that it is more important to demonstrate an homogeneity of variance across the modelled results so that we may have confidence that changes in behaviour of the modelled system are reflective of parametric changes and are not the result of heteroscedasticity of model outputs.

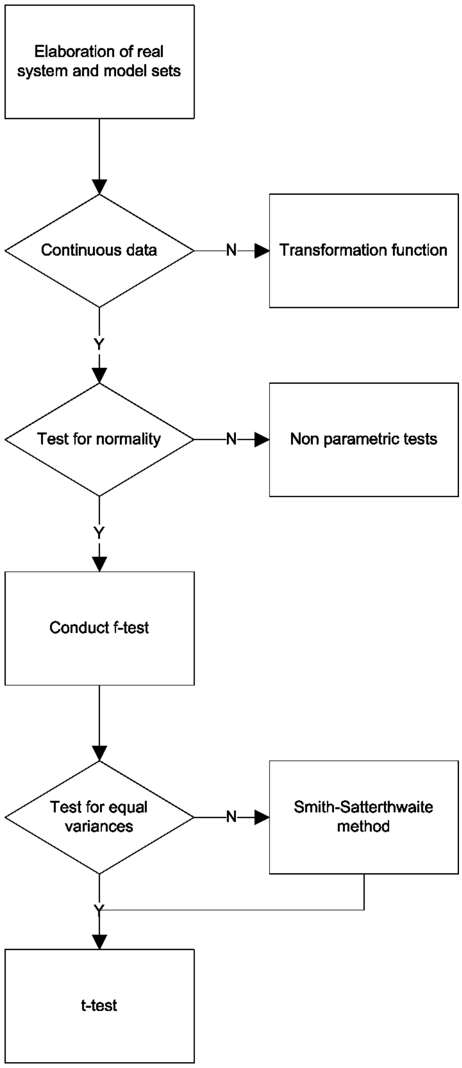
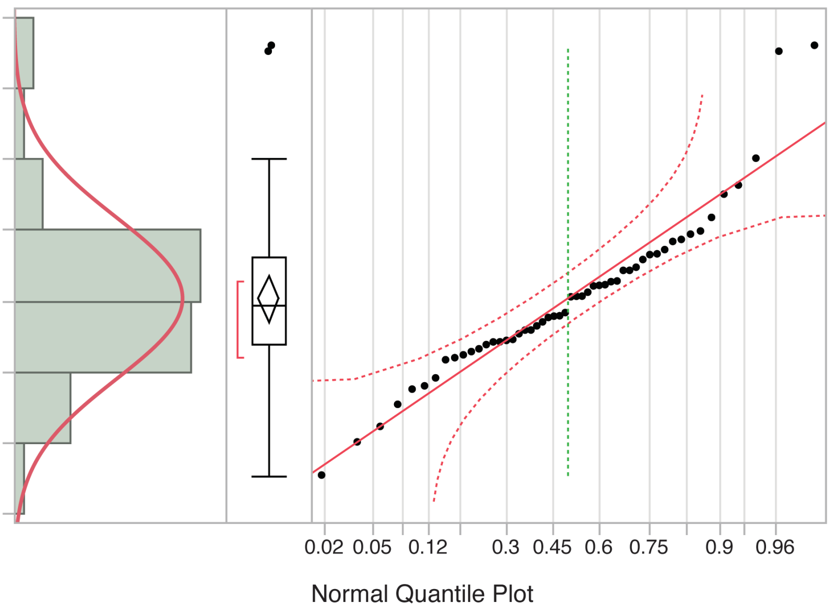


Figure 33: Statistical Operational Validation Method (after [221])

It is not possible to have a perfectly validated model. In particular, when an overall simulation extrapolates beyond day-to-day operations, it may not be possible to obtain relevant real world data [222]. This is true even though each element is individually modelled on empirical data within an observed range. Published methodologies [221] only examine simulation outcomes in comparison with collected production data. However for a measuring device to be useful, it must be an invariant estimator of position changes. We therefore measured homogeneity of variance to ensure linearity of the estimator through the decision space.

In our studies the conceptual models were verified by reference to subject matter experts. For example, we reviewed the VSMs with other researchers and with company employees to ensure they were accurate and complete. We tested assumptions in the same way – for example, were we correct in excluding the quality assurance release as a model parameter. The behaviours of the processes were discussed in detail to ensure the observed and modelled process was a true representation of the real process. Data was gathered from business systems or collected and reviewed with employees. In addition, a large part of the software development process entailed debugging software and ensuring that the software behaved as expected – for example testing that the schedule triggered changeovers to the correct product or that production withdrew upstream WIP and deposited WIP downstream. These verification exercises were somewhat mechanical and therefore relatively trivial to this thesis and we therefore concentrate the remainder of this section on operational validation, which we feel is most important in demonstrating the accuracy of the models in use.

Since all of the data were continuously distributed, we began our statistical validation with an Anderson-Darling test for normality to ensure that we selected appropriate statistical methods. We simulated 52 data points (representing 52 weeks of production) using the fitted response surface obtained from JMP® for the first case study and tested this simulation output for normality using JMP®. The results are shown in Figure 34 - Figure 36. These show Normal Probability plots and the results of an Anderson-Darling test for Normality for each of Output, Losses and WIP. Each plot shows some degree of skew and leptokurtosis, however all Anderson-Darling values other than Figure 33 have $p > 0.05$, which indicates that the results are normally distributed[2].



[2] The null hypothesis, H_0, for the Anderson-Darling test is that data follow a Normal distribution; while the H_1 is that they do not. Since the p values are all > 0.05 we cannot reject H_0 and therefore the distributions are Normal.

Figure 34: Normal Probability Plot for Simulated Output ($A^2 = 0.7849$, $p = 0.0386$)

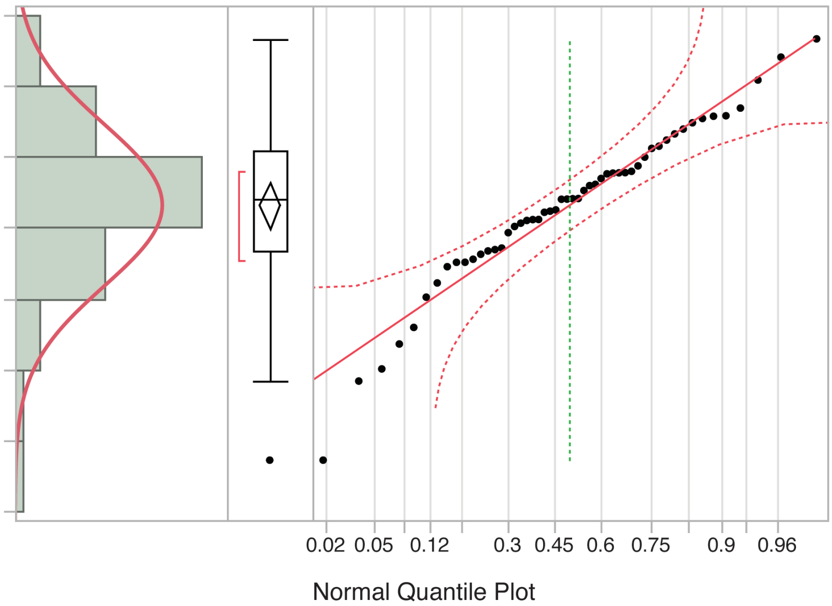


Figure 35: Normal Probability Plot for Simulated Losses ($A^2 = 0.5114$, $p = 0.1900$)

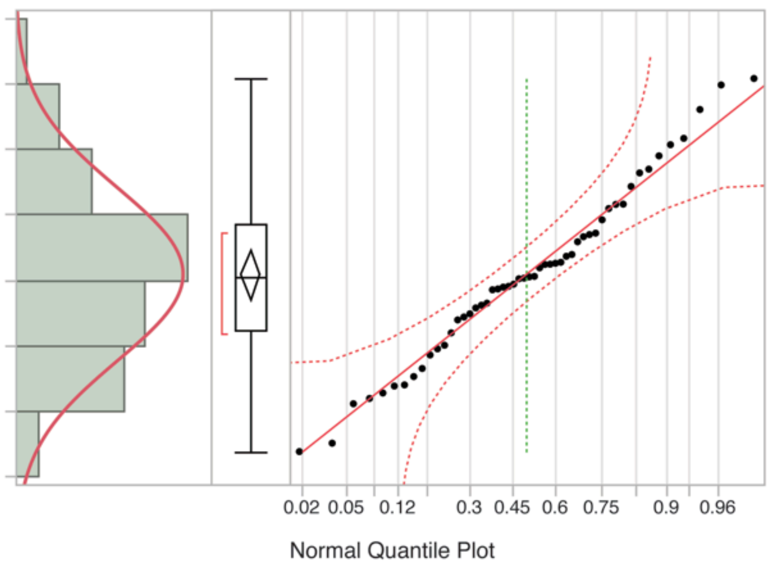


Figure 36: Normal Probability Plot for Simulated WIP ($A^2 = 0.2767$, $p = 0.6643$)

Having demonstrated normality, we then compared simulation results at increasing treatment levels in order to confirm homoscedasticity. We carried out pairwise Levene's tests for Output, Losses and WIP as shown in Figure 37 to Figure 45 below. The null hypothesis, H_0, for Levene's test is that population variances are equal; while the H_1 is that they are not. For most of the studied treatment levels the p values are > 0.05 so we cannot reject H_0 and therefore we have no evidence that the variances are unequal. The highest level of scrap and WIP are significantly different and so we should take some caution when examining results at this end of the region.

We therefore concluded that, for Output, the simulation results appear to be homoscedastic and therefore we have confidence that changes observed on the Pareto Frontier are more likely to be the true result of changes in treatment parameters than stochastic variation.

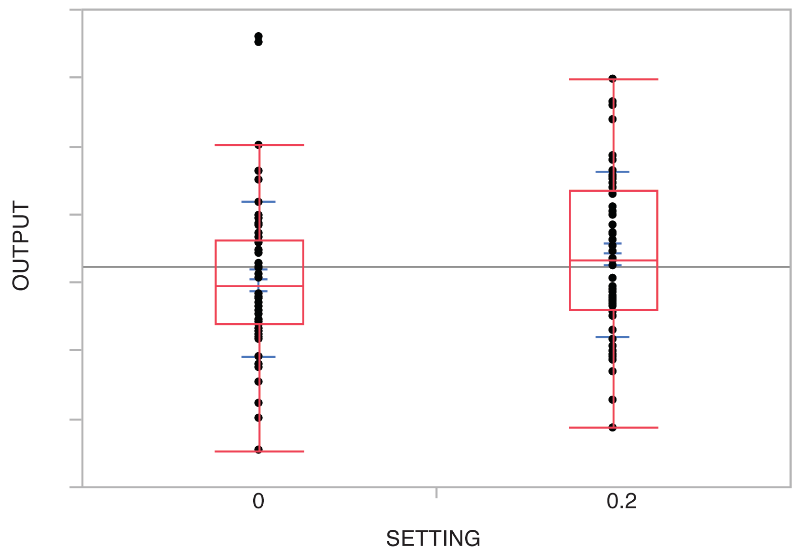


Figure 37: One Way Analysis of Output by Setting (Levene: F = 1.2000 p = 0.2759)

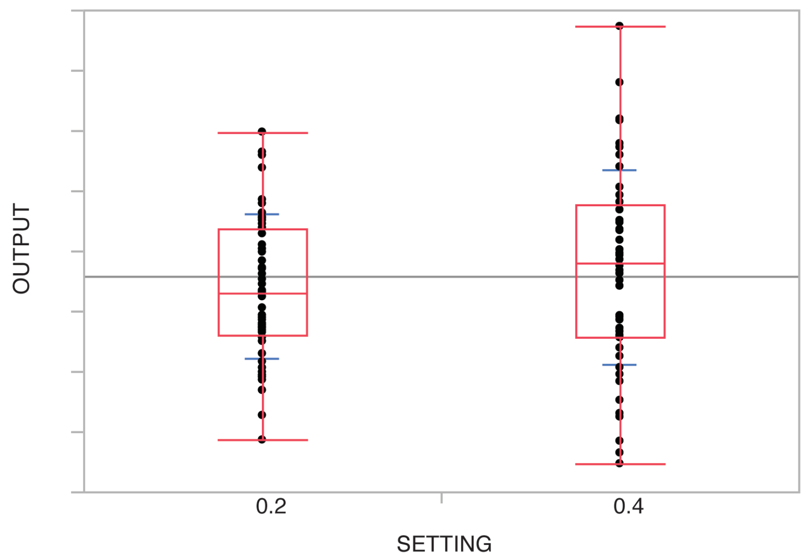


Figure 38: One Way Analysis of Output by Setting (Levene: F = 3.3072 p = 0.0719)

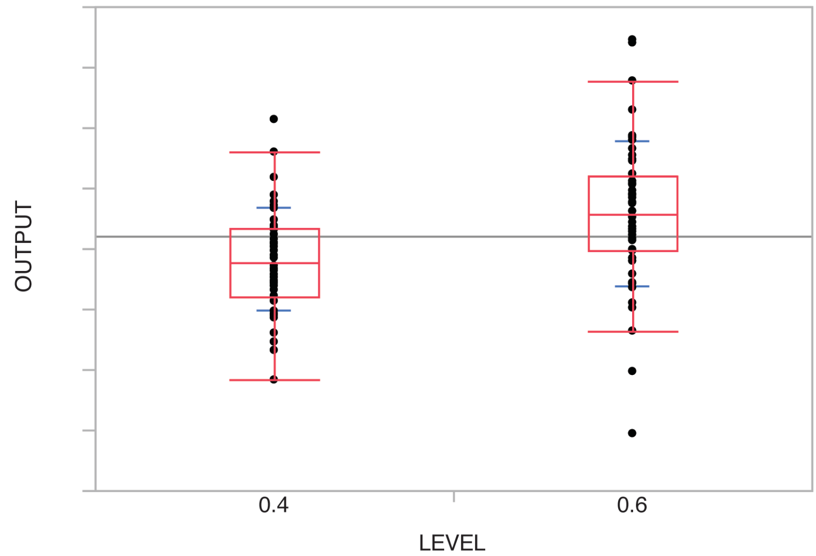


Figure 39: One Way Analysis of Output by Setting (Levene: F = 2.2257 p = 0.1362)

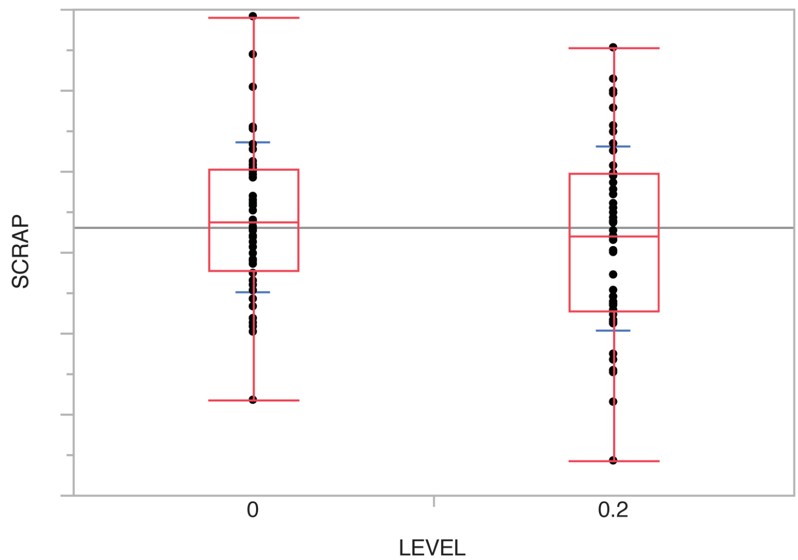


Figure 40: One Way Analysis of Scrap by Setting (Levene: F = 2.7954 p = 0.0976

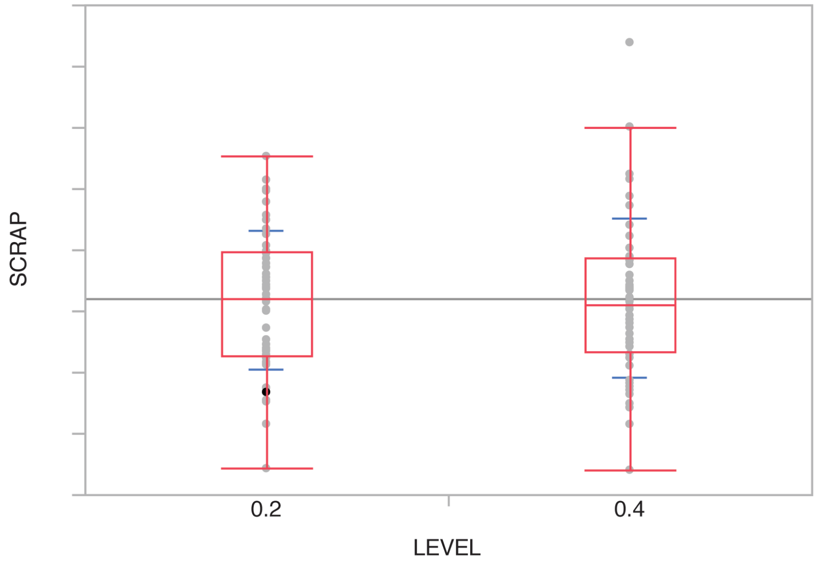


Figure 41: One Way Analysis of Scrap by Setting (Levene: F = 0.1874 p = 0.6660)

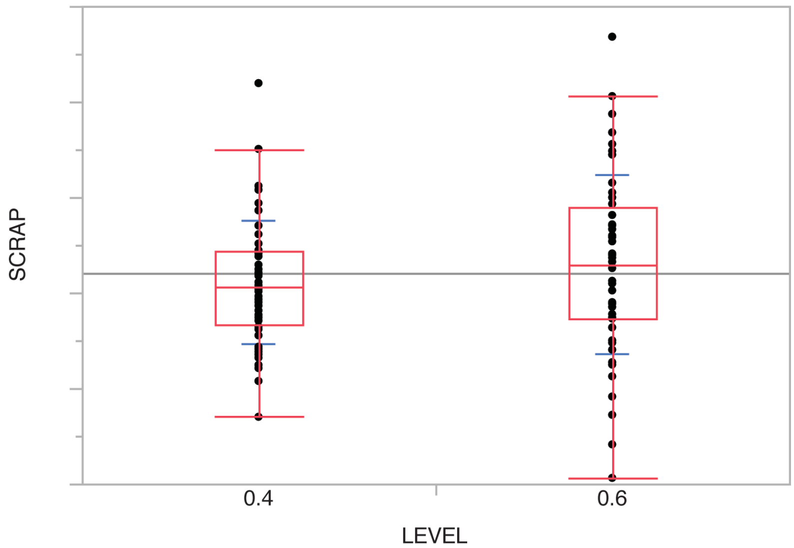


Figure 42: One Way Analysis of Scrap by Setting (Levene: F = 6.1349 p = 0.0149)

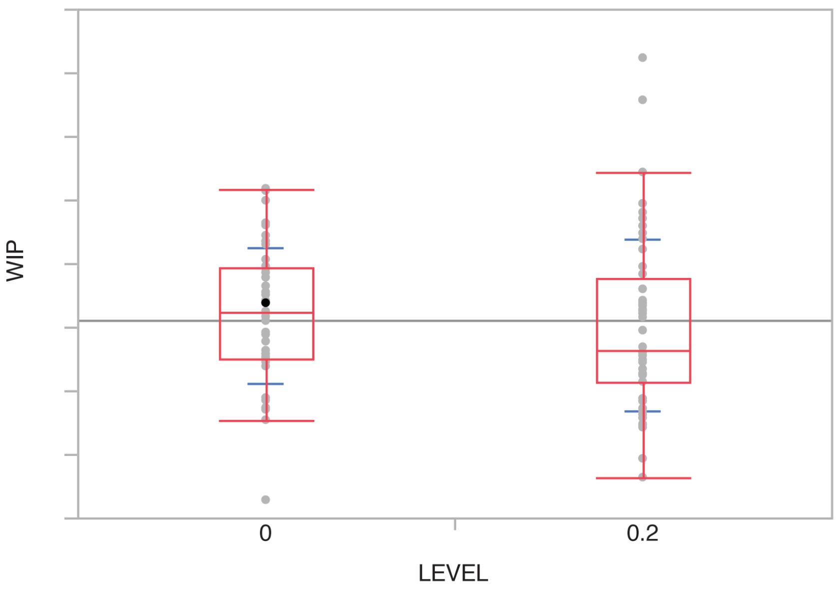


Figure 43: One Way Analysis of WIP by Setting (Levene: F = 2.5959 p = 0.1102

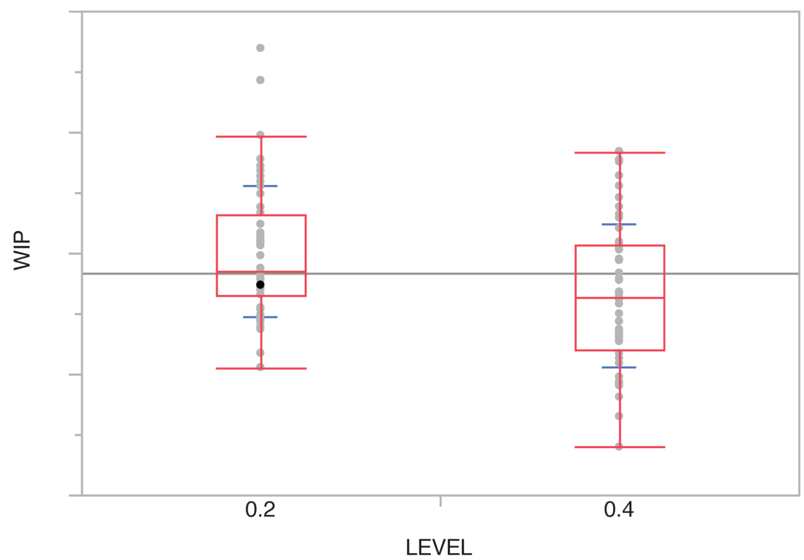


Figure 44: One Way Analysis of WIP by Setting (Levene: F =0.7406 p = 0.3915)

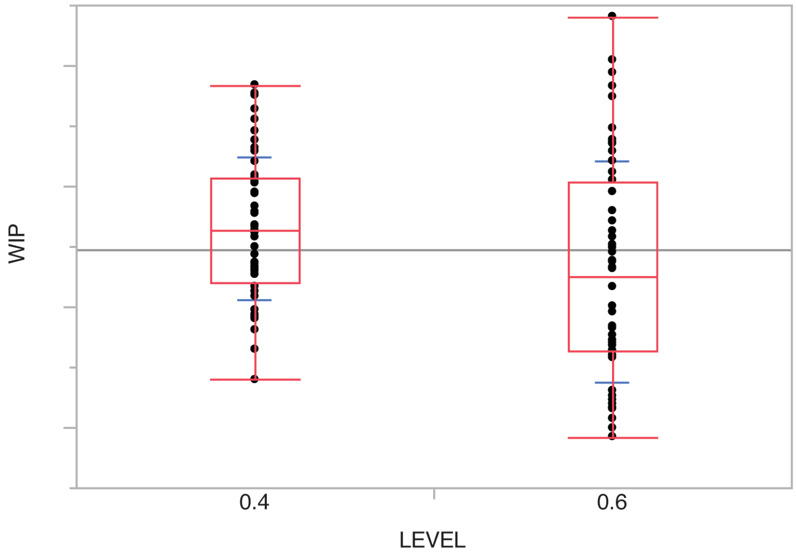


Figure 45: One Way Analysis of WIP by Setting (Levene: F = 11.1289 p = 0.0012)

Conclusions

The selection of efficient improvement portfolios plays a critical role in the realization of strategy and yet this is generally conducted without knowledge of Pareto Optimal solutions. Moreover, the technical literature offers little guidance.

We therefore set out to create a methodology for creating Pareto Optimal portfolios of improvement projects. Our method draws from biology in applying the concepts of meronomic classification, fitness landscapes and scale separation maps. We have also developed an original approach to simulation and modelling for multiobjective and multiscale problems, which provides both a visualization of the PF as a decision reference map as well as the precursor information required to conduct discrete optimization of the ensuing directed graphs.

From a preliminary and design-based perspective, this methodology meets our stated objectives, in that it is:

- Generic: The use of Object Oriented Modelling would ensure that the process objects are highly configurable, both in scale and type. It would be possible to use the behavioural prototypes to create machines or systems that follow any behaviour that could be modelled empirically or mathematically. Moreover these behaviours could be those of a unit process, a machine, a production line or a factory.

- Scalable: The flexibility created by the generic design should allow us to model and simulate processes at varying scales. Thus an object may be unit process, a machine, a production line or a factory. In addition, since the methodology allows recursion, each process element may also encapsulate other processes.

  The response surface approach is also relevant across a variety of processes for it is commonly used to model processes from chemical to machine scale [212,224].

- Reliable: Our verification and validation have demonstrated that the model is internally consistent in a test case and that the changes observed on the Pareto Frontier are more likely to be the true result of changes in treatment parameters than stochastic variation.

In the next three chapters we explore the utility of the methodology in three exemplars. In Chapter 5 we apply the methodology to our first case - that of a relatively simple, single manufacturing facility. We then in Chapter 6 expand the use case to a more complex manufacturing facility. Finally, in Chapter 7, we explore the application of the methodology to a multi-site region comprised of thirteen factories across six countries. For each of these exemplars, we demonstrate the application of the methodology to create a Pareto Frontier that shows the current performance as well as Pareto Optimal outcomes.

5: Case Study One: A Simple SME

Process description

The first case we explored was a single manufacturing site for Large Multinational Enterprise (MNE) involved in the make-to-stock production of sterile injectable solutions.

Raw plastics including High Density Polyethylene (HDPE), Polypropylene (PP) and Polyvinyl chloride (PVC) were brought to the factory in bulk form and pulled into the production process via an on-demand vacuum transfer system from storage silos. These raw plastics were formed into a small variety of plastic sheeting intermediaries predominantly via continuous sheet and blown film extrusion processes. One extrusion line produced all PVC sheeting specifications, whereas there were three others for HDPE.

The intermediary sheeting was produced across a 3-shift 5-day (3S5D) operation at the pull signal of kanbans and a few days of inventory were held for use in the manufacture of primary and secondary packaging components. All of the primary packaging was formed on two lines, one of which was dedicated for the high production volume Stock-Keeping Units (SKUs) with few size changeovers, whereas the second machine was scheduled for short-run, high variety production with a wide range of set-up requirements. Both operated 3S6D and were independently managed at the shop floor, again by operators using kanbans, which in this case maintained hours or days of primary packaging components. Secondary packaging was formed from sheeting either on a third line or on the filling lines themselves.

The filling area was where solutions were prepared and filled into primary packaging and this was managed as the pacemaker of the facility. These process elements were scheduled using the principles of demand levelling and a fixed repeating schedule. Varying lot sizes of solutions were prepared on the day that they were to be filled and primary packaging was drawn from the kanban (thus contributing the initial signal to pull HDPE and PVC production). Four filling lines each took primary packing components, added printed labels, completed a solution fill, sealed the primary packaging, fitted and sealed the secondary over-packaging as a continuous process. These lines were dedicated to fill-volumes and presentation form combinations, but these also largely represented production-volume differences of SKUs as well. Hence the production runs and changeovers were quite different between lines, as were the operating schedules, which ranged from 1S5D to capacity constrained 3S7D.

As product was filled, it was collected into part-batches of between 176 to 1480 units and loaded onto a variety of trolley for transportation through the sterilization process. Sterilization was carried out in fixed lot sizes in a deterministic process. Trolleys were brought to one of several queues depending of the product type in an E/D11/∞/FCFS multi-queue/multi-server system and there was a considerable degree of crossover between queues and autoclaves.

Once the process of sterilization was complete, the trucks were assembled into complete batches in E/G/∞/GD multi-queue/multi-server system for packing and transfer to the replenishment centre warehouse.

The process described is shown at a high level in the simplified VSM in Figure 46. In defining the VSM, we chose to exclude certain functions that were secondary to the main value stream – for example, the Quality Assurance process. Although quality release could impact throughput, it was excluded as a simplifying assumption in this, our first case study. Of the value stream, we also noted that the sterilization process was essentially deterministic. Thus we did not manipulate any parameters of these process elements. As there were eleven autoclaves in the process, even three parameters would have more than doubled the number of parameters in our study.

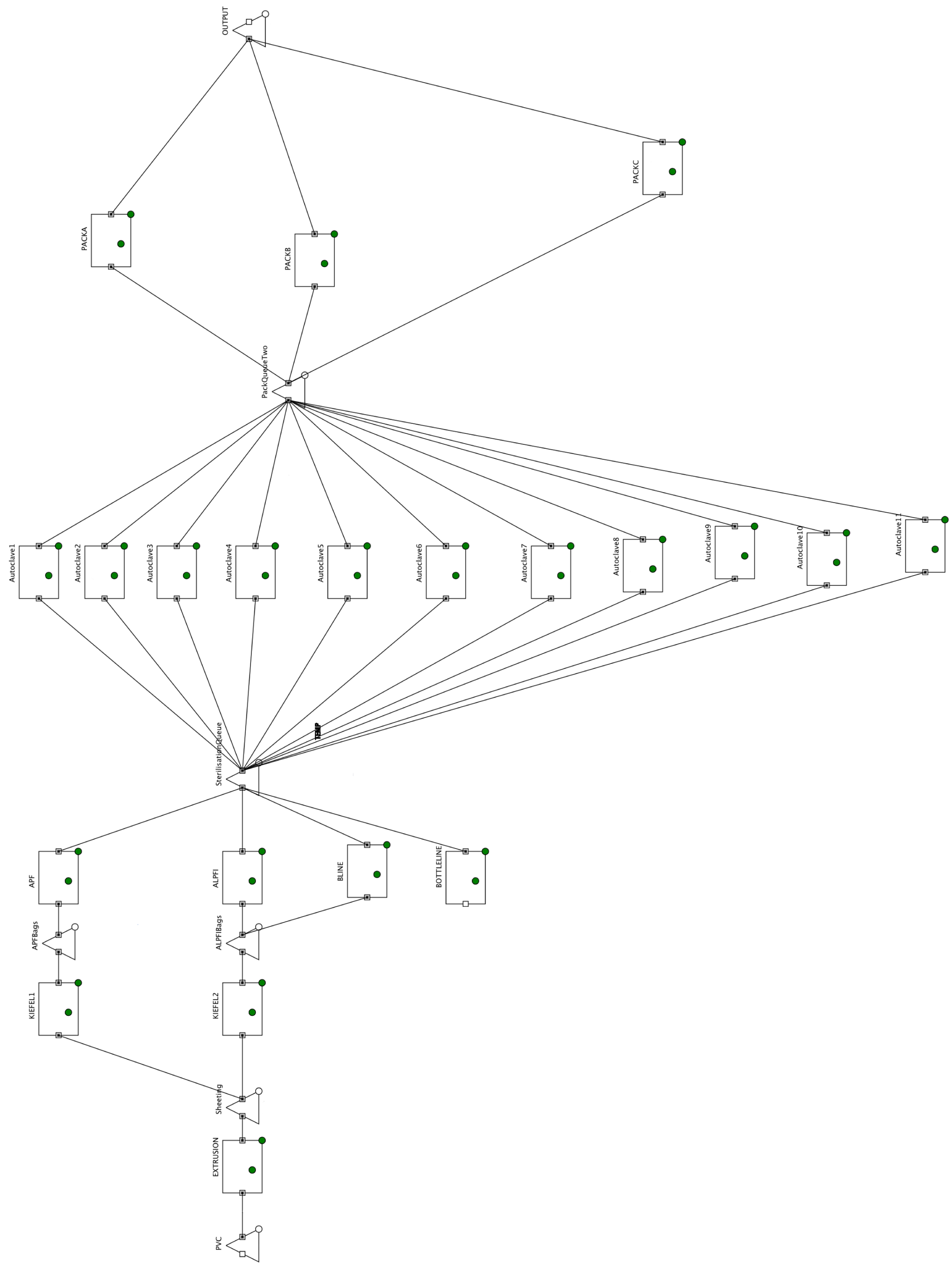


Figure 46: VSM for Case Factory (process details redacted for confidentiality).

System Definition and Process Mapping

Our study began by defining the system modelling boundaries, which was achieved by defining the Decision Making Unit (DMU) for which the portfolio was to be constructed. In this case study, the site was one of seventy manufacturing sites operated around the world by this MNE. Although the site did require materials from other sites, it operated more or less independently, producing product only for its local market. The decision maker was the factory manager whose emphasis was to develop a portfolio of improvements for a single factory. Thus the factory represents the DMU, whereas suppliers, customers, third-party logistics providers and so on were considered to be externalities, in order to simplify the modelling and data collection.

Nevertheless, this is an important process step, as it will not always be the case that the DMU is so confined. A manager might choose to involve suppliers in the improvement process or they might be responsible for optimizing multiple factories simultaneously. Erroneously scoping the model boundaries will impact the validity of the final Pareto Frontier and any decisions that arise from its use.

Having determined the model boundaries, we set about to determine the relevant strategic metrics for the DMU as we have previously described in Chapter 3 and Kornfeld & Kara [9].

Once the boundaries of the system were defined, the process was mapped. This was done first as a Value Stream Map (VSM) and then more detailed process mapping was performed for certain elements to better understand their behaviour for later modelling.

Data Collection

The organization studied manufactured several hundred Stock Keeping Units (SKUs) of sterile solutions. Examination of these products showed that these vary in the components of the solution and not in the manner in which they are manufactured. Thus, for example, all 1L SKUs were produced using the same equipment with similar machine-dependent variables such as changeover time, production rate and scrap losses. We therefore decided to examine production in terms of the simplifying assumption that product sizes are relatively homogenous and therefore focussed on ten product size groups.

For each product size, at each process step, we identified data collection requirements and sources as set out in Table 6:

Data Element	Sample	Source
Bill of Materials	FY2013 standard	Planning standards in ERP
Input component costs	FY2013 standard costs	Financial standards in ERP
Changeover time (actual/ theoretical)	Sample of 1 month	OEE records in SCADA
Scrap (actual/ theoretical)	Sample of 1 month	OEE records in SCADA
Production rate (actual/ theoretical)	Sample of 1 month	OEE records in SCADA

Table 6: Data Collection Requirements and Sources

Where: FY: Financial Year; ERP: Enterprise Resource Planning (System); OEE: Overall Equipment Effectiveness; SCADA: Supervisory Control And Data Acquisition (System)

In addition, we obtained a copy of the (weekly) production schedules for one month from the production-planning department and also a copy of the improvement portfolio for the most recent 6-month planning period.

We analysed the changeover, scrap and rate data to identify minimum, mean and distribution and obtained theoretical maxima from design or other guidance.

Modelling

We constructed a model of the factory in AnyLogic® and Java® using the method previously described in Chapter 5 and Kornfeld & Kara [4]. This involved construction of a Value Stream Map (VSM) in AnyLogic® and the definition of production models in Java®.

Dimensionality

The studied organisation had a balanced scorecard with six strategic measurement areas: customer; financial; people (including safety); innovation; quality and operational excellence, within which there are 25 detail metrics. Although ideally we ought to be able to develop a 25 dimensional model we did not for three reasons:

1: The transfer functions for some metrics were not easily identifiable – for example there was no clearly discernable relationship between machine speed and the Lost Time Index for safety.

2: A number of metrics overlapped or were collapsible, for example yield and scrap could both be measured as conversion loss

3: The objective of the decision maker for this DMU was to develop a portfolio of improvements that had Profit & Loss (P&L) impact. Thus certain measures, albeit important to the organisation (such as percentage of training that is current), might have little P&L impact.

As a result, the final model took on the dimensionality of throughput, Work in Process (WIP) and losses (scrap and yield losses). In order to ensure that simulation outputs were commensurate throughout the VSM, we dollarized these dimensions. Thus we obtained the input and output costs at every machine, using output costs to reflect downstream WIP production, the average of output and input costs for scrap and yield losses and the output costs at the end of the VSM for throughput value.

Factors

The final model was composed of 20 process elements and 7 areas of WIP as shown in Figure 46 above. Of these, eleven process elements were the deterministic controlled autoclaves and thus were simulated but we did not manipulate process variables for them in this experiment.

For each of the 9 main process elements, we varied three parameters – changeover time, production rate and yield – from low to mid-range to high, resulting in a 3^{27} I optimal DoE of 3 336 runs including replicates. Each production run lasted for one week of simulated production, the equivalent of running the factory experimentally for 70 years. The duration was chosen as the factory operates on a one-week Fixed Repeating Schedule and thus one week is a practical representation of activity.

The simulation variables were chosen as examples of the three orthogonal components of OEE: Availability, Performance, and Quality [225] as follows:

Changeover time was selected as an example of controllable stoppages that can lead to production losses. Although breakdowns and other unplanned stoppages were also important, changeovers were more common, more predictable and were also the subject of a SMED (Single Minute Exchange of Die [226]) changeover reduction programme at the time. The purpose of this programme was to reduce changeovers in order to increase availability, as well as to reduce batch sizes and thus reduce inventory.

Rate variations were the largest cause of performance losses in the factory. In addition, some lines were capacity constrained and therefore increasing production rates by improving the line cycle times was a key focus for improvement at the factory under study.

Scrap and yield losses contributed to reduced Rolled Throughput Yield (RTY) in the factory. Again, given the capacity constraints on some production lines, scrap reduction was considered to be an opportunity to increase capacity with little or no capital outlay. We note that this is an output measure, which we have used as proxy measure for a large number of controllable variables (for example Rovema sealing heat temperature, Kieffel die levelling, injection port turbine settings and so on).

Simulation

The results were fitted to a degree 2 polynomial with three way interactions in JMP®. In a model with many potential explanatory variables, R^2 will increase simply as a result of the number of terms and is not reflective of the quality of the model. In our case, we were examining not only the primary production variables, but also second and third degree interactions. In this case a falsely high R^2 is to be expected and therefore we chose to conduct stepwise parameter selection of regression by forward selection [220] in JMP®. The regression model fit is shown in Table 7, Table 8 and Table 9 below, R^2 Adj (R^2 Adjusted) being the appropriate measure of goodness of fit.

SSE	DFE	RMSE	R^2	R^2 Adj	Cp	p	AICc	BIC
4.606e+12	1218	61495.494	0.9099	0.7533	1054.8805	2118	91302.82	96866.65

Table 7: Stepwise Fit for Throughput

SSE	DFE	RMSE	R^2	R^2 Adj	Cp	p	AICc	BIC
1.101e+12	925	34497.689	0.9430	0.7943	1622.7562	2411	92336.72	94468.75

Table 8: Stepwise Fit for Losses

SSE	DFE	RMSE	R^2	R^2 Adj	Cp	p	AICc	BIC
52815099	1257	204.97996	0.9035	0.7440	955.16147	2079	52783.52	58599.6

Table 9: Stepwise Fit for WIP

Where: SSE: Sum of squares; DFE: Degrees of freedom; RMSE: Root mean square error; R^2 coefficient of determination; R^2 Adj: Adjusted R^2; Cp: Mallow's Cp criterion; p: Number of parameters in the model, including the intercept; AICc: Corrected Akaike's Information Criterion; BIC: Bayesian Information Criterion

In addition to the overall prediction model, prediction profiles and interaction plots for all parameters were also examined. The prediction profile is shown below in Figure 47 -Figure 50. These indicate that some of the strongest predictors of throughput (row 1) were the filling line yields and the bag making change over times, whereas the packing line rates and the extrusion line yield and rate were the strongest influencers of losses (row 2).

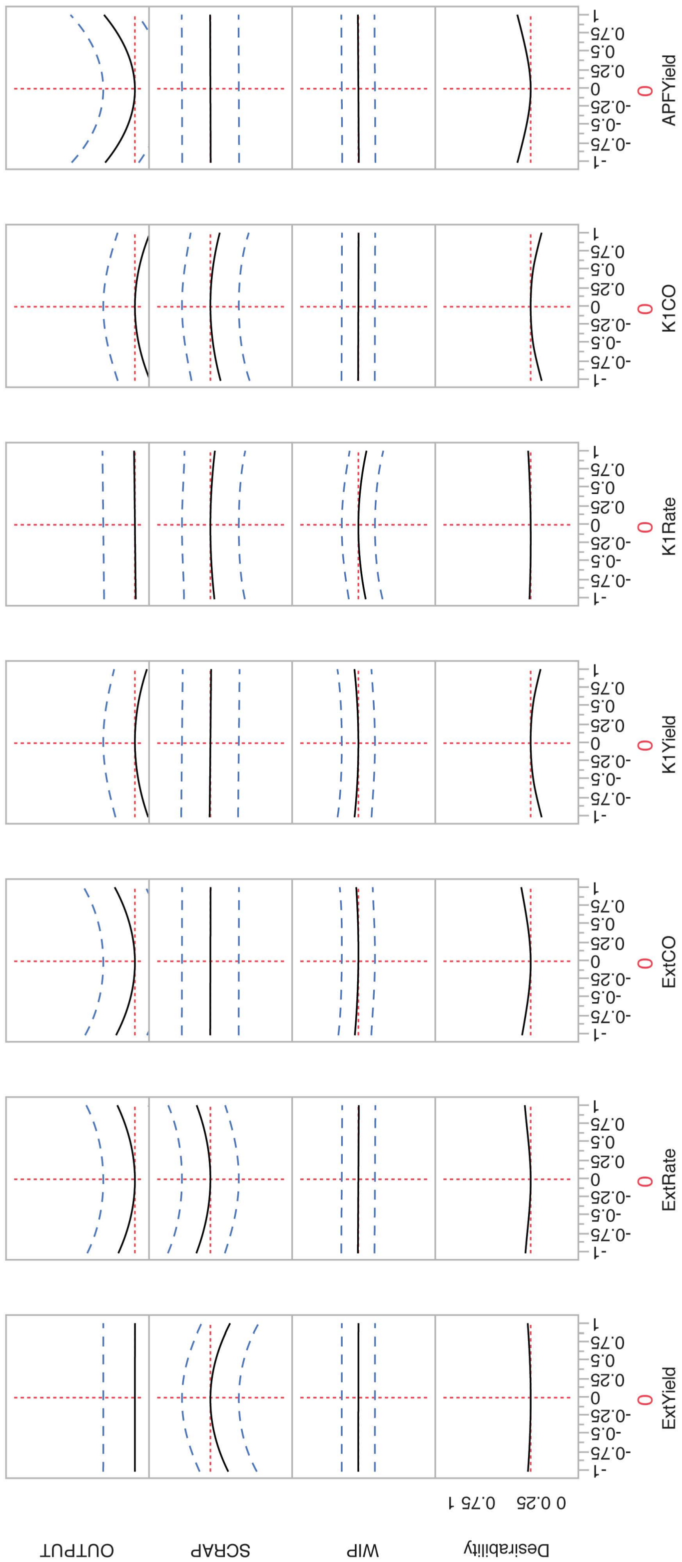


Figure 47: Prediction Profile (Scales Redacted)

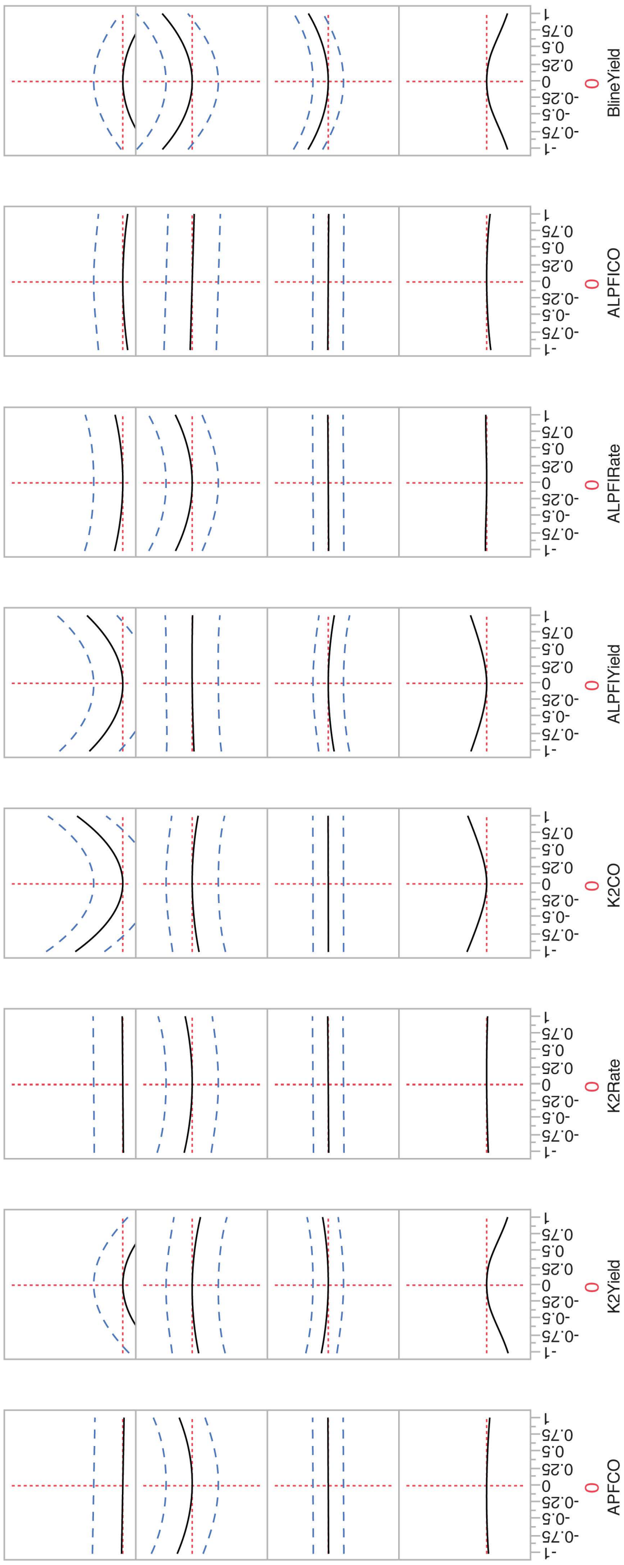


Figure 48: Prediction Profile (Scales Redacted)

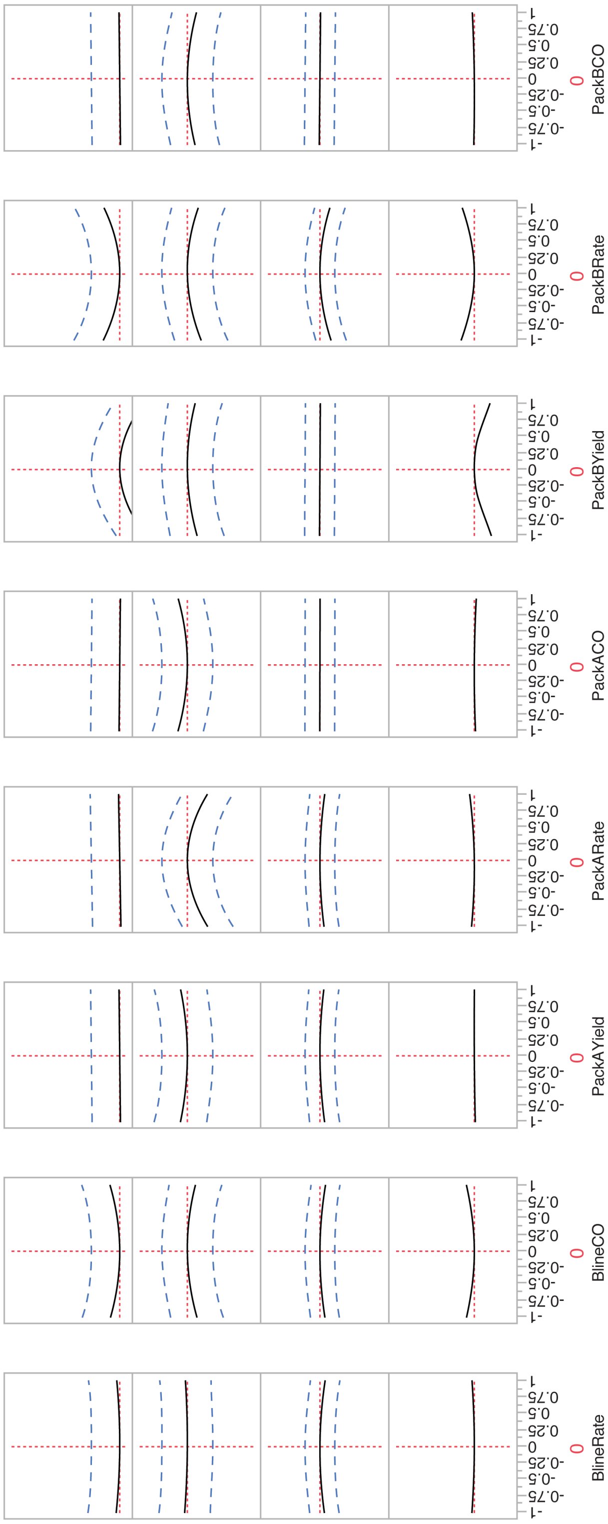


Figure 49: Prediction Profile (Scales Redacted)

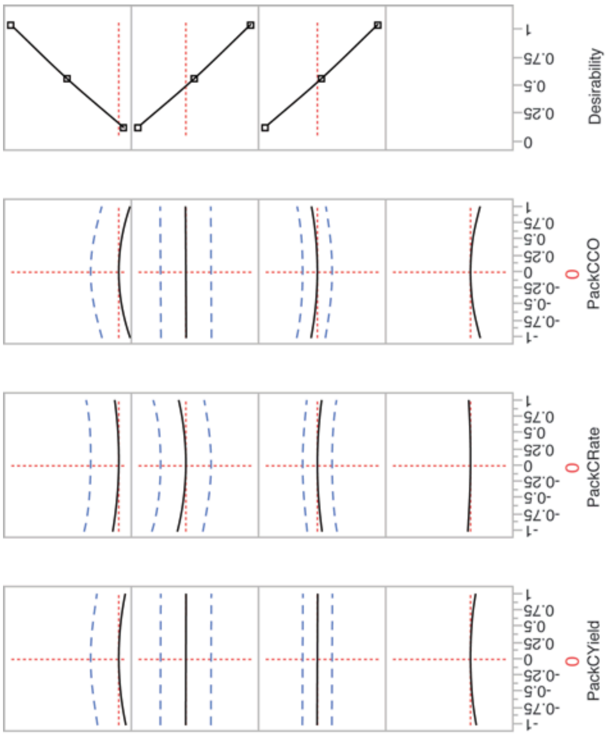


Figure 50: Prediction Profile (Scales Redacted)

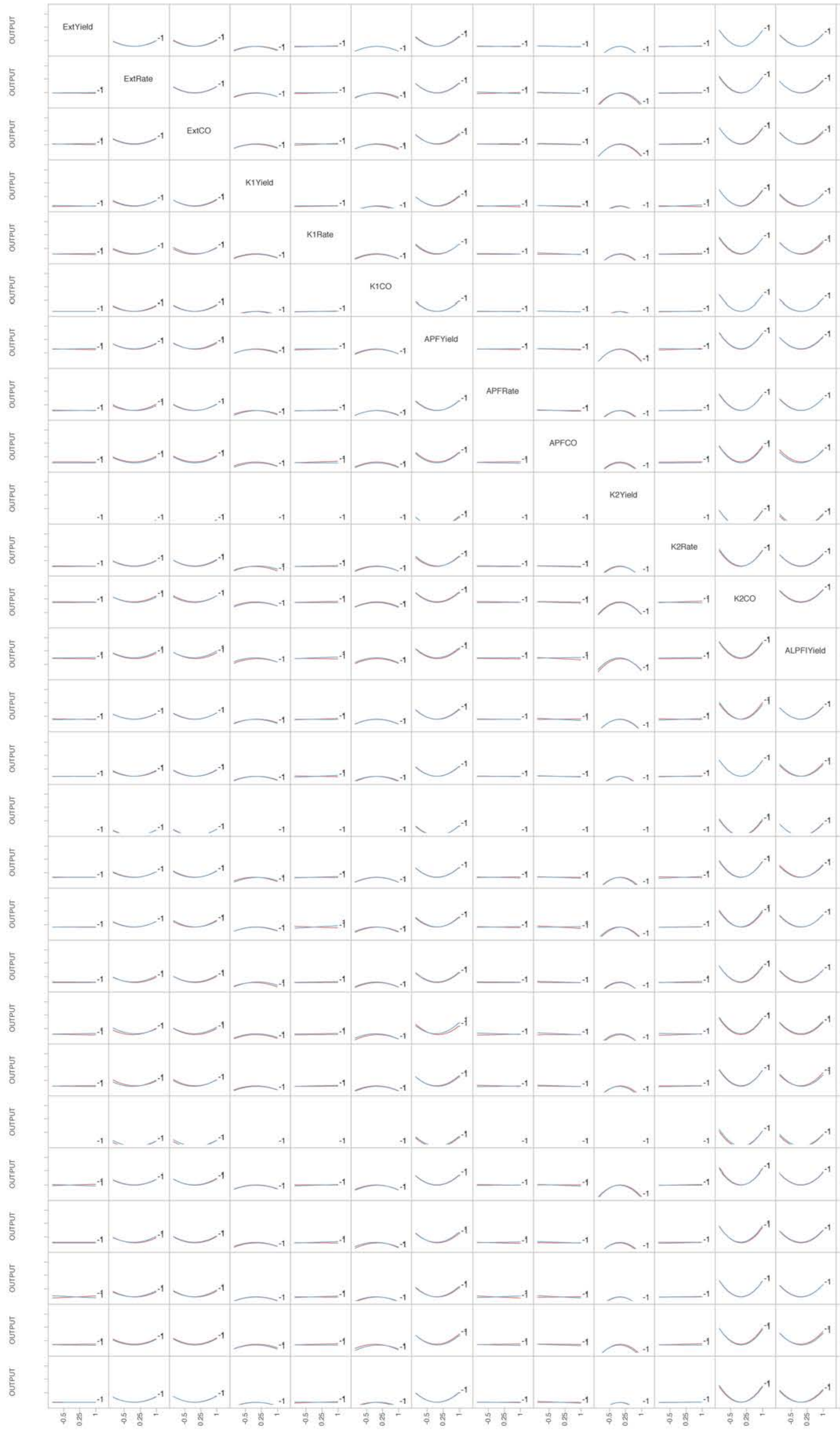


Figure 51: Interaction Profiles for OUTPUT (scales redacted).

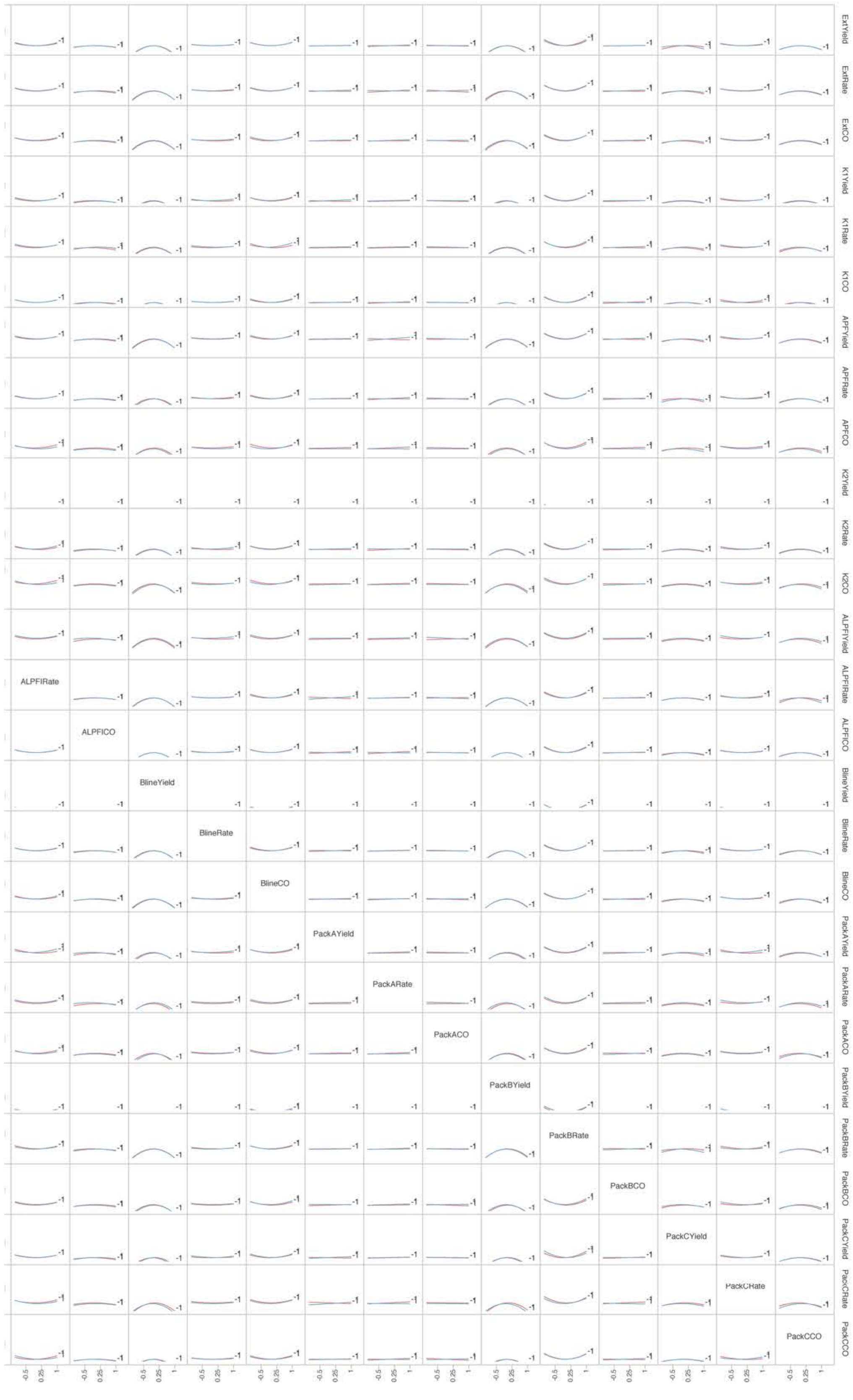


Figure 52: Interaction Profiles for OUTPUT (scales redacted).

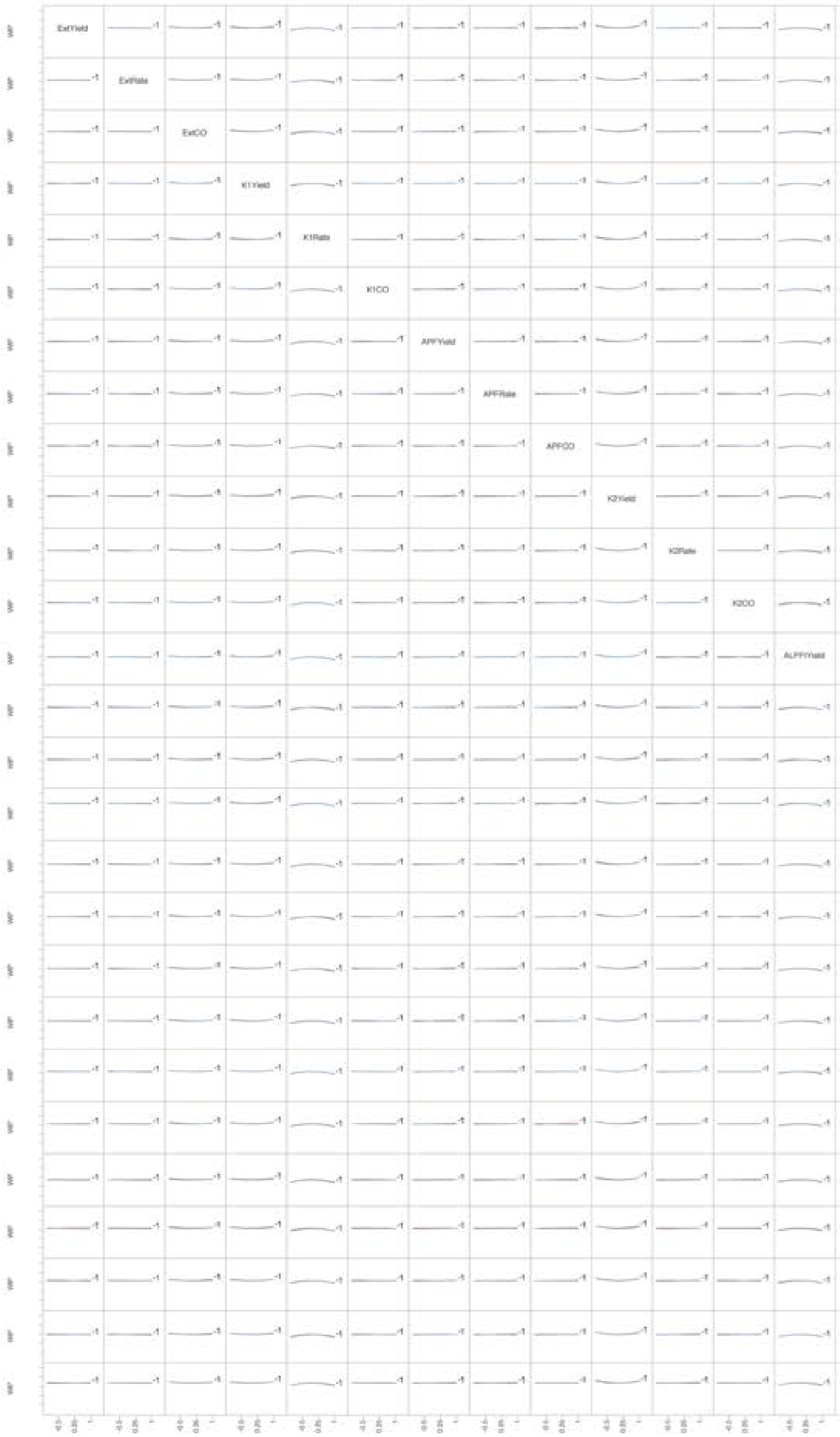


Figure 53: Interaction Profiles for WIP (scales redacted).

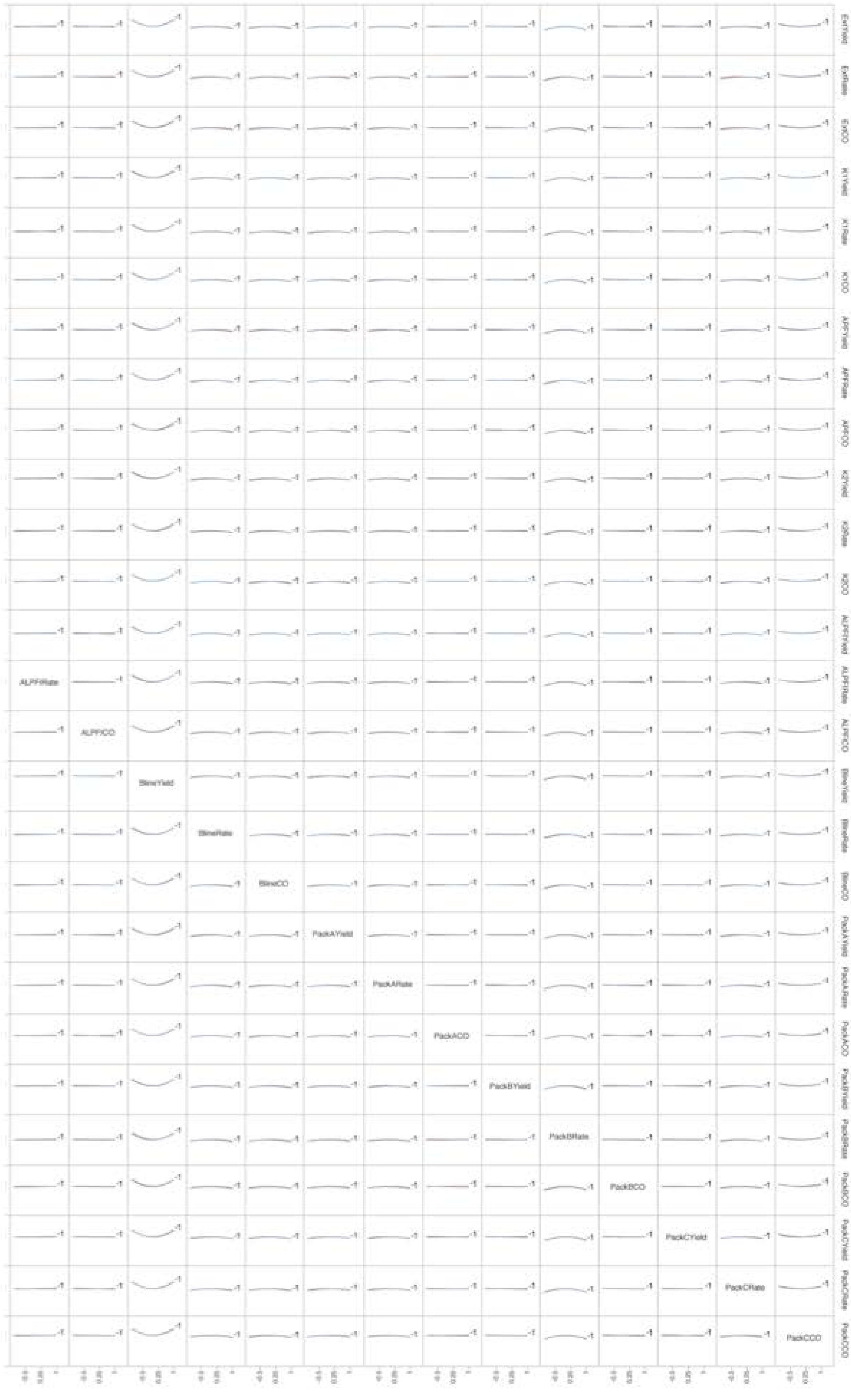


Figure 54: Interaction Profiles for WIP (scales redacted).

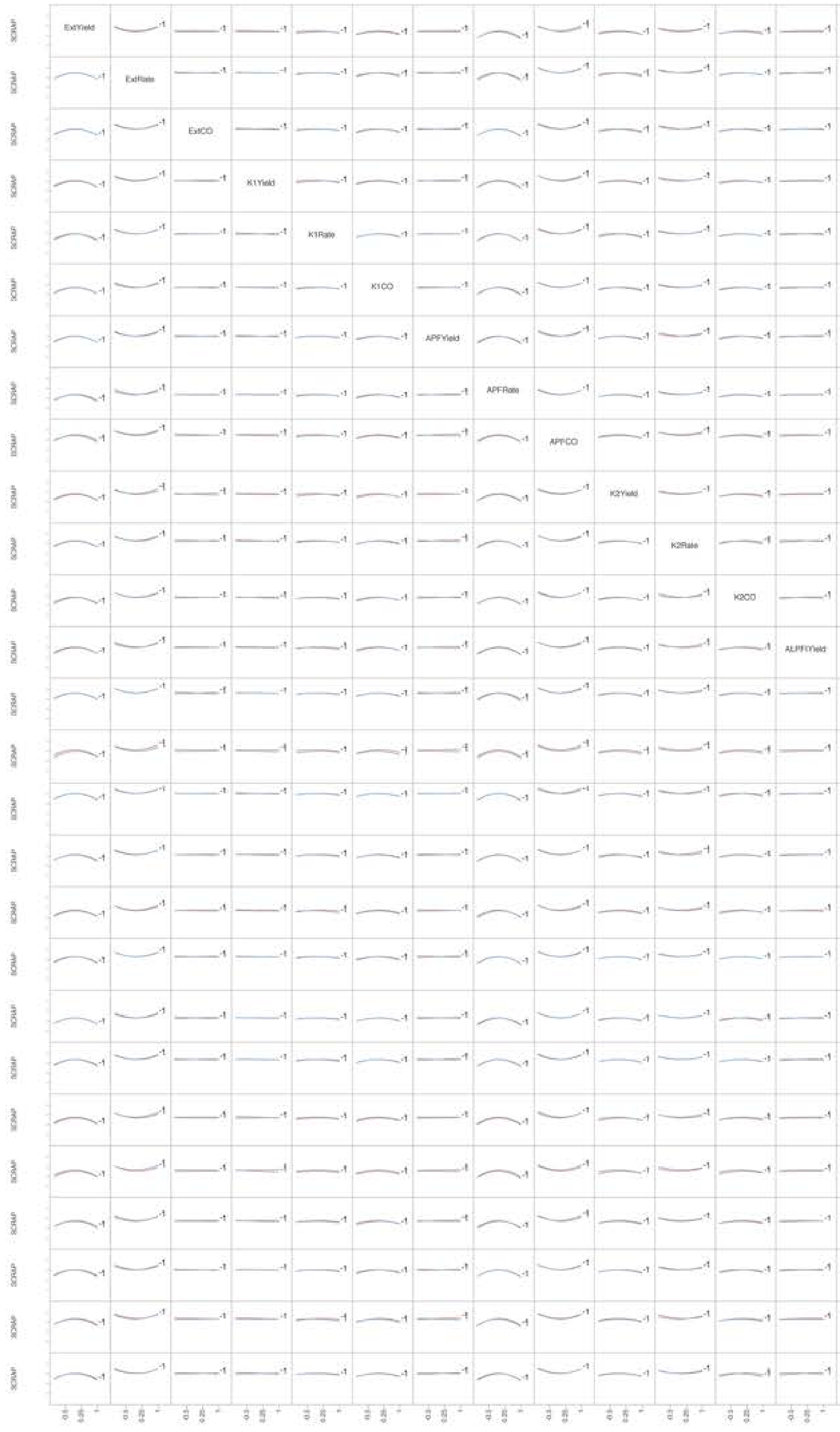


Figure 55: Interaction Profiles for LOSSES (scales redacted).

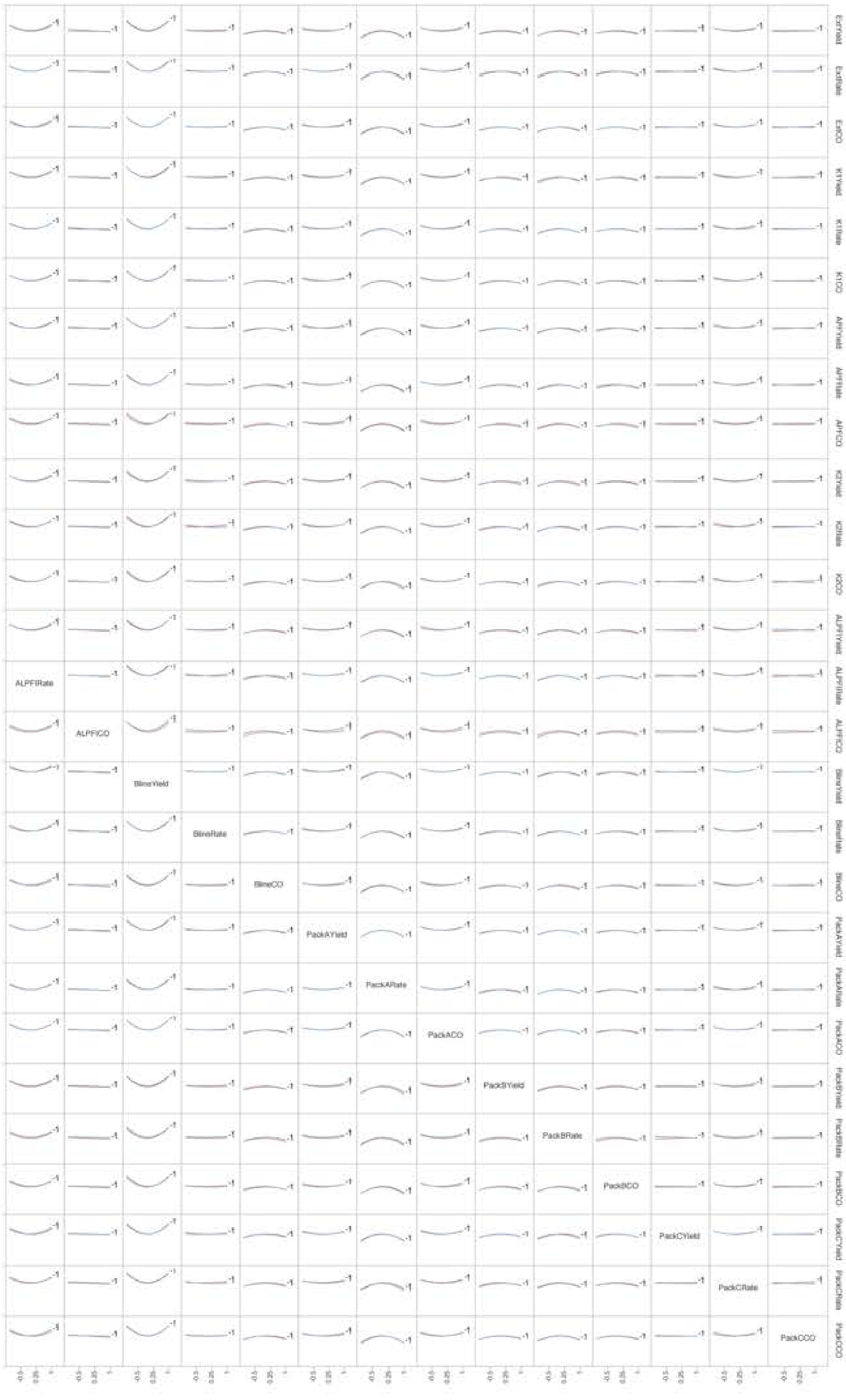


Figure 56: Interaction Profiles for LOSSES (scales redacted).

The results of our simulation are shown as a surface plot in Figure 57 and as a contour plot in Figure 58 below. These show the Pareto Frontier for the organization with current factory processes across the range of feasible production parameter variation. The axes are monetized values for throughput (on the z-axis), production losses (on the y-axis) and WIP (on the x-axis). These have been redacted in order to remove potentially sensitive commercial information.

In this diagram, higher peaks reflect better production outcomes, whereas outcomes towards the bottom of the figure imply greater production losses and outcomes to the left reflect greater WIP. The white marker indicates the current performance of the factory and the yellow, magenta, cyan, red and green indicate the five highest peaks. Here the yellow point is a strict Pareto-Optimal solution (x^*) for the facility.

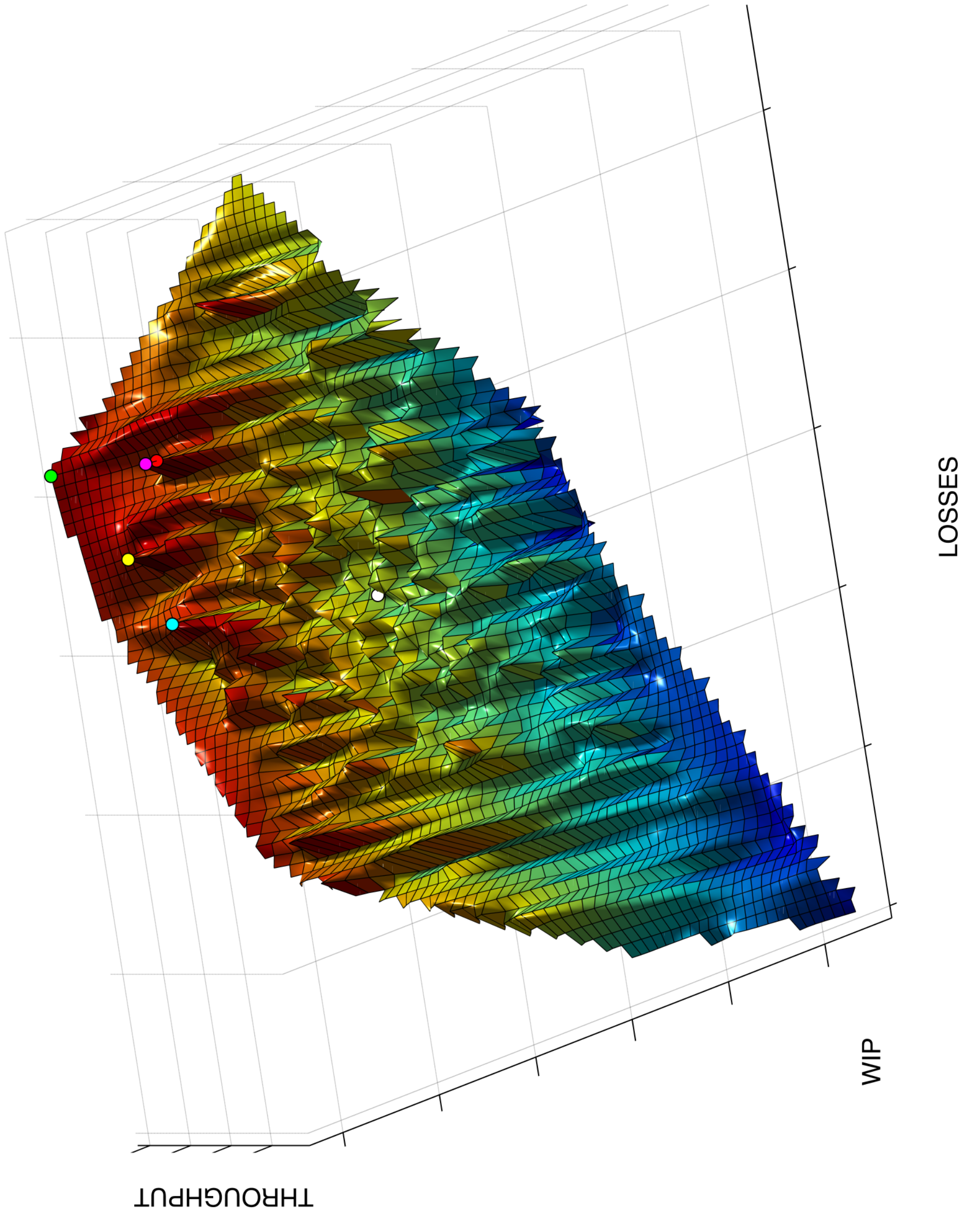


Figure 57: Fitness Landscape for Case Study Factory (Scales Redacted)

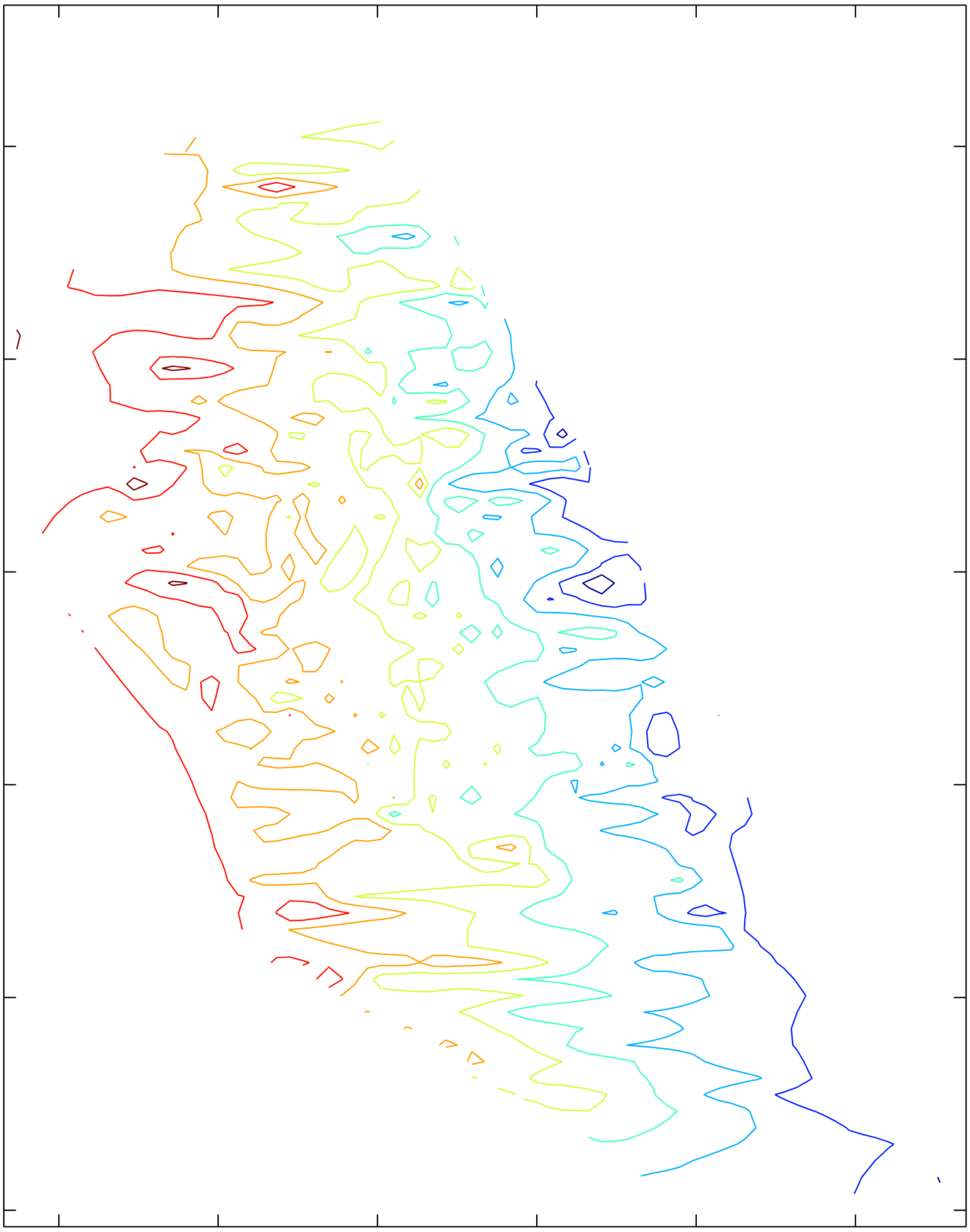


Figure 58: Contour Plot of Fitness Landscape for Case Study Factory (Scales Redacted)

Project Portfolios

The resultant data points were transferred to JMP® statistical software for analysis of the response surface and also to MatLab® for visualization. Once the response surface was generated in MatLab®, we added data points generated from the calculated response surface function for projects defined by the organization under study as well as for those defined by us. We then compared the location of the organization's proposed portfolio with the Pareto Frontier and the alternative projects.

Each six months the organization under study would review its VSMs and the progress made on the last portfolio of improvement activity. Even though the VSM offers some degree of focus, the methodology used was still subjective and relied to a large degree on brainstorming. As we have found [6], subjective methods such as brainstorming are common in industry practice. Voting was used to prioritise the resultant portfolio and this resulted in a subset of projects, which were then implemented in the following six-month period.

As well as the extant strategy, there were other considerations for the business in selecting an improvement portfolio: a management target of cost reductions to the total value of production output; compliance works and capital maintenance. The portfolio thus included projects of the following types:

Project Type	Strategic Fit
Rate increase	Performance
Scrap reduction	Quality
Source changes	Cost reduction
Energy source	Cost reduction
Quality improvement	Quality
Capital works	Availability, compliance,
Regulatory	Compliance

Table 10: Types of Improvement Projects Considered

We considered those relevant to the studied dimensionality and excluded projects such compliance related or pure capital upgrade projects. The red marker on the response surface

(Figure 59 and Figure 60) indicates the contemporaneous performance of the facility. From this starting point we examined various portfolio options:

(i) The extant filling line rate improvement approach (magenta)

(ii) A strategy of filling line loss reduction (green)

(iii) Local Pareto optimum (white)

The cyan marker denotes the peak already identified previously in Figure 57.

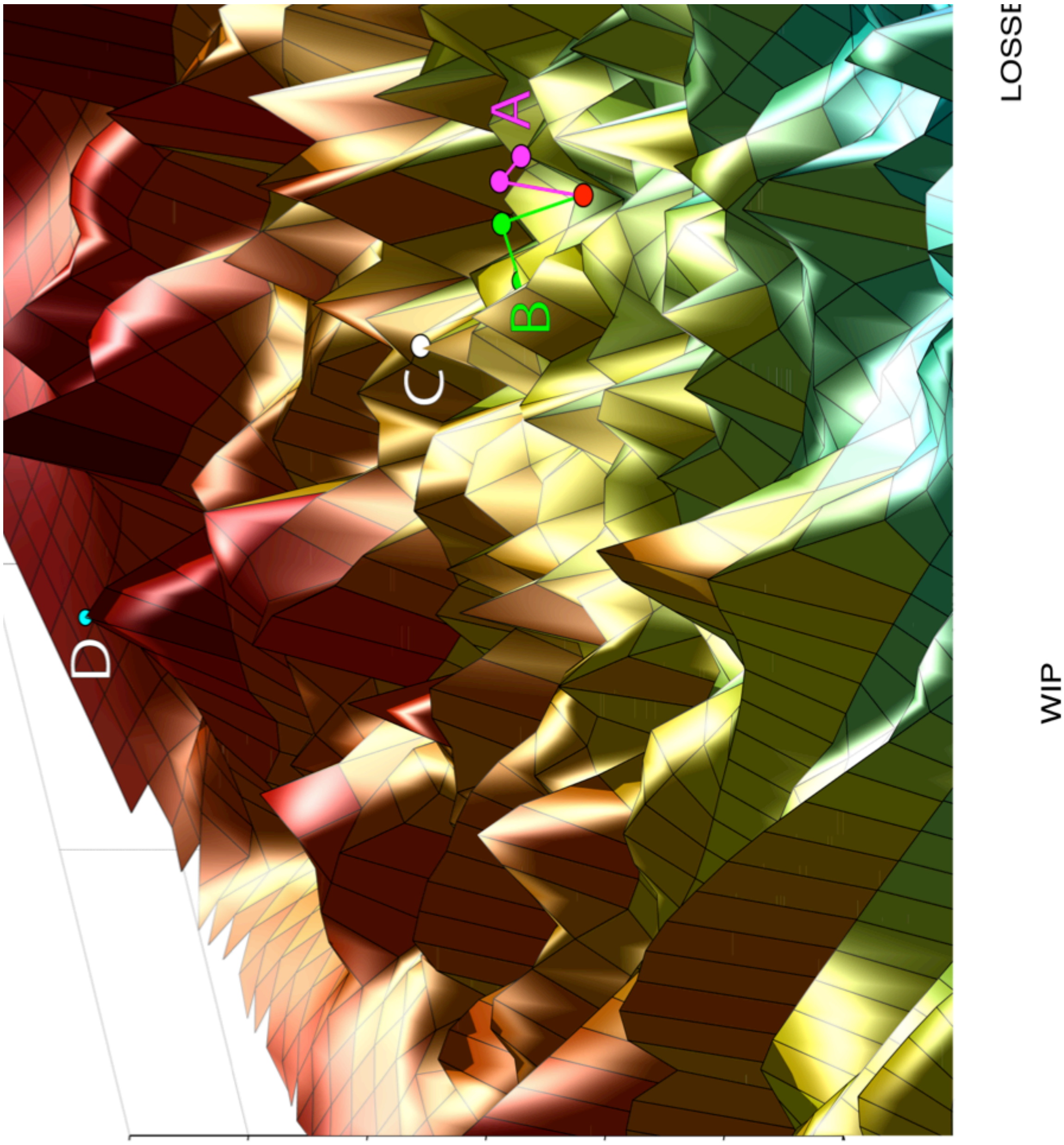


Figure 59: Fitness Landscape with Portfolio Paths (Scales Redacted)

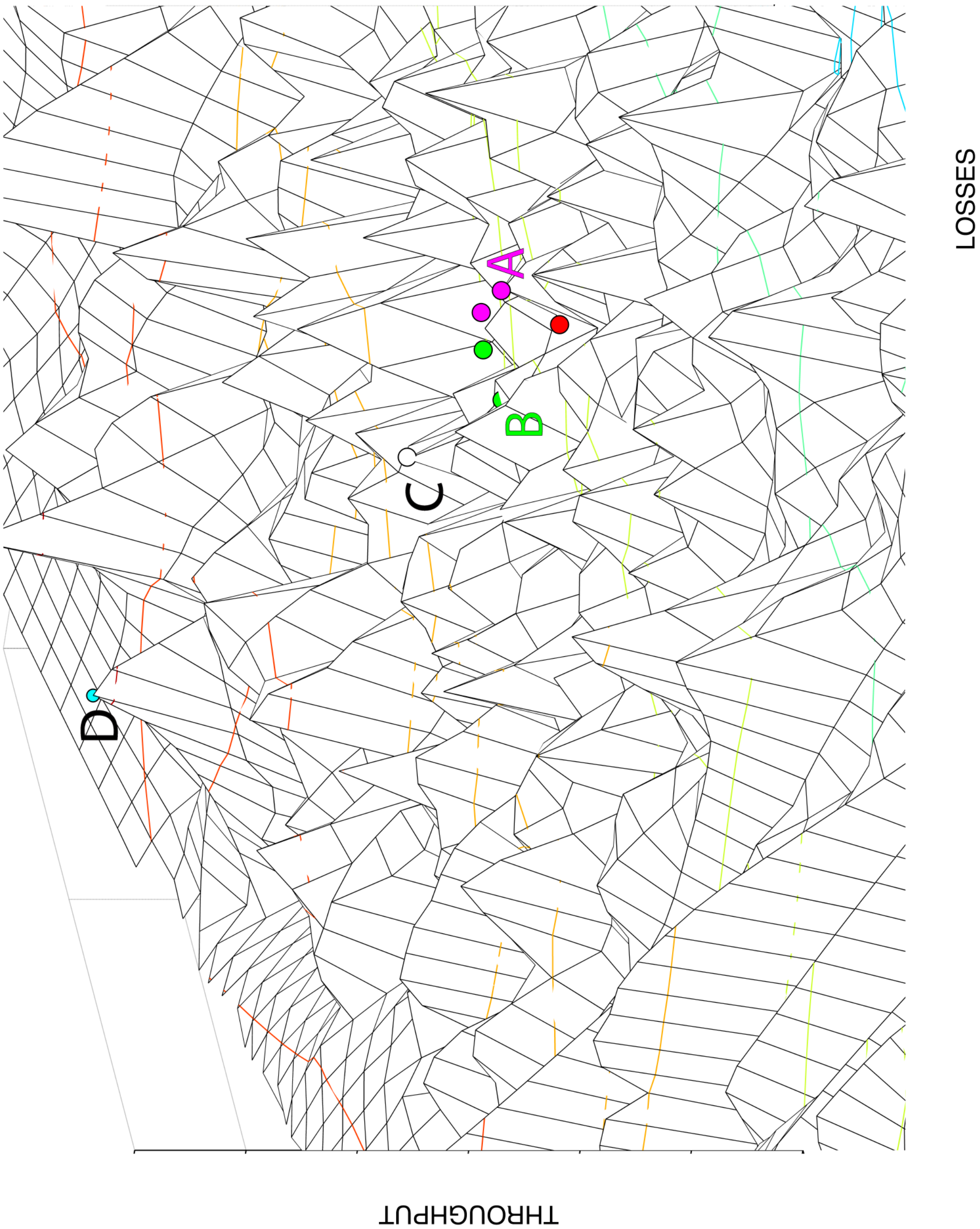


Figure 60: Fitness Landscape with Portfolio Paths (Scales Redacted)

The factory performance at the time of this study reflected moderate downstream losses in a facility that had otherwise good production rates and high capacity utilisation. The prevailing improvement approach of management's for this facility was to reduce production rate losses for the key filling lines (shown in magenta in Figure 59). More specifically, this included numerous modifications to Filling Lines A and C over time, not to increase the lines' theoretical maximum output but to bring the actual output rate closer to nominal. Our simulation indicated that continuation of the current improvement portfolio had the potential to increase overall throughput by up to 10.9% (point 'A' in Figure 59).

We note that the predicted throughput paradoxically dropped off as these filling lines increased towards their theoretical maximum output rates, possibly due to starvation or blocking since no other production equipment was altered under this approach. For example, since these lines compete for the same inputs, it is possible for one to starve the other.

Alternatively, this organization might have chosen to increase throughput not by increasing the rate of a machine but rather by reducing yield losses due to unfavourable material variances such as scrap. This stratagem is shown on Figure 59 as the green path and had the potential to realise lower losses and WIP with higher overall output (point 'B' in Figure 59). Once again we observed an increase in predicted overall throughput that would drop off as the machines were driven to their theoretical maximum (100%) yield.

Both of these approaches were flawed, however, since they (i) concentrated on machines at a single point of the value stream and (ii) sought to improve a single factor of production. In doing so each approach failed to recognise the complex interactions across the factory that would prevent one from formulating a priori conclusions about the optimal portfolio choice. Instead we posited that an efficient improvement approach must first identify the Pareto Optimal target and then the portfolio or portfolios that could achieve that result.

Our third approach was thus to find a local Pareto Optimum (point 'C' in Figure 59) and then apply the prediction model to identify a portfolio of changes that would realise this outcome. We found that we could achieve the local Pareto Optimum by: increasing the yield (10%) and rate (16%) of the extrusion line; increasing the rate (30%) of one of the forming lines; increasing the rate (50%) and yield (50%) of the two main filling lines; the yield (50%) of one of the packing lines and the rate (50%) of the other packing line.

Discussion

The extant improvement strategy of the firm – to increase production rates of the main filling lines - seemed on the surface to be sound. Indeed it could potentially lead to a 10.9% increase in throughput over time. However a strict single point improvement focus (for example, on a parameter such as rate, or an element of a value stream such as a machine) was unlikely to result in an optimal outcome because of the complex interactions across the factory as a whole. Indeed some of the largest effects on factory output in our study (positive or negative) were due to three-way interactions, such as:

- Extrusion changeover * Filling Line A yield * Packing line A rate ($p<0.001$)

- Extrusion rate * Forming B rate * Filling Line C rate ($p<0.001$)

- Extrusion yield * Filling Line A yield * Packing line C yield ($p<0.001$)

The appearance of positive interactions could signify a shifting bottleneck, which would necessitate a continual rebalancing across a value stream. In such a case point improvements could result in starvation or blocking due to WIP rather than an improvement in output. Alternatively it might have indicated that product was being drawn from a shared resource to higher value-adding process streams. This could occur if the output from one resource fed multiple production lines. Conversely a negative interaction suggests that the increased product was drawn to a lower value-adding process stream.

The Fitness Landscape showed a general trend towards high throughput with low losses and low WIP as we might expect. However it was not at all uniform and local optima were widespread and visible as peaks. This is as we might have expected. Firstly, interactions between machines and their defining factors could be expected to either reinforce or negate one another, as production at one point starves or blocks or even promotes production at another.

The range of WIP in this case study was narrow relative to the other dimensions. This reflected the impact of earlier Lean manufacturing efforts, which had already resulted in the reduction of WIP from an average of 12.1 weeks to an average 0.7 weeks. The narrow band and relative insignificance (one tenth of the magnitude of the x- and z-axes) suggests that other dimensionality might have been of greater interest to decision makers.

In this experiment we examined potential outcomes within the dimensionality of one of many possible strategic intents – cost leadership. This is very often the approach applied in manufacturing, even in those cases where the overall strategy may be based on marketing differentiation, as manufacturing savings are used to generate cash flow for product marketing and advertising. However there are alternative generic strategies and these can be based upon other manufacturing capabilities including quality, delivery performance, flexibility and service [139,144]. This would alter the dimensionality of the Pareto Frontier and necessitate changes to the data required. For example, an organisation might compete using a differentiation strategy that is based upon its quality and service capabilities. In such a case, it would not be relevant to create a monetized Pareto Frontier, nor would the incommensurate nature of these measures be so easily reconciled. We believe that resolving these more complex situations is an important area for future research.

Moreover we note that this model examines possible production outcomes within the current production construct, for a multiplicity of designs would render the approach to be too complex to manage. Hence, we have not examined alternative production routings, planning strategies or process redesigns. If warranted, each of these ought to be modelled separately and compared with the total baseline Pareto Frontier.

Furthermore, in this study we measured traditional direct factors of production. Yet, in highly capital intensive processes, other factors (such as energy) may be significant enough that they ought to be considered as variable costs rather than as overhead [227]. As a consequence, we feel that energy and resource consumption ought to be included in future modelling exercises. Our approach, with its ability to include multiple parametric behavioural models, already has the potential for this and thus requires only the creation of predictive unit process models, such as we have described elsewhere [228].

The success of any modelling exercise hinges upon the quality of the input data and this is particularly true for this present modelling approach, which requires a broad range of data inputs including commercially sensitive intermediate cost data. Thus data acquisition (whether data is acquired) and availability (the ease with which data is accessed, whether this relates to the degree of automation or the sensitivity of said data) are potentially the most significant potential hindrances to conducting research of this present type. We have been most fortunate in the current case study to have worked in an organization that collects a good deal of data automatically (e.g. via SCADA) and which gave us access to detailed costing information from its ERP system. This is not always the case and in other work we will attempt to replicate the current study in an organization where there are more severe restrictions on data acquisition and availability.

In general, the gold standard for data collection is for the experimenter to collect the data and document all relevant conditions. This was the case for the FIP case. In this case, however, the SCADA system is a validated system that is used for quality control and release and therefore the integrity of the data is without question.

We posited that typical naïve cognitive models used by mangers are generally under-parameterised and they do not consider factor interactions. Therefore, our approach attempted to more fully explore production factors and make them explicit in a business model. There is, however, the risk of creating over-parameterised models and thus we recommend a cautious approach is taken to setting modelling boundaries, the removal of less significant and secondary elements of the VSM, as well as the application of stepwise parameter selection of regression by forward selection during model evaluation. Additionally, we would suggest taking an iterative DoE approach in future studies in order to further limit less significant factors through statistical analysis to create a reduced model [214].

Conclusions

In this chapter, we have presented a case study using multiscale simulation and Design of Experiments to prepare a Pareto Frontier of production to examine alternative production improvement strategies and outcomes. As far as we can ascertain, this is the first example of its kind.

Our results demonstrated that there was a complex interplay between factors of production, which would prevent one from formulating a Pareto Optimal portfolio of improvement projects a priori. In our view, the method of first producing a Pareto Frontier, followed by the determination of local Pareto Optima would better enable managers to identify efficient improvement portfolios.

This study demonstrated preferences of various improvement strategies, based on their relative potential impact on factory performance. We have not yet however demonstrated preference based on their relative feasibility. We are currently examining ways in which we might also include resources, time and so on into this analysis. This work includes examination of heuristic and discrete optimization approaches to portfolio selection.

We suggest that this methodology could be further enhanced and refined in order to assist decision makers in setting optimal portfolios of improvement projects for their organizations.

6: Case Study Two: A Complex SME

Process description

Following the initial case study, we used the methodology to analyse a Small to Medium Enterprise (SME) manufacturer of composite friction materials for brake shoes and disc pads that were produced for the construction and maintenance of railway bogies. This factory produced approximately 100 SKUs of varying composition and shape, from 63 friction material recipes, which were grouped into 3 product families. The process is shown at a high level in the simplified VSM in Figure 61.

The process originated with raw materials, which were dispensed and weighed according to product formulae for different friction material. The weighed material, which could vary from between 100 to 900kg, was then transported to one of three mixers to blend the batch. Each mixer was dedicated to a product family. After around 40 minutes the material would be transferred to biscuit presses (BP), where the mix was formed into compressed biscuit blocks. There were five biscuit presses, four of which were shared across products and one that was product family specific. These preformed blocks were then brought together with product-specific back plates in one of ten moulding presses and heated by RF for 7 to 8 minutes. The back plates were made on a separate line consisting of a 120 Tonne press, a 90 Tonne press and a degrease-and-coat station. Part numbers were then painted on to each block and the product was placed in one of five curing ovens for 24 hours causing the friction material within the product to homogenize and harden. Each oven had different capacity and could be adjusted to the requirements of the various product lines

The Production Planner was responsible for preparing a weekly production schedule. The Planner would determine the product routing when preparing the schedule, which was developed to best utilise the ten moulding presses.

System Definition and Process Mapping

The facility under study was the sole manufacturing site for composite friction materials for brake shoes and disc pads for the SME. Bulk raw materials were purchased from a number of third party suppliers and finished goods sold directly to end users in Australia. Therefore the system boundaries were simply defined to be the start and end of the local production process as shown in Figure 61 and as managed by the local factory manager.

The final product, an industrial consumable, was purchased under contract or tender and, whilst a specialty item, was subject to cost pressure from the SME's customers. The production imperatives were to maximise throughput and delivery responsiveness whilst minimising production costs.

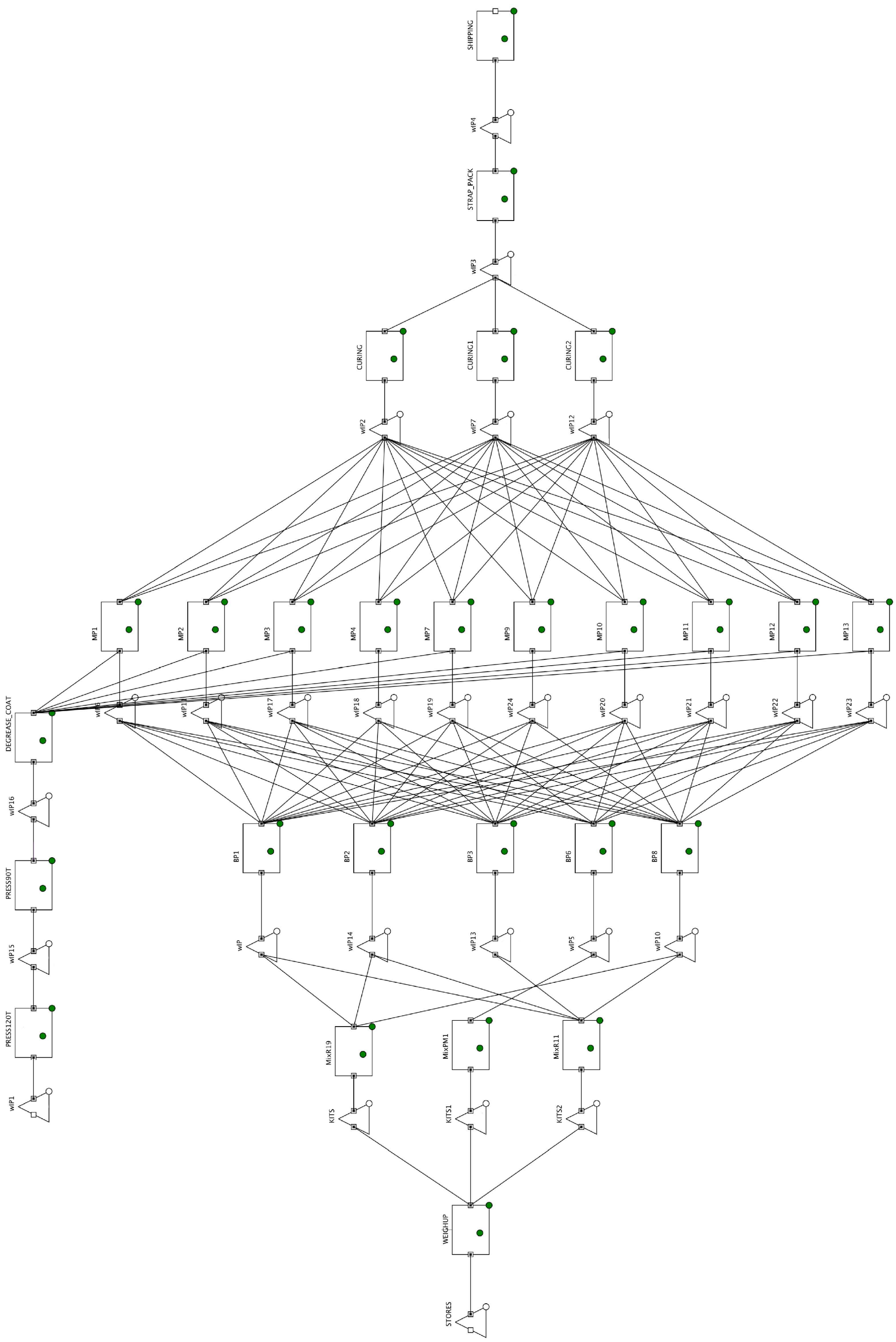


Figure 61: VSM for Case Factory

Data Collection

During the month of June 2013, we gathered data on the production of 57 products from 25 friction materials across 846 production batches.

Data Element	Sample	Source
Bill of Materials	Not available to study	Not available to study
Input component costs	Not available to study	Not available to study
Changeover time (actual/ theoretical)	Sample of 1 month	(i) Production records, (ii) Electronic measurement and (iii) Observation of production
Scrap (actual/ theoretical)	Sample of 1 month	(i) Production records, (ii) Electronic measurement and (iii) Observation of production
Production rate (actual/ theoretical)	Sample of 1 month	(i) Production records, (ii) Electronic measurement and (iii) Observation of production

Table 11: Data Collection Requirements and Sources

Financial data was not made available for study, in part due to its sensitive nature and in any event the company did not keep records of intermediate costs. We recognised, however, that our method does not need absolute costing data, but rather the relative costs throughout the process. We therefore made a subjective scale of intermediate costs starting from raw materials and incrementing at each stage in the process. Although not ideal, this allowed us to reflect the increased embodied cost of WIP for our analyses.

The studied organisation did not have a SCADA system for centralised data acquisition and therefore production parameters were obtained by direct measurement (for example the mix time), from the equipment PLC (for example the cycle time of the mixers) or from production data (for example the cycle time of the biscuit presses). Some OEE data was provided but was of questionable validity for our purposes (for example most machines were indicated to have 100% uptime and 100% availability).

Dimensionality

The organization under investigation did not possess a balanced scorecard, as was the situation in Case Study One, however it did have the production imperative of maximising throughput and delivery responsiveness whilst minimising production costs. Since we sought to demonstrate that our methodology could replicate the outcomes from the earlier case, we chose to investigate the dimensionality of throughput, Work in Process (WIP) and losses (scrap and yield losses) as before.

Factors

The factory under study was composed of twenty-seven process steps, each with three factors (rate, yield and change-over time). Even an optimally designed DoE at three levels (3^{81}) for this process would require a minimum of 88 729 runs, which was unacceptably large. Moreover, one cannot make an a priori assessment of the value or validity of all of these factors in determining the ultimate transfer function. As illustrated in Figure 62, whereas one may be aware of many possible factors (the investigator's 'knowledge space') not all are amenable (not measurable) or relevant (not influential or controllable) to study. Ideally one ought to focus on control factors – those that fit into all three categories, while those that are controllable and measurable, but not influential or those that are controllable and influential but not measurable should be held constant. Process understanding provided us with some foreknowledge of which factors were controllable and measurable, however it was unlikely that all would be influential and we therefore conducted a screening study to reduce the number of factors and thereby create the most parsimonious DoE simulation set. Therefore this study began with a screening DoE.

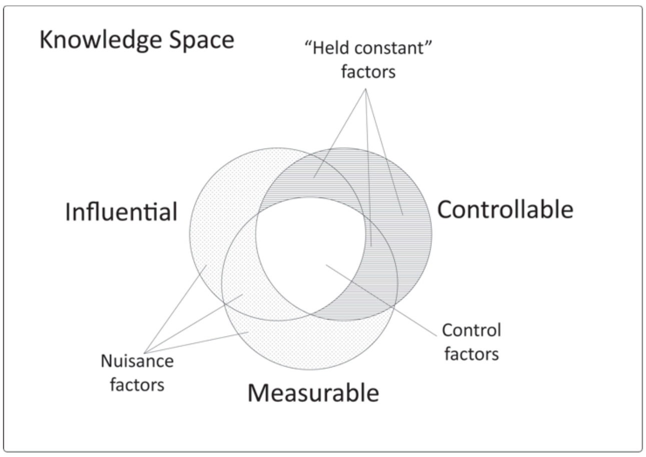


Figure 62: Relevance and selection of study factors in DoE design (after [229,230])

Screening DoE

A 'Screening DoE' is an experimental design intended to isolate the most significant factors from the knowledge space and may additionally have the identification of main effects only and not interactions as its primary purpose. The justification for emphasising main effects in screening DoE experimentation is the effect hierarchy principle, which states that lower-order effects are more likely to be important than higher-order effects and effects of the same order are equally likely to be important [231]. Therefore screening designs often ignore interactions, assuming them to have negligible influence or they may limit themselves to two-factor interactions. Screening designs are also parsimonious because they are based on an assumption of effect sparsity - that is, they assume processes have only a few influential factors.

Given the complexity of the process under study, we believed that there would likely be a number of two-factor interactions and thus we chose a 256 run Fractional Factorial screening design with resolution IV. A screening design was prepared in JMP®, simulated in AnyLogic® and the results analysed in JMP® as summarized in Figure 63 to Figure 68. These figures show the Factor Screening Report and Half Normal Plot for each of the responses – Output, WIP and Losses.

The factor screening reports (Figure 63, Figure 65 and Figure 67) provide contrast estimates for factors, which for orthogonal designs is the same as the regression parameter estimate. None of the contrast estimates in this study were forced orthogonals. The contrast estimates have been ranked by their individual p-value and significant p-values have been marked with an asterisk. The JMP® software generates random orthogonalized effects to absorb variation and thus provide complete saturation in the model and these appear as Null *x*.

The Half Normal Plots (Figure 64, Figure 66 and Figure 68) compare the absolute value of the contrast estimates with the normal quantiles for the absolute value normal distribution with significant factors diverging from the line in the upper right corner.

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value	Simultaneous p-Value
MP13Yield*BP3Yield	22619.0	2.71	0.0097*	0.5751
MP9Yield*BP2Yield	22086.0	2.64	0.0112*	0.6305
MP13Yield*WEIGHUPRate	-19881.4	-2.38	0.0206*	0.8258
CURING1Yield	19504.6	2.34	0.0232*	0.8556
CURINGYield	-18937.2	-2.27	0.0272*	0.8964
Null119	-18446.6	-2.21	0.0310*	0.9262
MixMP1Yield	-17754.7	-2.13	0.0371*	0.9557
CURINGYield*SHIPPINGYield	17721.7	2.12	0.0374*	0.9566
Null123	-16914.0	-2.03	0.0473*	0.9804
MP9Yield	-15453.0	-1.85	0.0671	0.9967
MixR11Rate*DEGREASE_COATYield	-15386.9	-1.84	0.0678	0.9969
CURING1Yield*CURINGYield	15361.9	1.84	0.0683	0.9970
MP13Yield*BP2Yield	-14431.4	-1.73	0.0845	0.9995
SHIPPINGYield	-13578.7	-1.63	0.1052	1.0000

Figure 63: Extract of Factor Screening Report for OUTPUT

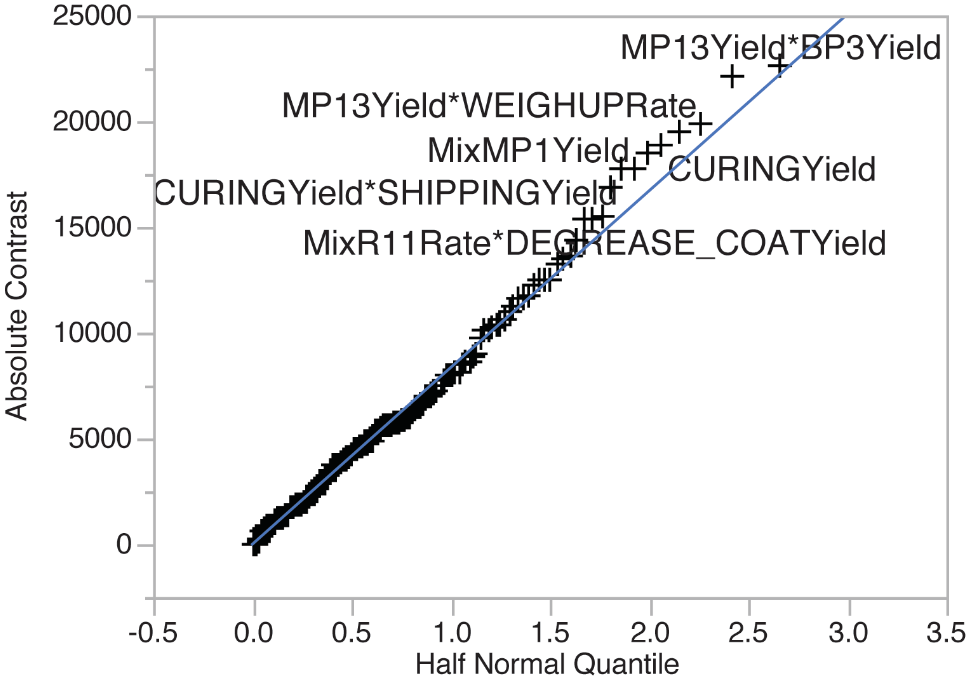


Figure 64: Half Normal Plot Screening for OUTPUT

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value	Simultaneous p-Value
MixR11Rate	-39901.4	-3.63	0.0009*	0.0822
MP13Rate*CURING2Yield	28836.9	2.62	0.0125*	0.6476
MP2Yield	25530.4	2.32	0.0239*	0.8648
MP1Rate	-25524.8	-2.32	0.0239*	0.8650
PRESS90TRate*MP1Yield	24140.8	2.19	0.0322*	0.9318
Null117	23955.4	2.18	0.0334*	0.9383
MixR11Yield*BP8Yield	-23438.5	-2.13	0.0360*	0.9553
MP13Rate	-21372.2	-1.94	0.0553	0.9909
MixR11Yield*MP7Rate	-21248.8	-1.93	0.0565	0.9918
MP9Yield	-21194.5	-1.93	0.0569	0.9920
MixR11Rate*PRESS90TRate	20962.1	1.91	0.0589	0.9940
Null118	-20614.5	-1.87	0.0632	0.9960
MixR11Rate*MP2Yield	20498.5	1.86	0.0642	0.9963
MP13Rate*MP9Yield	-20080.2	-1.83	0.0700	0.9983
MixR11Yield	-19920.4	-1.81	0.0721	0.9986
MP2Yield*MP3Rate	-18640.3	-1.69	0.0917	0.9998
PRESS90TRate	18326.7	1.67	0.0968	0.9999
MP3Rate	17153.5	1.56	0.1172	1.0000

Figure 65: Extract of Factor Screening Report for WIP

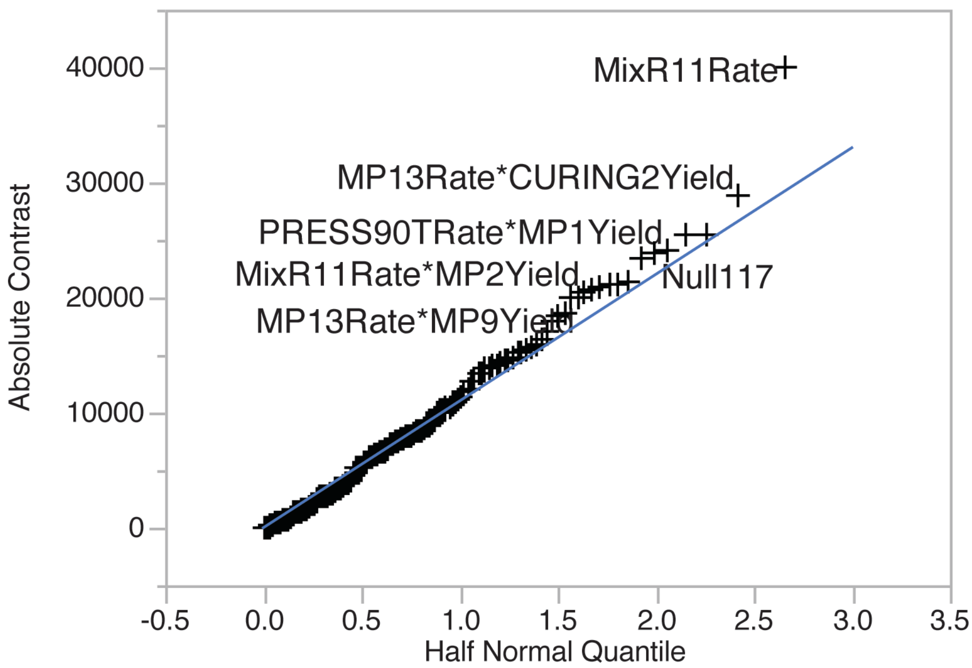


Figure 66: Half Normal Plot Screening for WIP

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value	Simultaneous p-Value
Null117	313529	2.40	0.0186*	0.8100
Null128	-291450	-2.23	0.0269*	0.9147
DEGREASE_COATYield*CURING2Rate	-277138	-2.12	0.0335*	0.9582
Null118	-268749	-2.06	0.0378*	0.9734
WEIGHUPYield	250536	1.92	0.0551	0.9928
MP13Rate	249670	1.91	0.0556	0.9930
Null124	222018	1.70	0.0912	0.9997
STRAP_PACKYield*MP12Rate	-216623	-1.66	0.0993	0.9998
MixR11Rate*DEGREASE_COATYield	214581	1.64	0.1016	0.9999

Figure 67: Extract of Factor Screening Report for LOSSES

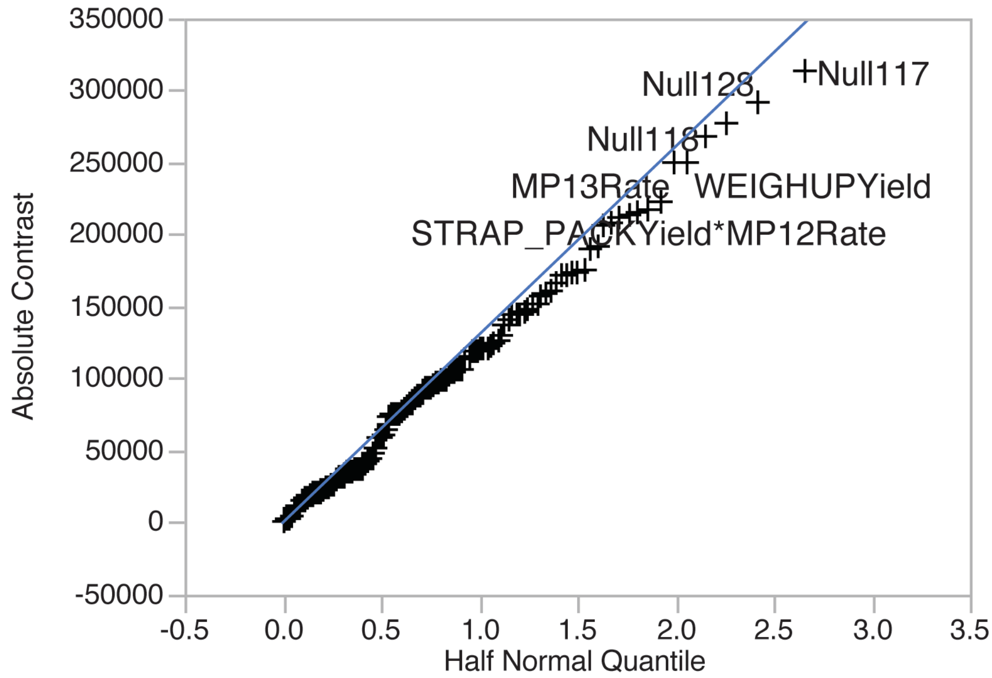


Figure 68: Half Normal Plot Screening for LOSSES

Simulation

From the screening study, we identified the following subset of 20 factors, which had p < 0.1 first- or second-degree interactions, for further study:

- BP2Yield,
- BP3Yield,
- Curing1Yield,

- Curing2Rate,
- Curing2Yield,
- CuringYield,
- MixPM1Yield,
- MixR11Rate,
- MixR11Yield,
- MP12Rate,
- MP13Yield,
- MP1Rate,
- MP1Yield,
- MP2Yield,
- MP3Rate,
- MP7Rate,
- MP9Yield,
- PRESS90TRate,
- WEIGHUPRate, and
- WEIGHUPYield.

Based on this assessment, an I optimal 3^{20} DoE with two- and three-way interactions was designed in JMP® (Table 12) and this was then simulated in AnyLogic® using the method that was previously described.

The results of the simulation were fitted to a degree 2 polynomial with two- and three-way interactions in JMP® using stepwise parameter selection of regression by forward selection as previously described. The regression model fit is shown in Table 13, Table 14 and Table 15 below.

D Efficiency	G Efficiency	A Efficiency	Prediction Variance
28.2910	39.5539	4.3823	1.1939

Table 12: Design Diagnostics - I Optimal Design

SSE	DFE	RMSE	R^2	R^2 Adj	Cp	p	AICc	BIC
3.446e+11	290	34472.861	0.9653	0.8353	843.99996	1087	40940.28	38399.98

Table 13: Stepwise Fit for Throughput

SSE	DFE	RMSE	R^2	R^2 Adj	Cp	p	AICc	BIC
6.397e+13	430	385693.12	0.9187	0.7399	695.23403	947	43829.22	44581.07

Table 14: Stepwise Fit for Losses

SSE	DFE	RMSE	R^2	R^2 Adj	Cp	p	AICc	BIC
1.203e+11	234	22671.524	0.9775	0.8677	982.25799	1143	42666.81	37355.18

Table 15: Stepwise Fit for WIP

Where: SSE: Sum of squares; DFE: Degrees of freedom; RMSE: Root mean square error; R^2 coefficient of determination; R^2 Adj: Adjusted R^2; Cp: Mallow's Cp criterion; p: Number of parameters in the model, including the intercept; AICc: Corrected Akaike's Information Criterion; BIC: Bayesian Information Criterion

In addition to the overall prediction model, prediction profiles and interaction plots for all parameters were also examined. The prediction profile is shown below in Figure 69 to Figure 71. These indicate that some of the strongest predictors (both positive and negative) of throughput (row 1) were the BP2 (Back Plate) yield, BP3 (Back Plate) yield, Curing2 rate and yield, MixPM1 yield and the MP1 yield.

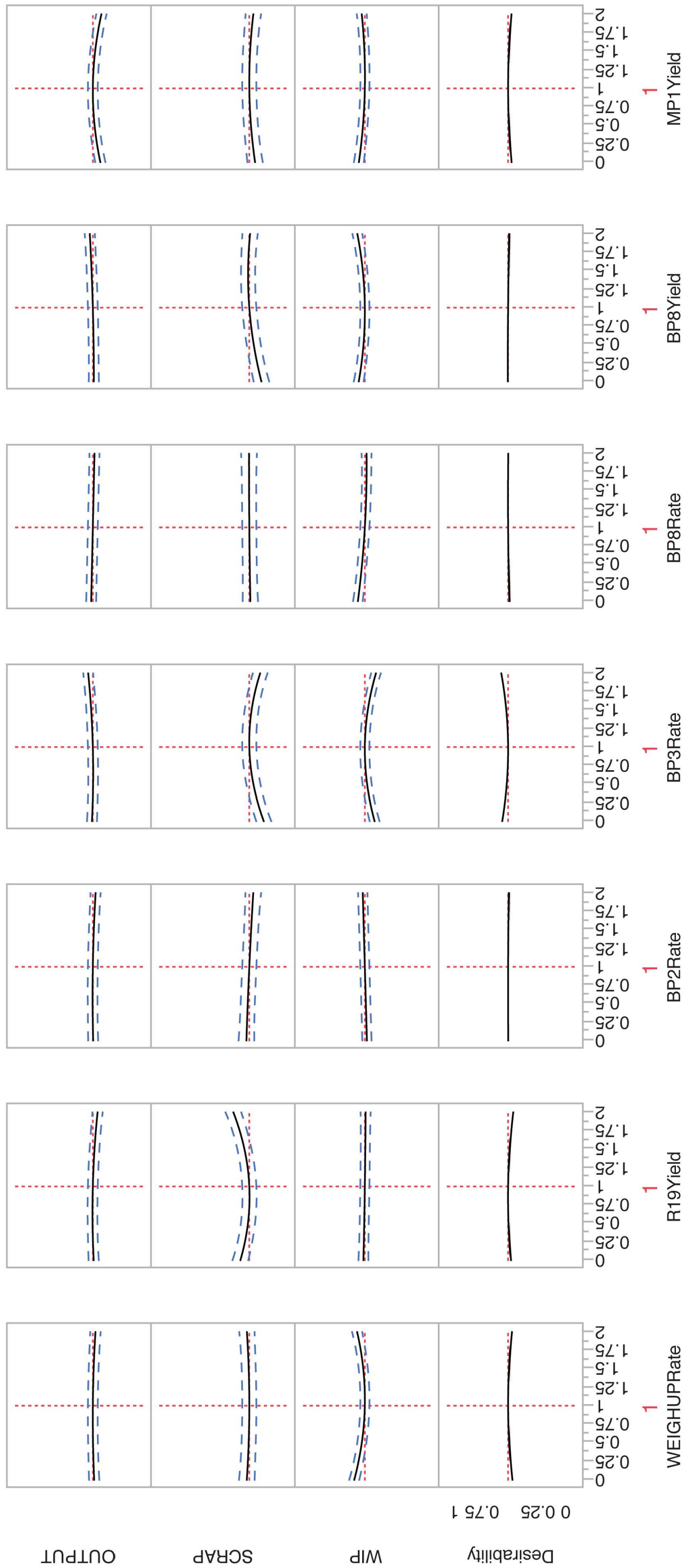


Figure 69: Prediction Profile (Scales Redacted).

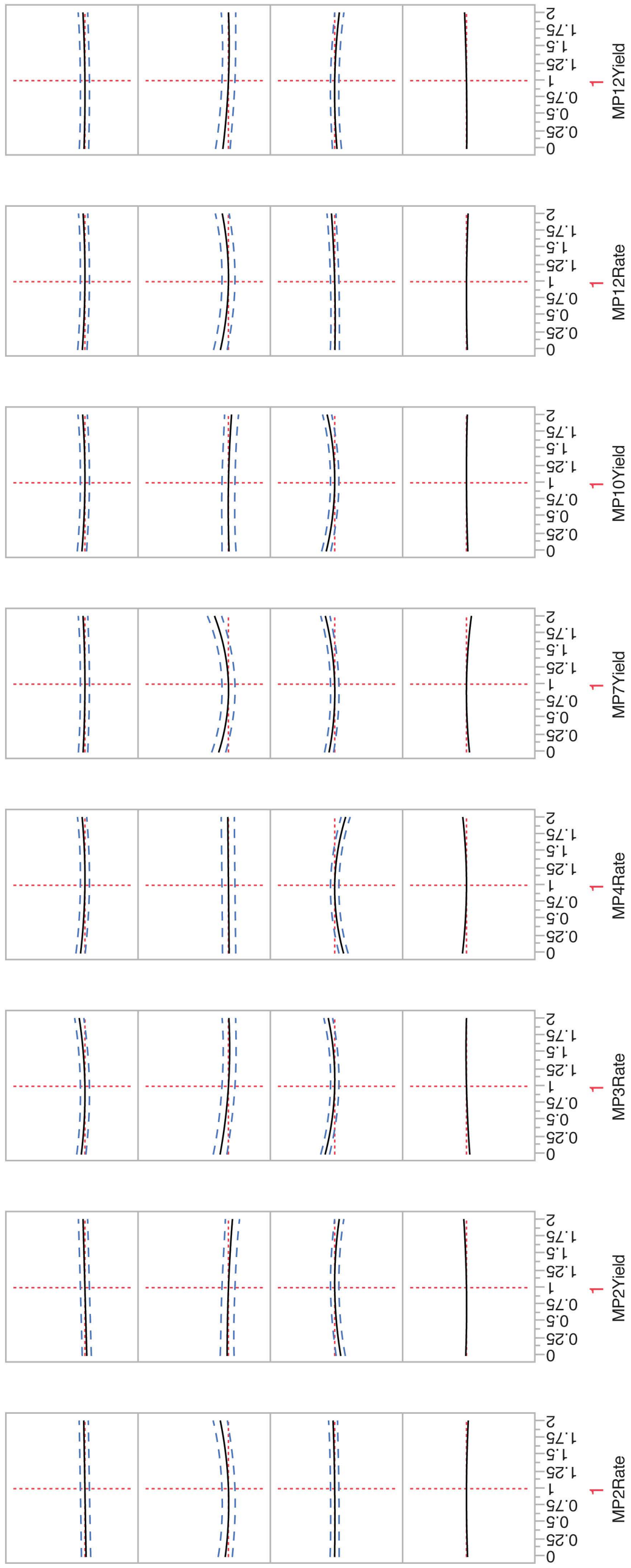


Figure 70: Prediction Profile (Scales Redacted).

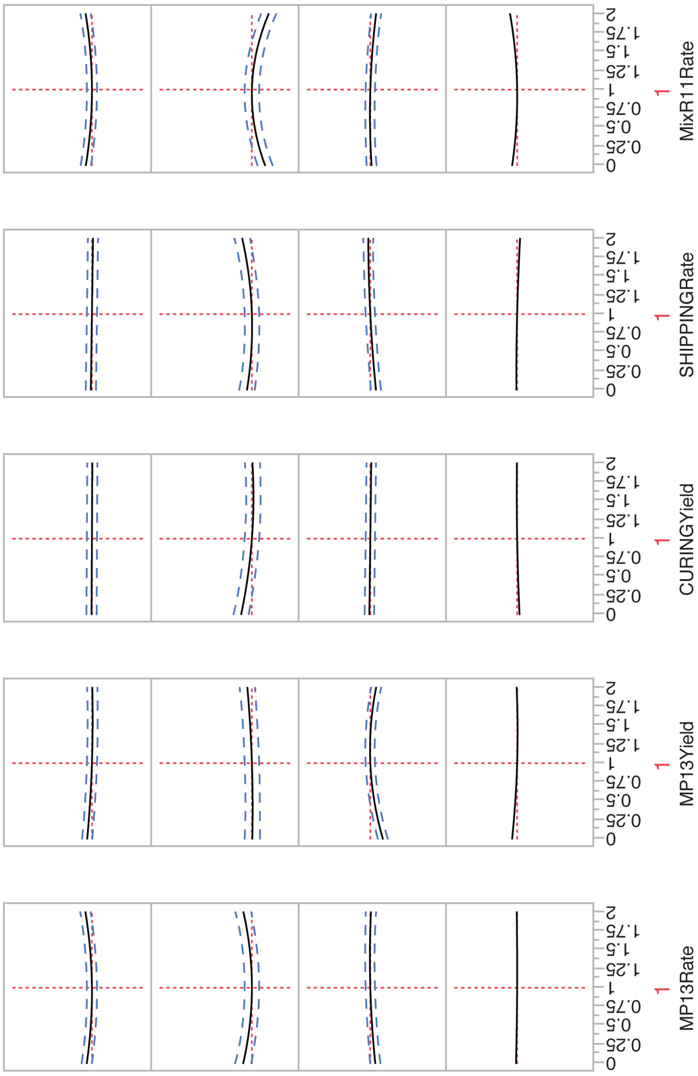


Figure 71: Prediction Profile (Scales Redacted).

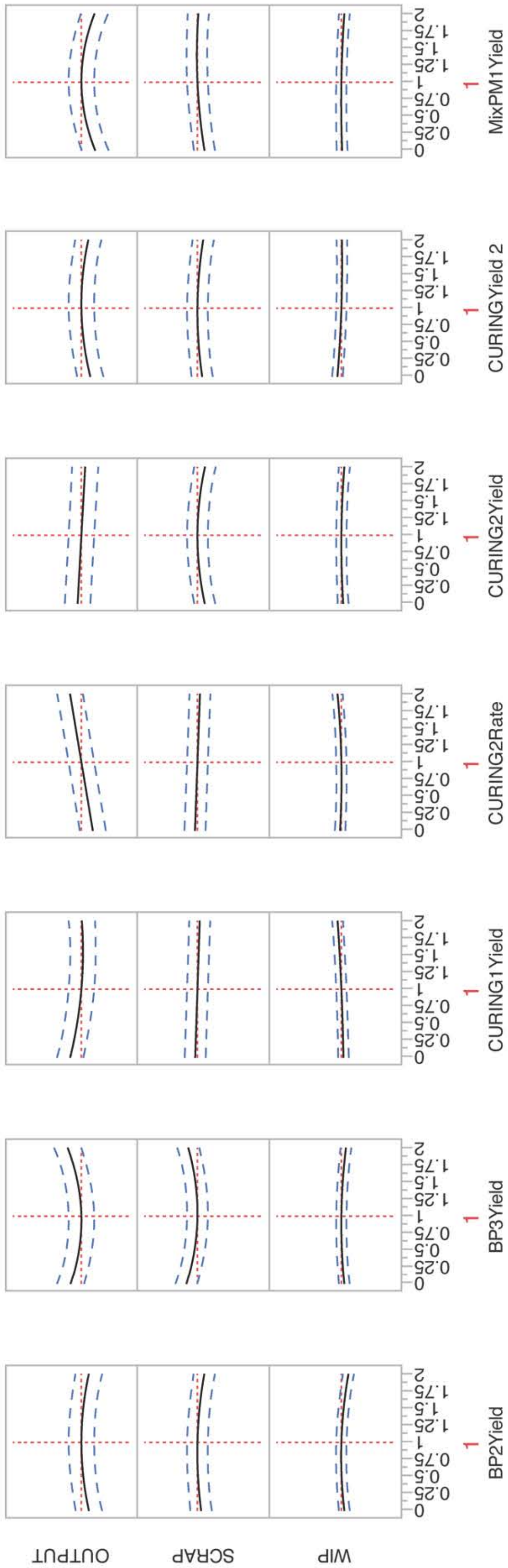


Figure 72: Prediction Profile (Scales Redacted).

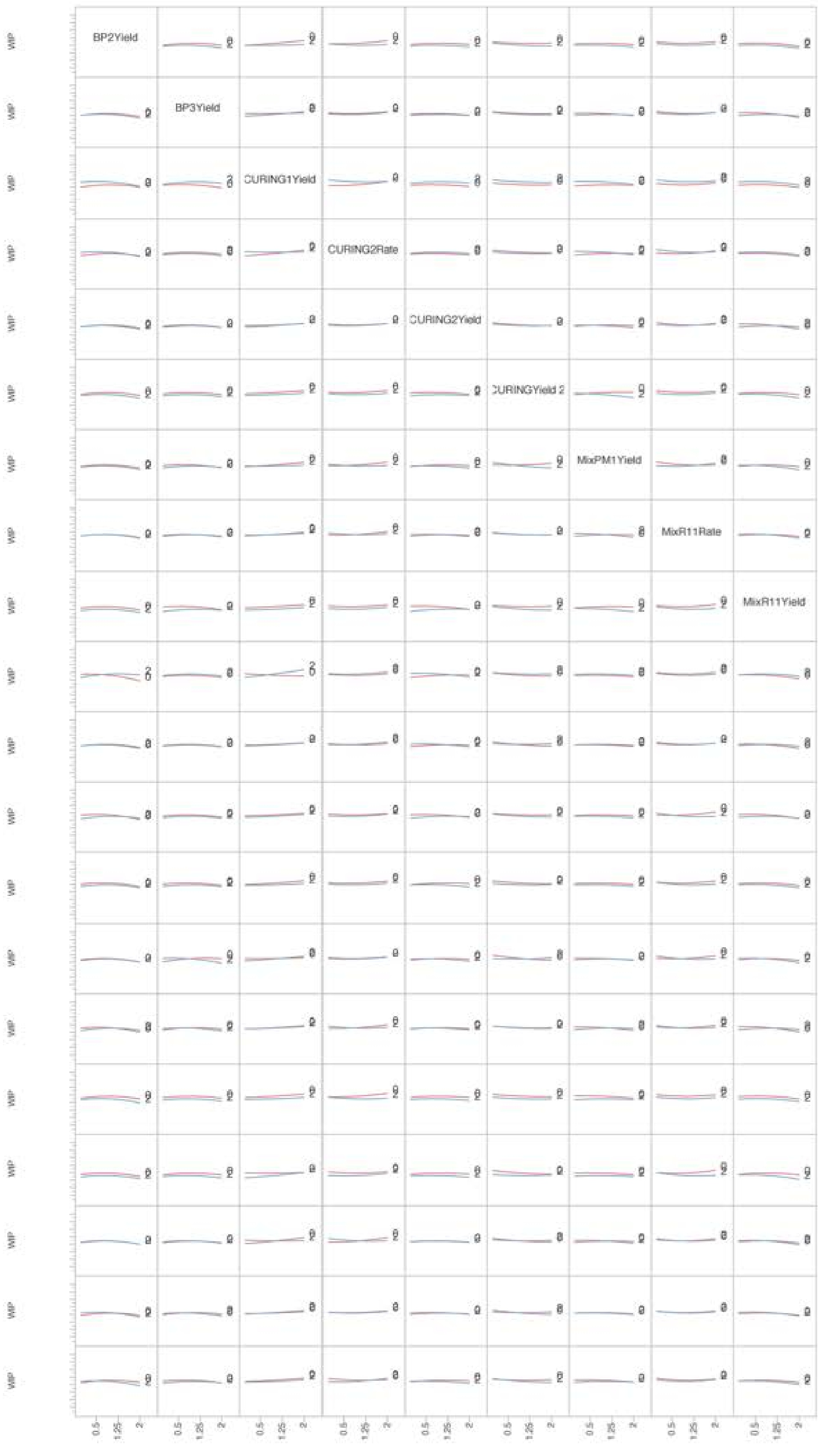


Figure 73: Interaction Profiles for WIP (scales redacted).

Figure 74: Interaction Profiles for WIP (scales redacted).

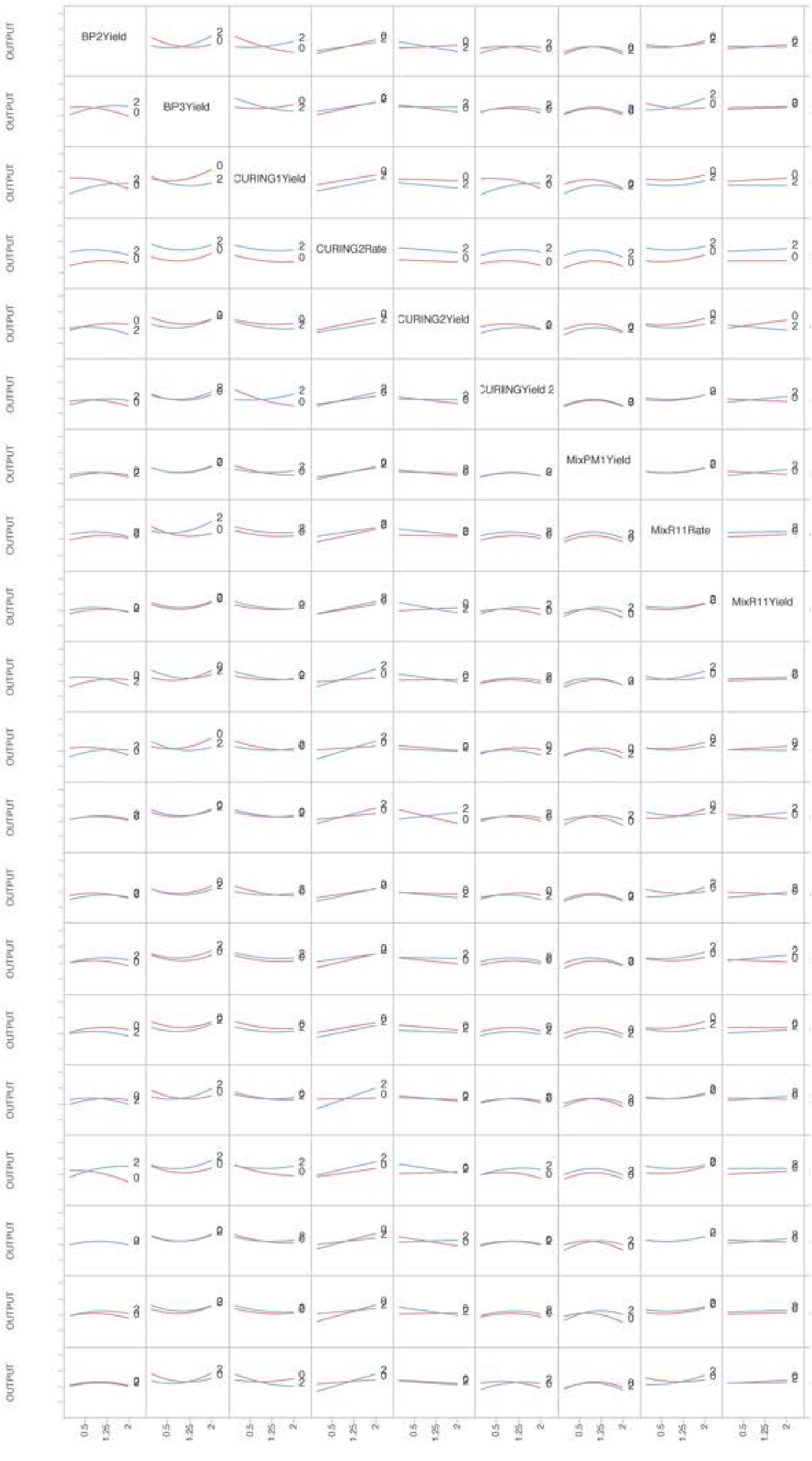


Figure 75: Interaction Profiles for OUTPUT (scales redacted).

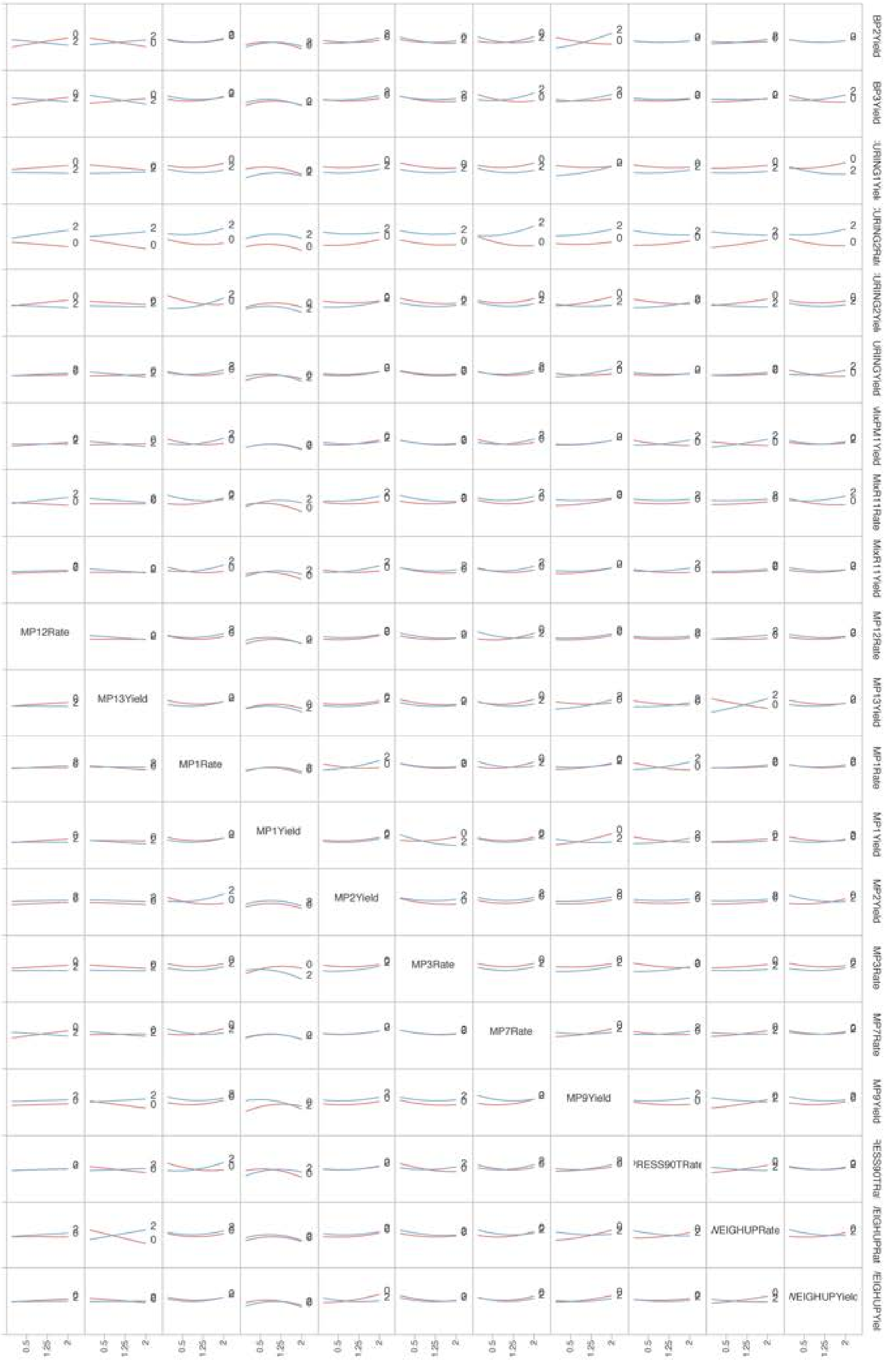


Figure 76: Interaction Profiles for OUTPUT (scales redacted).

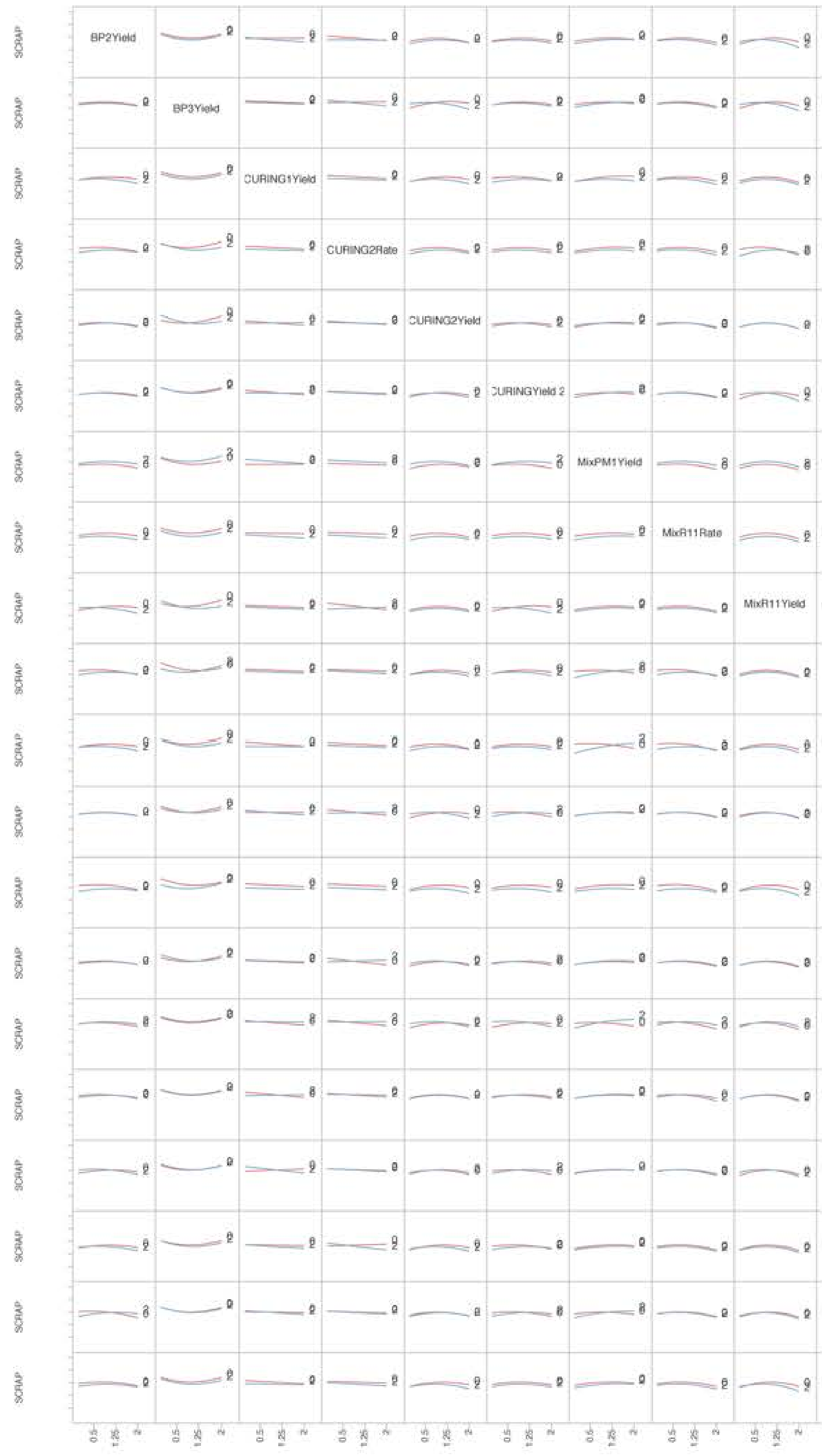


Figure 77: Interaction Profiles for LOSSES (scales redacted).

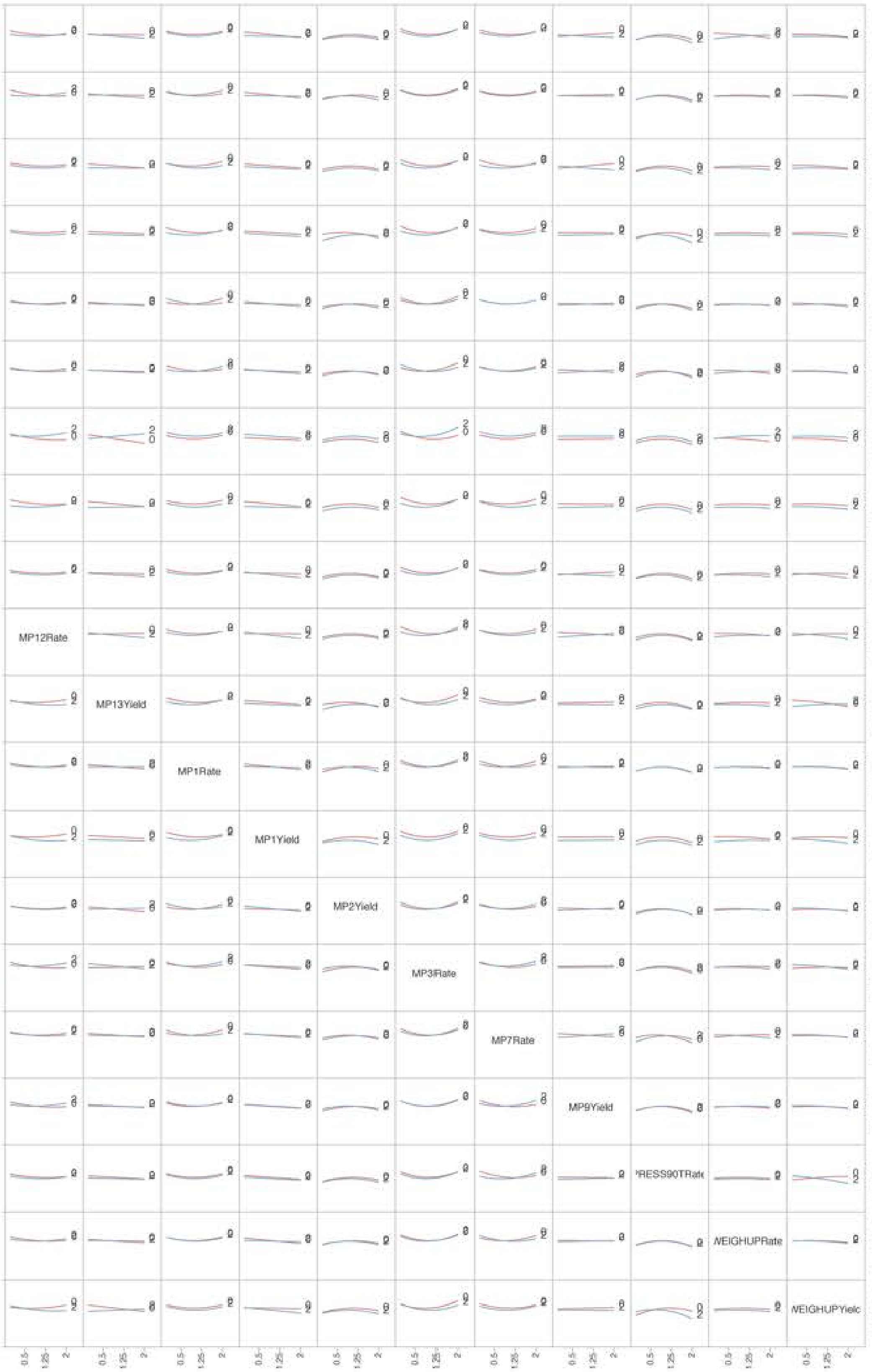


Figure 78: Interaction Profiles for LOSSES (scales redacted).

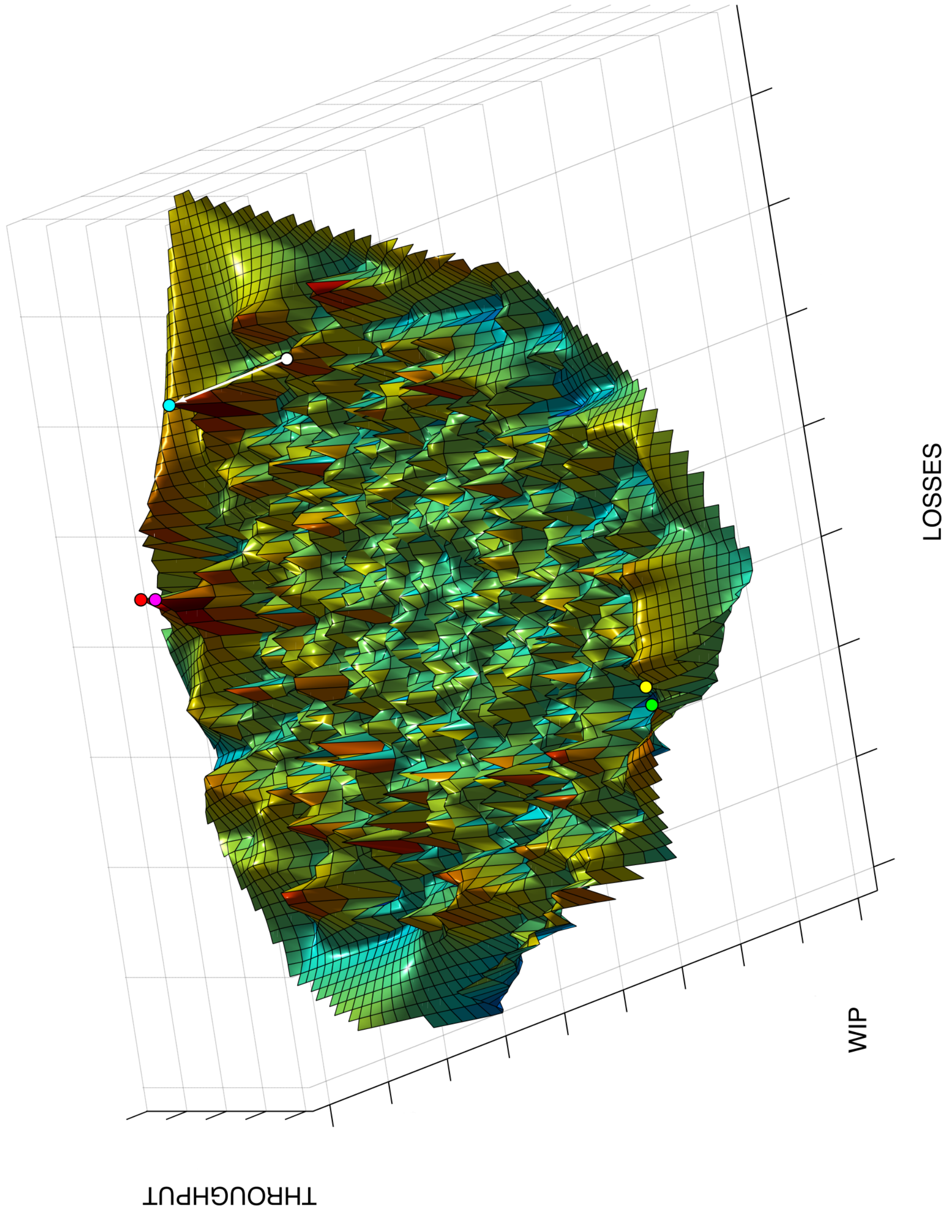


Figure 79: Fitness Landscape for Case Study Factory (Scales Redacted)

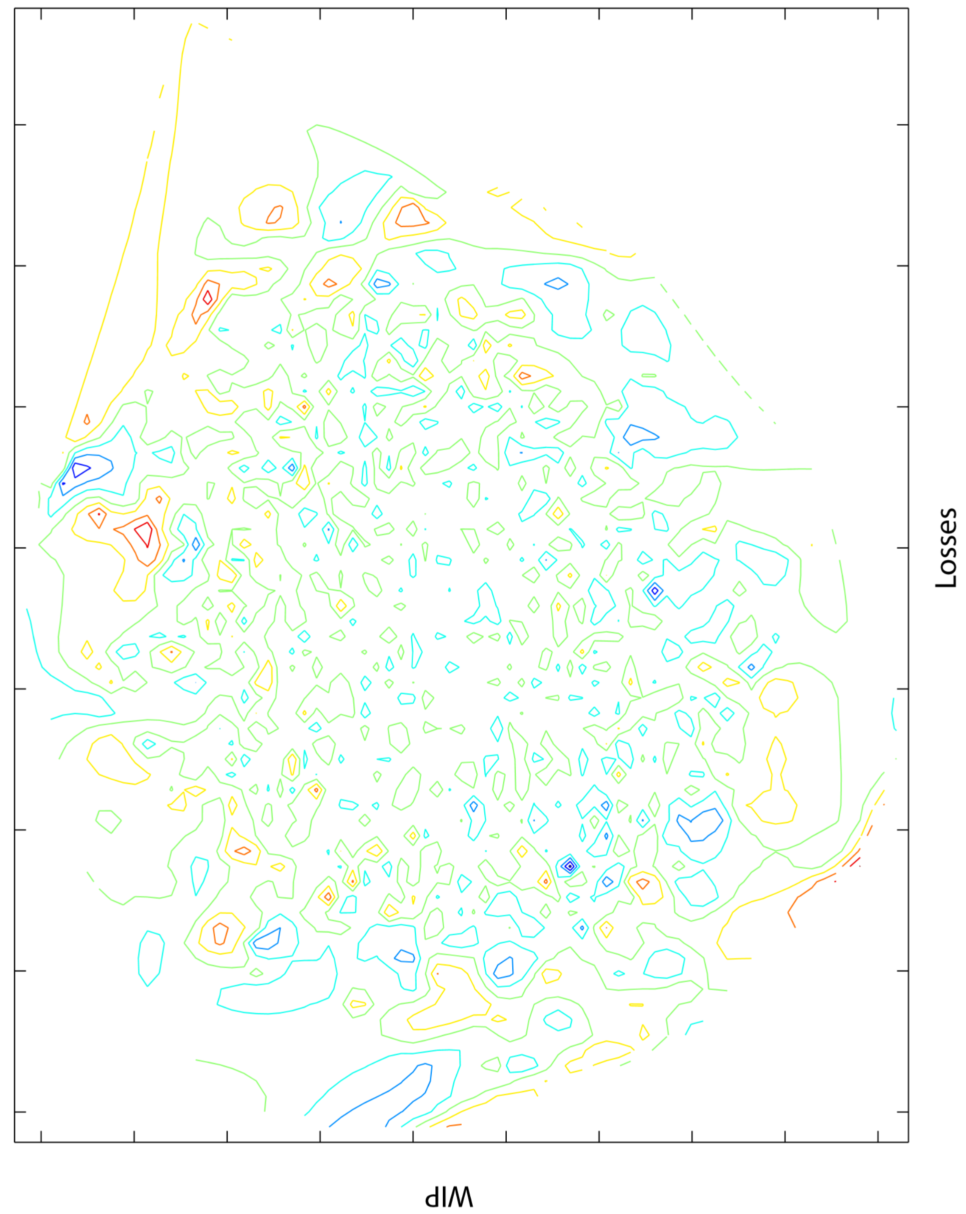


Figure 80: Contour Plot of Fitness Landscape for Case Study Factory (Scales Redacted)

Project Portfolios

The performance of this facility sat atop a ridge of high throughput and low losses as shown by the white marker on the fitness landscape in Figure 79 above. The feasible result space was generally concave with respect to throughput, though it was once again marked with numerous areas of local optimality as can be observed in Figure 80 above.

This ridge is more easily seen in Figure 81 as yellow-orange-red highlights with the factory's performance shown again by the white marker. A local Pareto optimum is marked in cyan on the ridge above. From this perspective it can be seen that the factory's performance and the ridge of local optimality were not particularly robust to change, dropping away quickly to lower green and blue throughput valleys. Therefore it was important for the organization to identify a rational portfolio of improvements, lest it unintentionally drive throughput down into a performance valley.

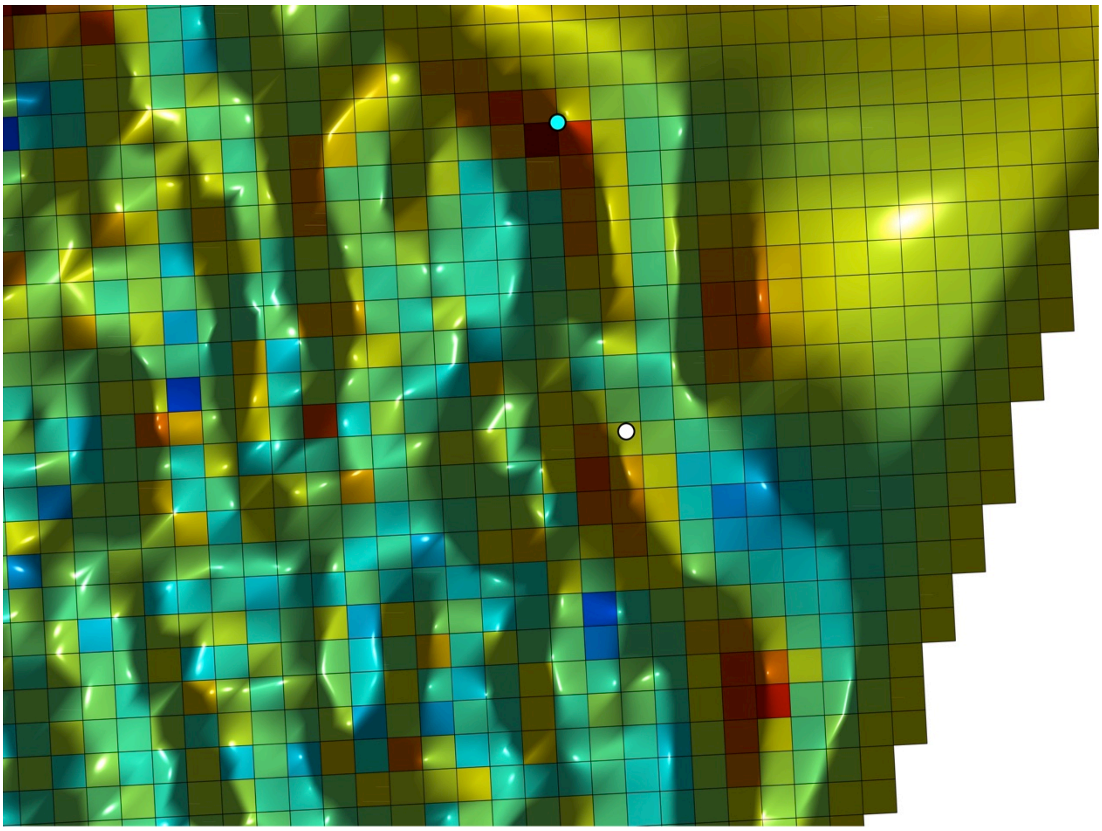


Figure 81: Fitness Landscape Showing Ridge of Local Optimality

Applying the model equation from the DoE experiment, we identified that the organization could move its performance from the local throughput level (white marker) to the local Pareto optimum (cyan marker) by implementing a project portfolio that would maximize BP3 yield, Curing2 rate, MixPM1 yield, MixR11 rate, MP12 rate, MP2 yield and the Weighup rate within the existing feasible ranges.

Discussion

We examined a more complex factory in this second case study, one which included 81 potential factors, rather than the 27 explored in Case Study One. The resultant 3^{81} I-optimal DoE would have required a minimum of 88 729 runs, as compared to the 3 336 runs needed for a 3^{27} I-optimal DoE and, though possible using simulation, this would represent an unreasonable delay to managerial decision making. In order to deal with this additional complexity, we introduced a screening DoE study as an additional analytical step. Through the application of this additional step, we were able to reduce the size of the final I-optimal DoE to a 3^{20} design that required only 1 377 simulation runs. Even with the screening DoE included this represented a 98.2% reduction in the number of experimental runs that were required.

This case also posed additional challenges with respect to data acquisition and availability. Since the studied organisation did not have a SCADA system for centralised data acquisition, production parameters were obtained by direct measurement (for example the mix time), from the equipment PLC (for example the cycle time of the mixers) or from production data (for example the cycle time of the biscuit presses). This is more likely to be the case with most companies and therefore it is important to have a data plan that includes definitions and methods for collection to ensure that adequate and consistent data is acquired for study.

Financial data was not made available for analysis in this study. However we noted that, since our objectives were only to understand relative and not absolute differences in performance, our approach did not require absolute data. It was therefore more important to ensure that all measurements were made in a consistent manner and with consistent definitions, such that their relativity was maintained within the study. This was important not only here for the company's financial data but also for other types of data where definitions and means of collection may differ – for example how changeover times are measured, how stoppages are included in OEE calculations or how scrap is measured or estimated.

Thus, in this case study we developed a subjective scale of intermediate costs starting from raw materials and incrementing at each stage in the process. Although not ideal, this allowed us to reflect the increased embodied cost of WIP for our analyses.

In this case we demonstrated that the methodology could be applied generically across different processes, and industries. In addition, we were able to demonstrate reliability of the methodology. Since absolute financial information was not available, we were forced to make assumptions about relative costs across the process. In doing so we demonstrated that internal consistency through relative measurement was more important to the methodology than absolute measurement. Therefore observations regarding the current state, Pareto Optimal state and the efficacy of various improvement projects could be confidently made.

Conclusions

In this chapter, we have presented a second case study, which served to demonstrate that our methodology for preparing Pareto Frontiers of production was sound and could be replicated. Moreover, the results support our postulate that the complex interplay between factors of production would prevent one from formulating a Pareto Optimal portfolio of improvement projects a priori.

This study elaborated on the methodology utilized in our earlier case, in that it required a more refined approach to experimental design. Whereas one should routinely conduct screening studies for all but the simplest experiments, this is generally unnecessary in computer simulation since studies are conducted at low cost and without interfering with actual production. Given the scale of our experiments (in this case all 27 machines with three factors and three levels), the time taken can become prohibitive to timely decision-making.

7: Case Study Three: A Regional MNE

Process description

This study elaborated on the single manufacturing site case that was set out in Chapter 5. Rather than examining a single site from an MNE, we studied twelve sites that together comprised the Asia Pacific Region. In addition, we included one North American site that acted as the supplier of a key raw material to all twelve sites.

With a few exceptions, the thirteen sites serviced specific locales and/or product families in the region. Three external forces brought about this regional structure: market requirements (such as language, labelling and specific product characteristics), regulatory controls (such as requirements for local manufacture or local specifications) and economic forces (for example, proximity to market, access to low cost labour). Most raw materials, such as sodium chloride; dextrose; HDPE and PP entered the value stream from a variety of third-party providers, however bulk PVC was produced by the MNE in one of its own facilities in the United States. This was transported in bulk by sea with (in the case of Australia) a lead-time of 56 days and additional in-country safety inventory of around 28 days. For this reason, we considered this site and the stock in-transit to be part of the value stream that could by controlled by the company.

With the exception of the facilities in Suzhou and Mountain Home, each factory had the same fundamental value stream flow, which is shown in the exemplar in Figure 83. As was seen in Case Study 1, raw plastics (HDPE, PP and PVC) were brought to the factory in bulk and were then formed into a variety of plastic sheeting intermediaries predominantly via continuous sheet and blown film extrusion processes. This sheeting was then used to manufacture primary and secondary packaging components (bags) to contain the intravenous solutions. Solutions were prepared in bulk and then filled into primary packaging, which was then sterilized in a steam autoclave under heat and pressure. The final product was then allowed to cool before being packed into cardboard cartons for transfer to the warehouse and shipping.

The sites at Suzhou and Mountain Home were intermediary sites, Mountain Home produced virgin medical grade PVC, whilst Suzhou only produced components (sheeting, bags, injection sites and so on) for use by other facilities. Canlunbang in the Philippines produced product for export within Asia Pacific, whereas Manesar in India, Singapore and Suzhou in China produced product for both domestic and export (within Asia Pacific) markets. All other sites produced solely for domestic consumption - for example, the factories at Tianjin, Shanghai, Guangzhou A and Guangzhou B produced finished products solely for the Chinese domestic market.

The Vice President of Operations for Asia-Pacific for this organization oversaw the region while Factory Managers had full budget and scorecard accountability for their sites and managed each facility separately. In general, this meant that a site manager had autonomy for the activities at their site, including the selection of improvement activities. In practice, however budget issues or capacity shortfalls in one country would need to be made up elsewhere in the region and so Factory Managers were not entirely independent of the needs of the region as a whole. Over time this had driven a greater overall focus on continuous improvement and so this region (and the other regions that made up this MNE) took on common frameworks for Lean Manufacturing, the selection of continuous improvement projects, benchmarking and best practice sharing. Ultimately this should have reduced the possibility of local (factory level) optimization and also led towards enterprise value stream optimization. However the tools and processes for enterprise optimization were not yet available to this business at the time of this study.

System Definition and Process Mapping

When examining the current manufacturing system we could have considered any one of three levels of DMU. The first level was the entire Asia-Pacific region comprising all 13 plants, the second level was a sub-region (for example the five manufacturing facilities in China) and, finally, the third level was an individual factory as already elaborated in Case study 1. In that case study, we considered the Australian facility as the DMU and considered its suppliers and neighbouring plants to be externalities. This provided a decision-making framework from the standpoint of the individual Factory Manager enabling them to find Pareto optima for the site and thereby minimised the risk of local optimization within sections of the plant. However, when we stood back to examine the entire region, we saw that facilities competed for resources (for example PVC), had different cost structures, and played different roles (supplier, intermediary, end user and so on) in the supply chain network. Thus, from the standpoint of the Vice President of Operations for Asia Pacific, allowing the country DMU to determine improvements could potentially lead to local optimization within a country and not the regional Pareto optimum. In this chapter, we therefore examined the region as the first tier DMU and the individual factory as a contributor to that DMU.

At this level of abstraction, the decision maker would consider the region in its entirety and examine each factory as a whole, asking such questions as; how did factories compare with respect to overall conversion loss or total overhead spending and their actual versus planned WIP[3]. Since plans for the year would already be set in the prior year, the management discussion centred on deviations from plan for further discussion and investigation.

Given that there were thirteen factories in the region and since we might have very little information other than measures of total factory production for some of these, we could have simplified the modelling task to model and simulate each factory as a single process step. This would trade off an initial simplification in modelling for later effort modelling key areas of further interest and would disregard any available facility modelling. Indeed the multiscale approach set out in Chapter 5 allowed us to map and concurrently simulate processes at both the regional level and also at the level of a single site. Thus whilst most factories were modelled as a single process step, the machine level model of the Toongabbie factory could also be included.

For the purposes of this study, we made the simplifying assumption that the fundamental transfer functions of all facilities were the same, with only parametric differences between them. This was based on the fact that all facilities carried out the same processes in the same value streams, although the actual equipment used might have varied. We were therefore able to use the transfer function obtained in Case Study One and applied parameter estimates to each facility.

[3] These measures and others formed part of the region's Monthly Operations Review during 2014.

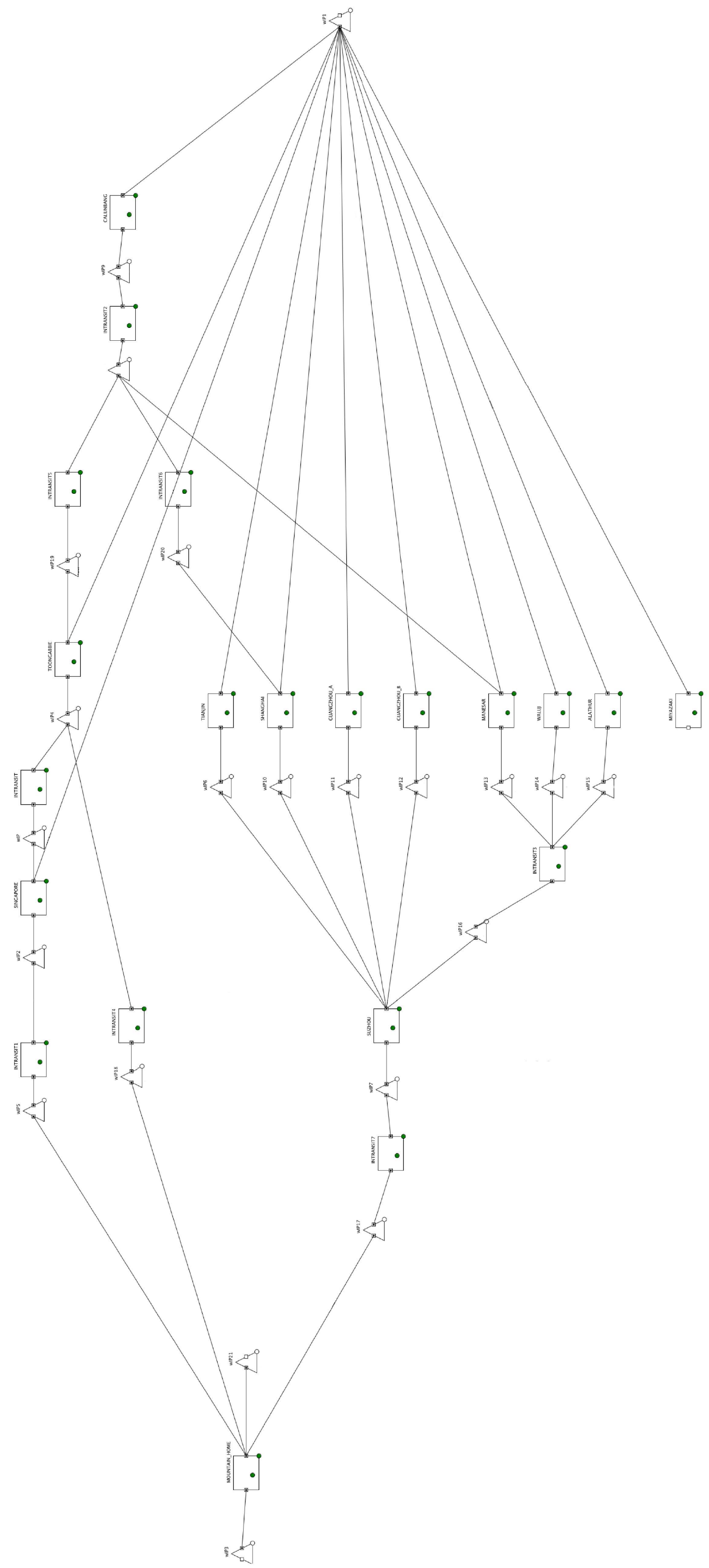


Figure 82: Enterprise Value Stream Map (process details redacted for confidentiality).

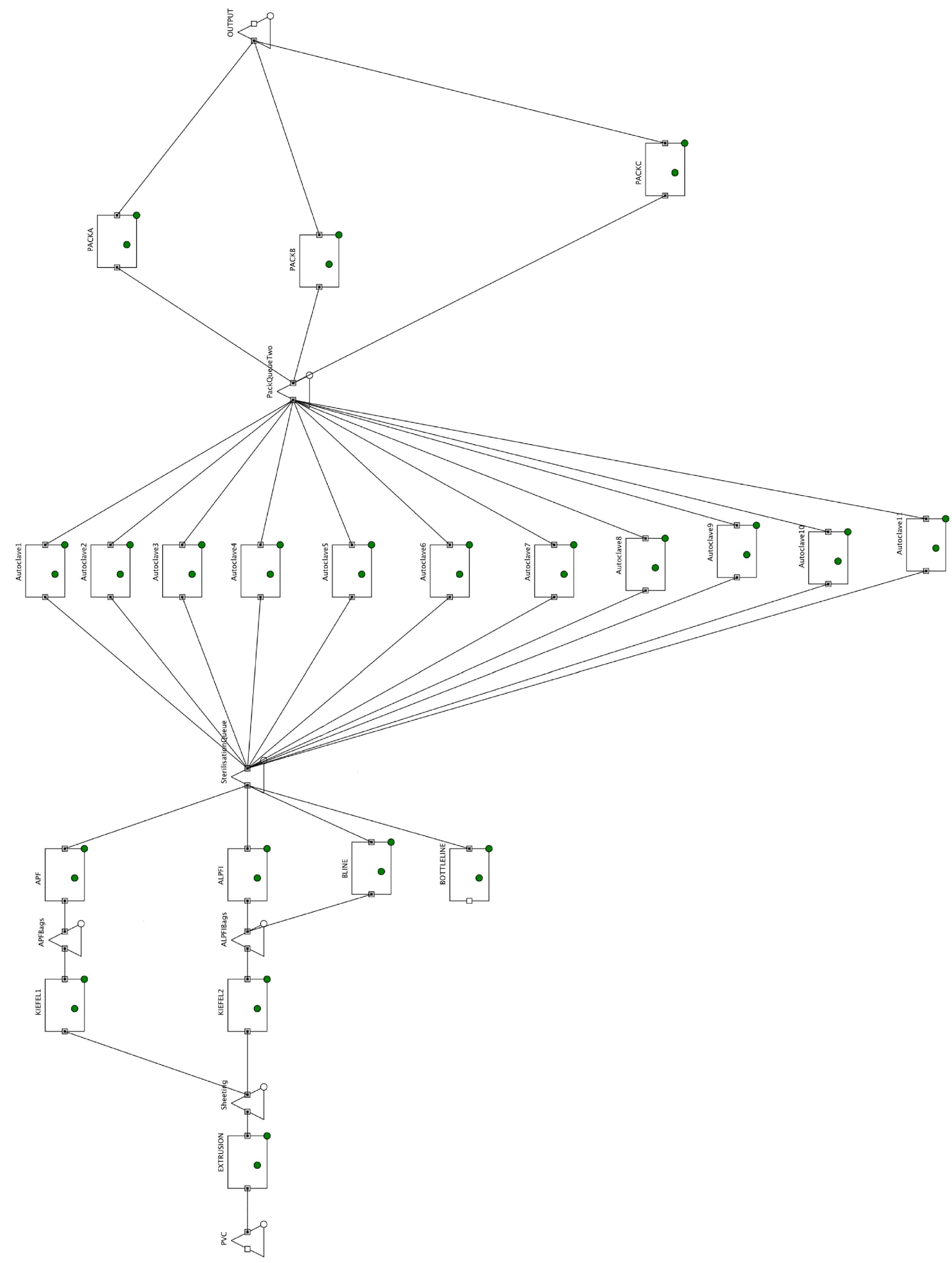


Figure 83: Toongabbie Value Stream Map (process details redacted for confidentiality).

Data Collection

As set out in Case Study One, the studied organisation had a balanced scorecard with six strategic measurement areas, these being customer, financial, people (including safety), innovation, quality and operational excellence. The regional management team reviewed these and their 25 encompassed metrics monthly in their regional Operations Review meetings.

The organization utilized a corporate ERP system, which meant that common financial, production and inventory data were available to managers across all sites and countries. Moreover, the organization had implemented a global approach to Lean Manufacturing, so that each site had developed VSMs, production metrics and improvement plans using a common approach. These were the same systems and practices that were utilized by the individual site in Case Study One.

Although obtaining detailed data for the individual case study proved relatively easy, obtaining detailed site-by-site data on an enterprise scale as an external investigator was more difficult. The following simplifying assumptions were therefore made:

- All VSMs were consistent and the fundamental transfer functions of all facilities were the same,

- Product sizes were relatively homogenous and therefore we considered the same ten product size groups,

- There were no material differences in demand across countries and therefore production schedules were common, and

- The focus of management was towards overall profitability of the region, rather than country market-share. Costs were therefore converted using GDP PPPs ([232]) to make them commensurate across the region.

Modelling

We modelled the regional VSM by the method previously described, however instead of each process step representing a machine, in this study each process step represented an entire factory (see VSM in Figure 82). Furthermore, we considered the in-transit inventory to be a process-WIP combination, since material needed to be released from in-transit inventory to WIP and because this also allowed us to model transit times and losses.

Since we had already modelled the Toongabbie factory, we were able to include this entire VSM within the Toongabbie factory step in the VSM. The resulting VSM was therefore multiscale and it was possible to drill down into the Toongabbie factory step in the enterprise VSM to see the simulation of the processes within that factory (Figure 84).

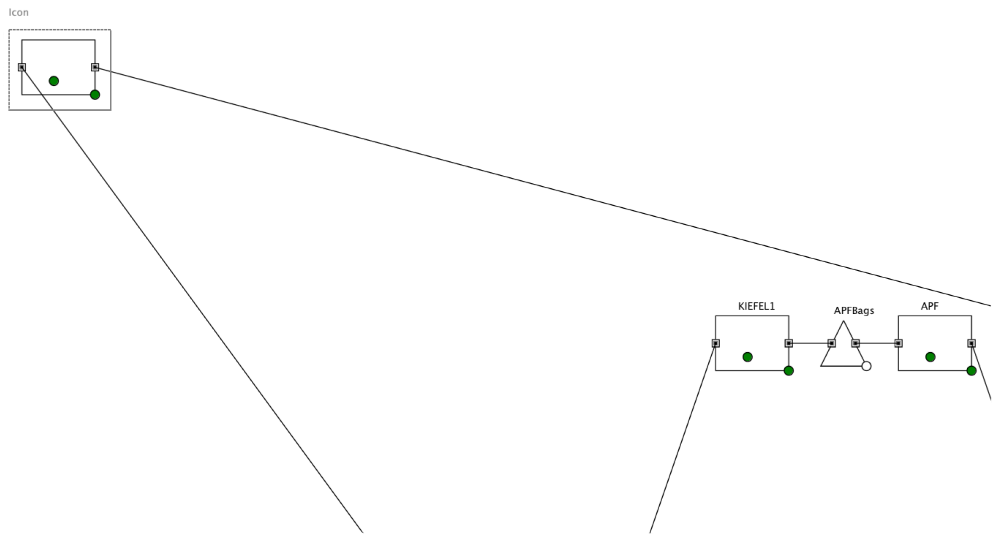


Figure 84: Extract of the Toongabbie Sub-VSM, Showing Input and Output Links to Icon

Dimensionality

As the balanced scorecard for this organisation was consistent across all sites, as previously described in Case Study One, the model took on the dimensionality of throughput, Work in Process (WIP) and losses (scrap and yield losses). Once again, in order to ensure that simulation outputs were commensurate throughout the VSM, we dollarized these dimensions. However in this study, we also converted all amounts to GDP PPP equivalent values to remove the effect of differences in currency valuations.

Factors

The final model was composed of 13 factory elements, 7 in-transit elements, 20 process elements and 27 WIP elements. Of these, eleven process elements were the deterministic controlled autoclaves and thus were simulated but we did not manipulate process variables for them in this experiment. For factory and process elements we once again considered rate, yield and changeover times, whereas only rate and yield were relevant for in-transit elements. The model was therefore comprised of 80 (39 + 14 + 27) production factors that could be controlled and studied. This would have required a 3^{80} I-optimal DoE of 85 487 runs. Once again, although possible, we deemed such a study would be unnecessarily protracted and therefore elected to conduct a preliminary screening analysis as was described in the previous chapter, Case Study Two.

Screening DoE

We chose to conduct a 256 run Fractional Factorial screening design with resolution IV in order to capture both main effects and some interaction information, since we suspected that there would be some degree of two and three way interactions. The screening design was prepared in JMP®, simulated in AnyLogic® and the results analysed in JMP® as summarized in Figure 85 to Figure 90. These figures show the Factor Screening Report and Half Normal Plot for each of the responses – Output, WIP and Losses.

SSE	DFE	RMSE	R^2	R^2 Adj	Cp	p	AICc	BIC
314335394	60	2288.8694	0.8597	0.7031	38.280017	68	2551.184	2581.423

Table 16: Stepwise Fit for Throughput

SSE	DFE	RMSE	R^2	R^2 Adj	Cp	p	AICc	BIC
5.653e+11	78	85133.677	0.6974	0.5073	0.9590795	50	3377.743	3453.407

Table 17: Stepwise Fit for Losses

SSE	DFE	RMSE	R^2	R^2 Adj	Cp	p	AICc	BIC
1.191e+14	63	1375173.6	0.8480	0.6935	34.117393	65	4167.82	4211.071

Table 18: Stepwise Fit for WIP

Where: SSE: Sum of squares; DFE: Degrees of freedom; RMSE: Root mean square error; R^2 coefficient of determination; R^2 Adj: Adjusted R^2; Cp: Mallow's Cp criterion; p: Number of parameters in the model, including the intercept; AICc: Corrected Akaike's Information Criterion; BIC: Bayesian Information Criterion

The factor screening reports (Figure 85, Figure 87 and Figure 89) provide contrast estimates for factors, ranked by their individual p-value and significant p-values have been marked with an asterisk. The Half Normal Plots are shown in Figure 86, Figure 88 and Figure 90 showing significant factors diverging from the line in the upper right corner. The screening study indicated that the most important production factors for further study were:

- Canlunbang rate,
- Canlunbang yield,
- Guangzhou B yield,
- Intransit 1 rate,
- Intransit 2 rate,
- Intransit 4 rate,
- Intransit 5 rate,
- Intransit 6 rate,
- Intransit 7 rate,
- Intransit 6 yield,
- Intransit 7 yield,
- Manesar Rate,
- Miyazaki Yield,
- Mountain Home Rate,
- Singapore Yield,
- Tianjin Yield,
- Tianjin Rate,
- Waluj Yield, and

- Toongabbie Rate.

It was not surprising to see that the lead times for inventory in-transit figured so prominently in a model of so large a geographic region.

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value	Simultaneous p-Value
SINGAPOREYield	1235.61	3.42	0.0014*	0.1310
MANESARRate	-1050.73	-2.91	0.0049*	0.4104
CALUNBANGRate	-852.79	-2.36	0.0190*	0.8375
TIANJINYield	751.13	2.08	0.0393*	0.9719
MIYAZAKIYield*TIANJINRate	-679.80	-1.88	0.0646	0.9964
SINGAPOREYield*INTRANSIT6Rate	675.26	1.87	0.0668	0.9967
GUANGZHOU_BYield	-665.98	-1.84	0.0707	0.9973
INTRANSIT6Rate	-651.65	-1.80	0.0762	0.9983
MIYAZAKIYield	649.84	1.80	0.0770	0.9984
SINGAPOREYield*INTRANSIT2Rate	643.63	1.78	0.0786	0.9986
INTRANSIT5Rate	-625.20	-1.73	0.0875	0.9994
INTRANSIT6Rate*INTRANSIT6Yield	-601.21	-1.66	0.0971	0.9998
SINGAPOREYield*MANESARRate	-580.03	-1.61	0.1090	0.9999
TIANJINYield*GUANGZHOU_BYield	555.56	1.54	0.1264	1.0000

Figure 85: Extract of Factor Screening Report for OUTPUT

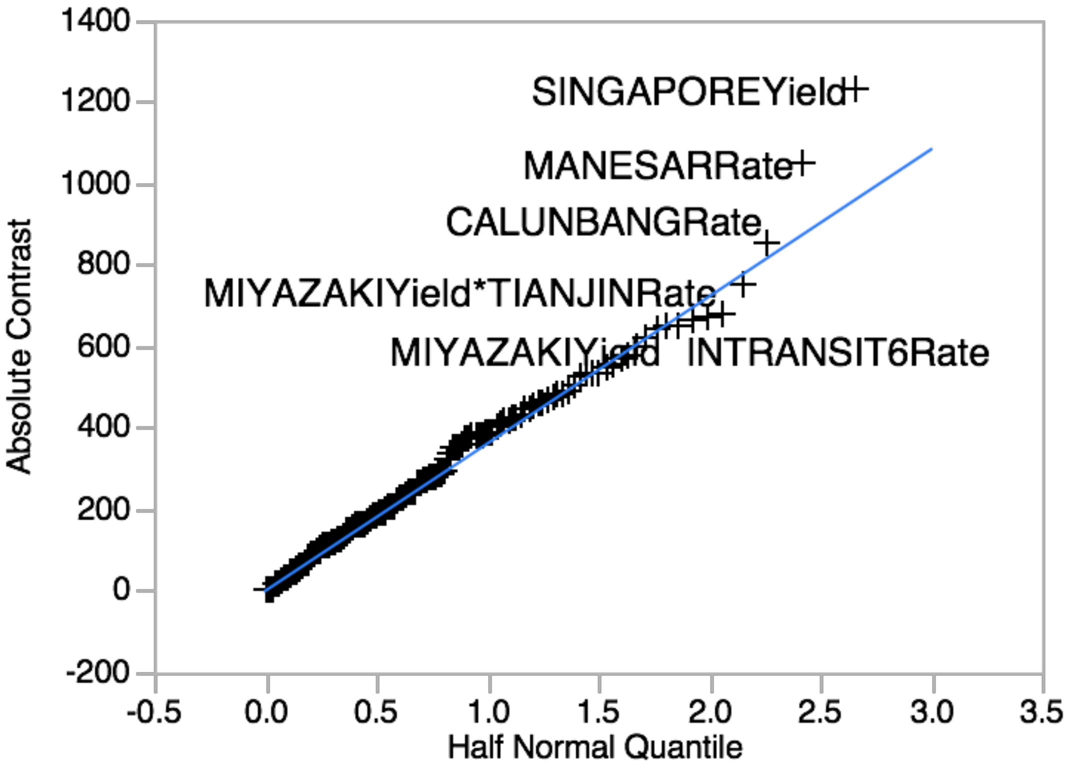


Figure 86: Half Normal Plot Screening for OUTPUT

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value	Simultaneous p-Value
CALUNBANGRate	27439.5	3.34	0.0016*	0.1630
SINGAPOREYield*TIANJINRate	-24747.5	-3.01	0.0046*	0.3382
INTRANSIT5Rate*INTRANSIT3Yield	24607.5	2.99	0.0047*	0.3512
INTRANSIT5Rate	22149.9	2.69	0.0099*	0.5845
INTRANSIT5Rate*WALUJYield	21170.1	2.57	0.0135*	0.6867
CALUNBANGRate*SINGAPOREYield	20197.3	2.46	0.0169*	0.7641
MOUNTAIN_HOMERate*CALUNBANGYield	-20051.6	-2.44	0.0177*	0.7785
INTRANSIT1Rate*MIYAZAKIYield	19431.0	2.36	0.0213*	0.8355
MANESARRate	18757.6	2.28	0.0247*	0.8883
CALUNBANGRate*INTRANSIT7Rate	-18566.7	-2.26	0.0258*	0.9017
INTRANSIT7Yield	18031.2	2.19	0.0303*	0.9318
INTRANSIT7Yield*INTRANSIT2Rate	17729.4	2.16	0.0325*	0.9455
MANESARRate*MOUNTAIN_HOMERate	17446.7	2.12	0.0353*	0.9564
INTRANSIT5Rate*MIYAZAKIYield	-17364.5	-2.11	0.0363*	0.9595
MOUNTAIN_HOMERate	16087.7	1.96	0.0496*	0.9879
MANESARRate*SINGAPOREYield	15730.9	1.91	0.0555	0.9921
CALUNBANGYield	-15309.7	-1.86	0.0625	0.9950
INTRANSIT4Rate*INTRANSIT1Rate	15071.3	1.83	0.0656	0.9964
INTRANSIT7Yield*INTRANSIT7Rate	15045.4	1.83	0.0659	0.9965
INTRANSIT5Rate*INTRANSIT7Rate	-14957.8	-1.82	0.0680	0.9971
INTRANSIT4Rate	14255.0	1.73	0.0828	0.9987
MANESARRate*CALUNBANGYield	-14186.8	-1.72	0.0840	0.9987
CALUNBANGRate*INTRANSIT7Yield	-13824.6	-1.68	0.0919	0.9993
INTRANSIT7Yield*INTRANSIT4Rate	13268.2	1.61	0.1063	0.9998
INTRANSIT3Yield	12810.0	1.56	0.1165	0.9999
INTRANSIT3Yield*INTRANSIT7Rate	12438.8	1.51	0.1276	1.0000

Figure 87: Extract of Factor Screening Report for WIP

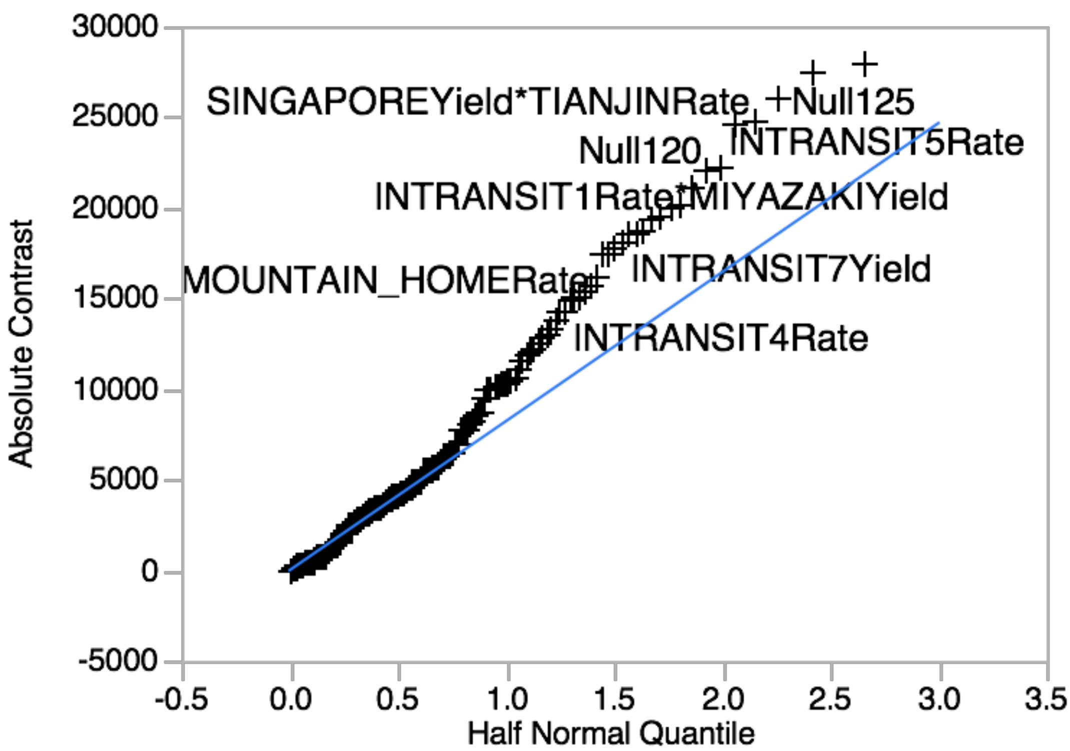


Figure 88: Half Normal Plot Screening for WIP

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value	Simultaneous p-Value
SINGAPOREYield	-701389	-3.30	0.0016*	0.1791
MANESARRate	609168	2.87	0.0063*	0.4436
CALUNBANGRate	468927	2.21	0.0303*	0.9268
TIANJINYield	-462226	-2.17	0.0325*	0.9395
SINGAPOREYield*INTRANSIT6Rate	-441329	-2.08	0.0419*	0.9700
MIYAZAKIYield	-413121	-1.94	0.0568	0.9911
INTRANSIT6Rate	378255	1.78	0.0784	0.9990
MIYAZAKIYield*TIANJINRate	377035	1.77	0.0790	0.9991
GUANGZHOU_BYield	371769	1.75	0.0835	0.9994
INTRANSIT5Rate	371053	1.75	0.0839	0.9994
TIANJINYield*GUANGZHOU_BYield	-362709	-1.71	0.0912	0.9997
INTRANSIT5Rate*INTRANSIT7Yield	358440	1.69	0.0945	0.9998
TOONGABBIERate*INTRANSIT4Rate	347666	1.64	0.1039	1.0000

Figure 89: Extract of Factor Screening Report for LOSSES

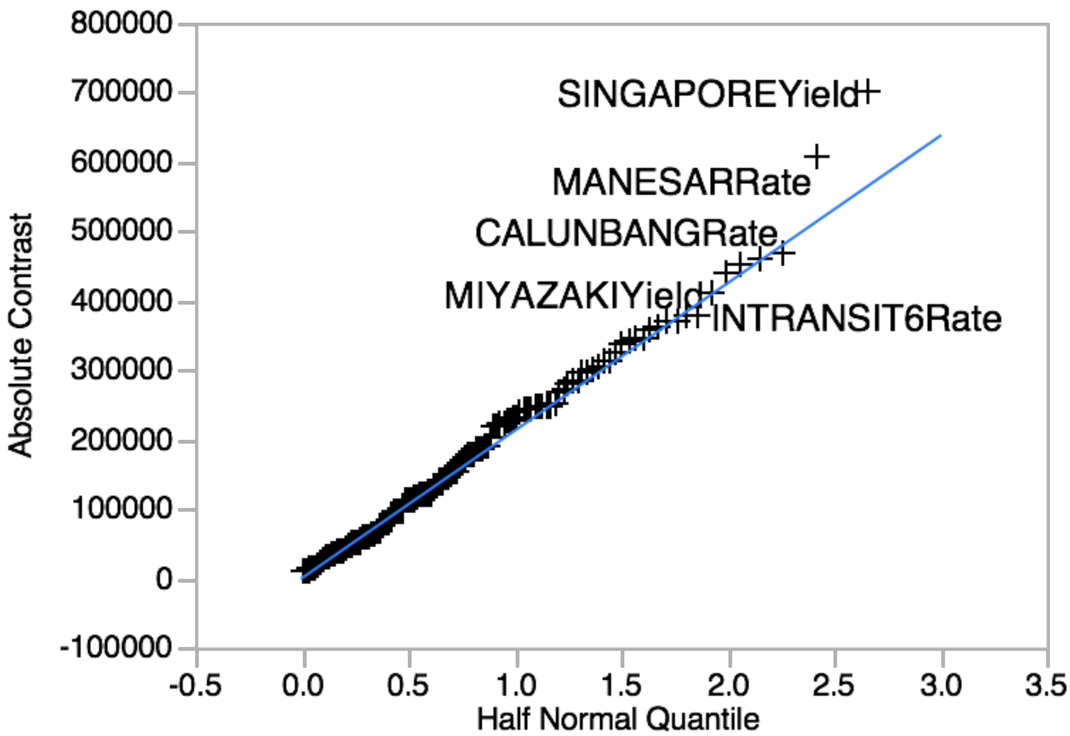


Figure 90: Half Normal Plot Screening for LOSSES

Simulation

With the screening output from the previous step, we designed an I optimal 3^{20} DoE with two and three way interactions using JMP® (Table 19) and this was then simulated in AnyLogic®.

The results of the simulation were fitted to a degree 2 polynomial with two and three way interactions in JMP® using stepwise parameter selection of regression by forward selection as previously described. The regression model fit is shown in Table 20, Table 21 and Table 22 below.

D Efficiency	G Efficiency	A Efficiency	Average Variance of Prediction
27.0659	41.3412	4.4243	1.1843

Table 19: Design Diagnostics - I Optimal Design

SSE	DFE	RMSE	R2	R2 Adj	Cp	p	AICc	BIC
4.678e+13	127	606906.08	0.9905	0.9112	941.29026	1058	52354.28	39770.71

Table 20: Stepwise Fit for Throughput

SSE	DFE	RMSE	R2	R2 Adj	Cp	p	AICc	BIC
3.3308e+9	433	2773.5053	0.8986	0.7226	461.48986	752	25099.55	26288.27

Table 21: Stepwise Fit for Losses

SSE	DFE	RMSE	R2	R2 Adj	Cp	p	AICc	BIC
2.602e+15	250	3225956.7	0.9695	0.8555	753.92704	935	45982.39	43662.09

Table 22: Stepwise Fit for WIP

Where: SSE: Sum of squares; DFE: Degrees of freedom; RMSE: Root mean square error; R^2 coefficient of determination; R^2 Adj: Adjusted R^2; Cp: Mallow's Cp criterion; p: Number of parameters in the model, including the intercept; AICc: Corrected Akaike's Information Criterion; BIC: Bayesian Information Criterion

In addition to the overall prediction model, prediction profiles and interaction plots for all parameters were also examined. The prediction profile is shown below in Figure 91 to Figure 93.

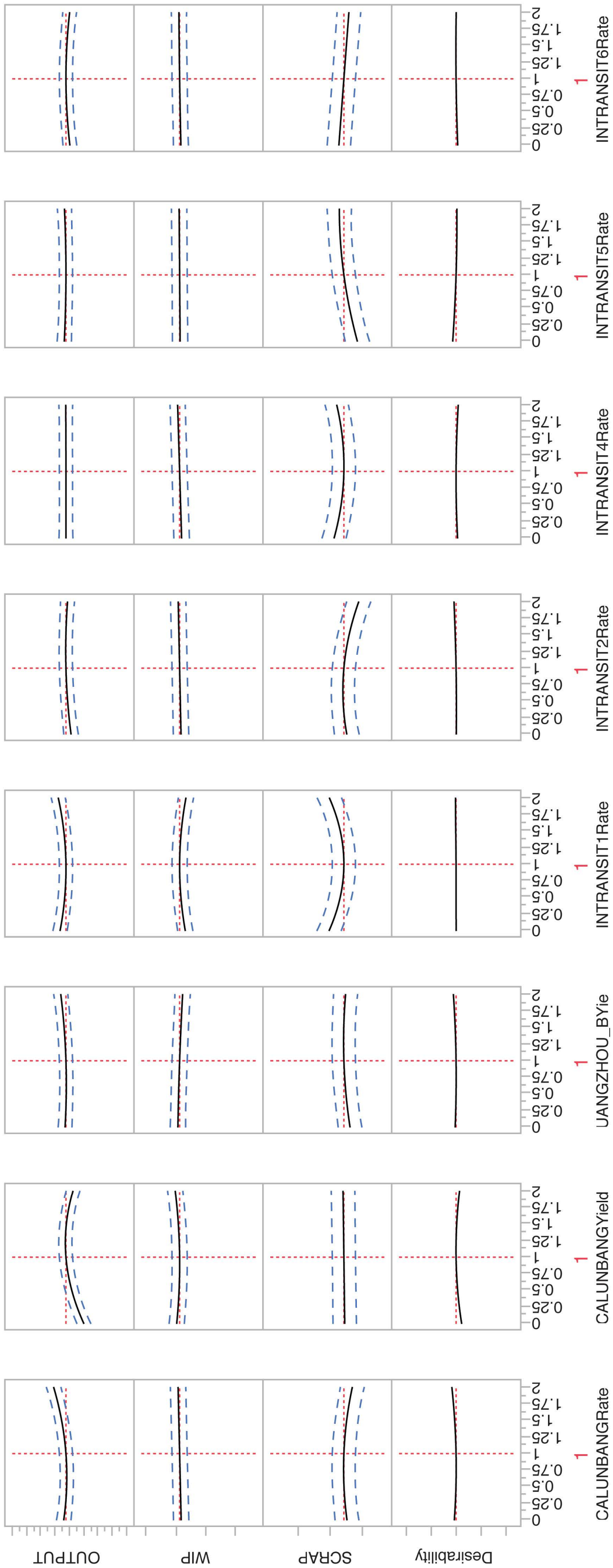


Figure 91: Prediction Profile (Scales Redacted)

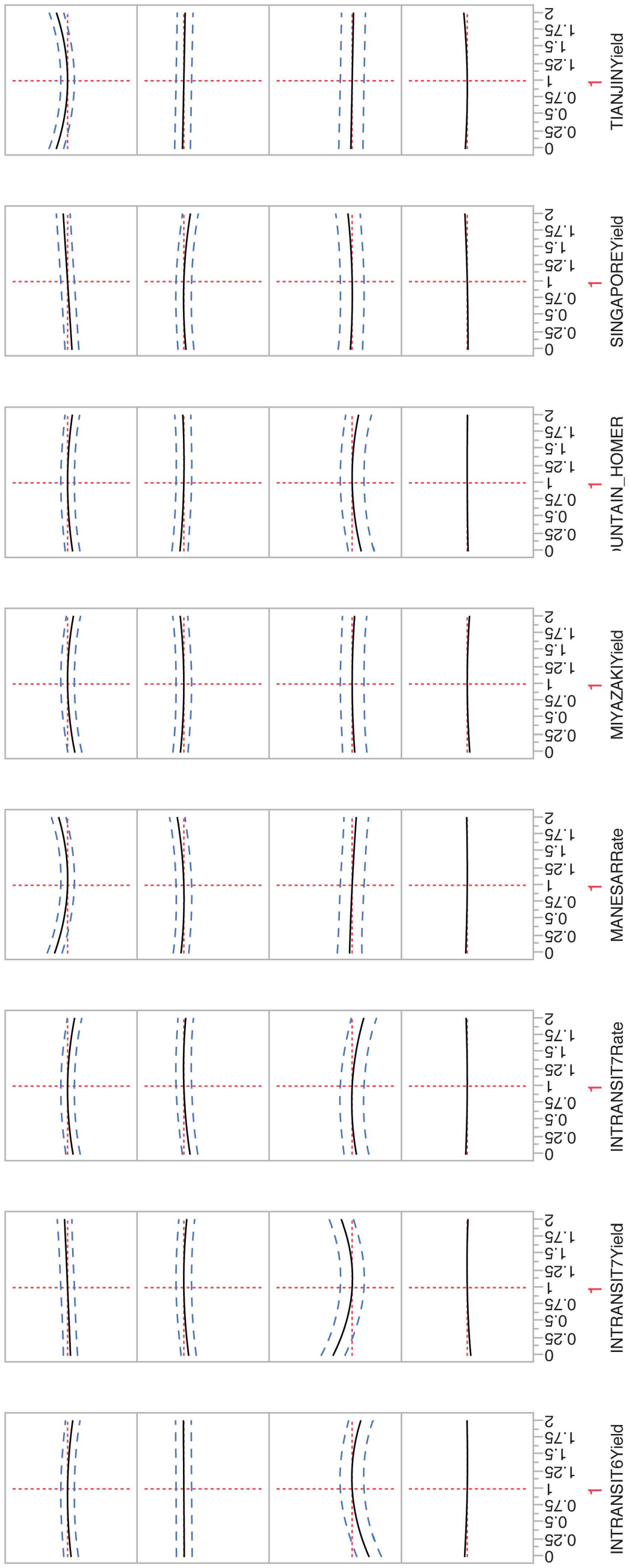


Figure 92: Prediction Profile (Scales Redacted)

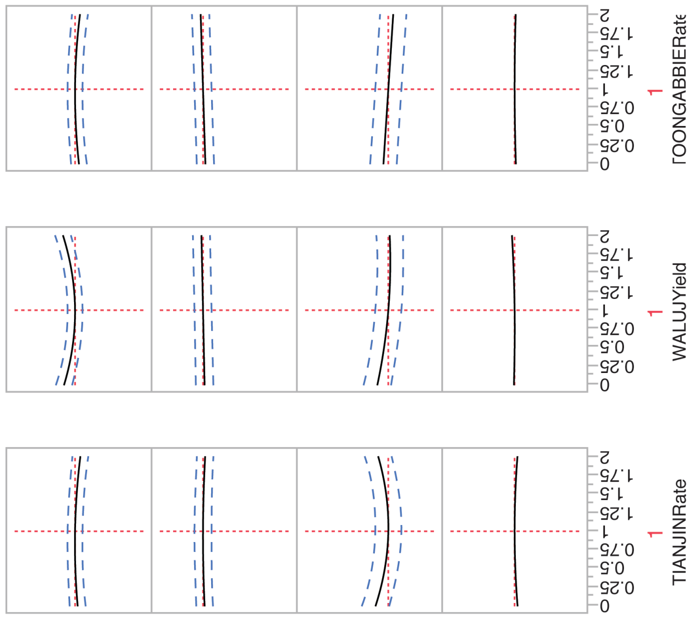


Figure 93: Prediction Profile (Scales Redacted)

Figure 94: Interaction Profiles for WIP (scales redacted).

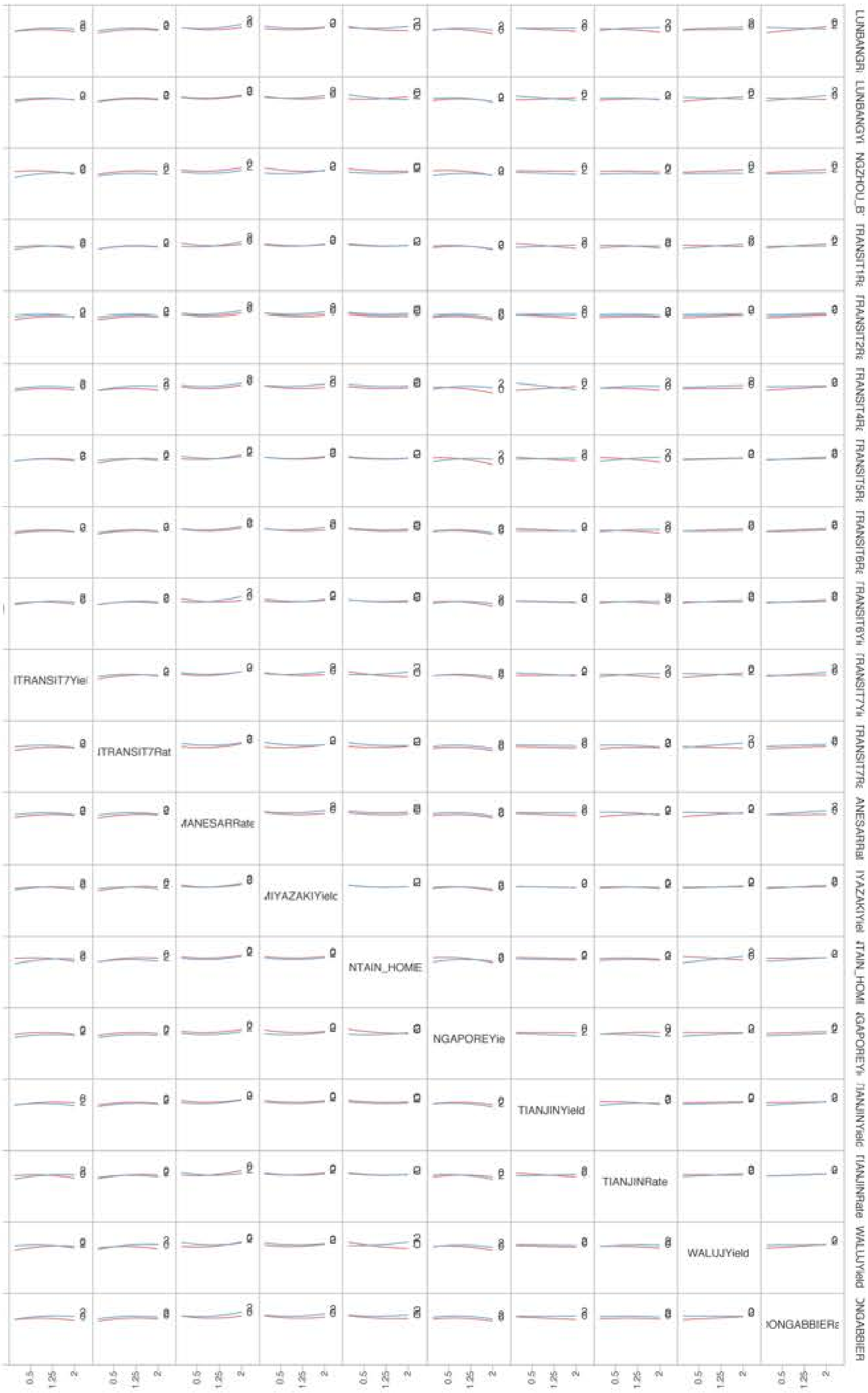


Figure 95: Interaction Profiles for WIP (scales redacted).

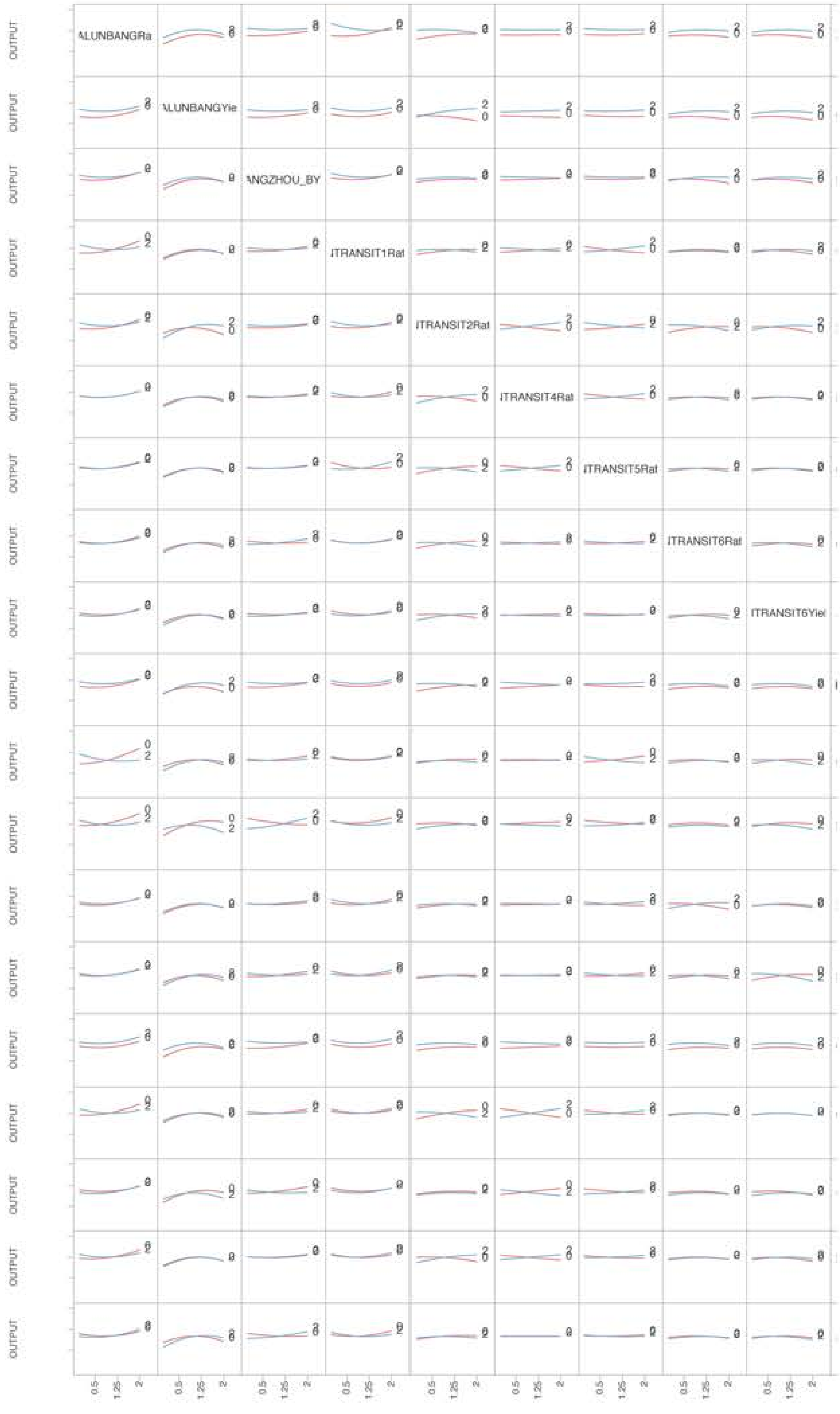


Figure 96: Interaction Profiles for OUTPUT (scales redacted).

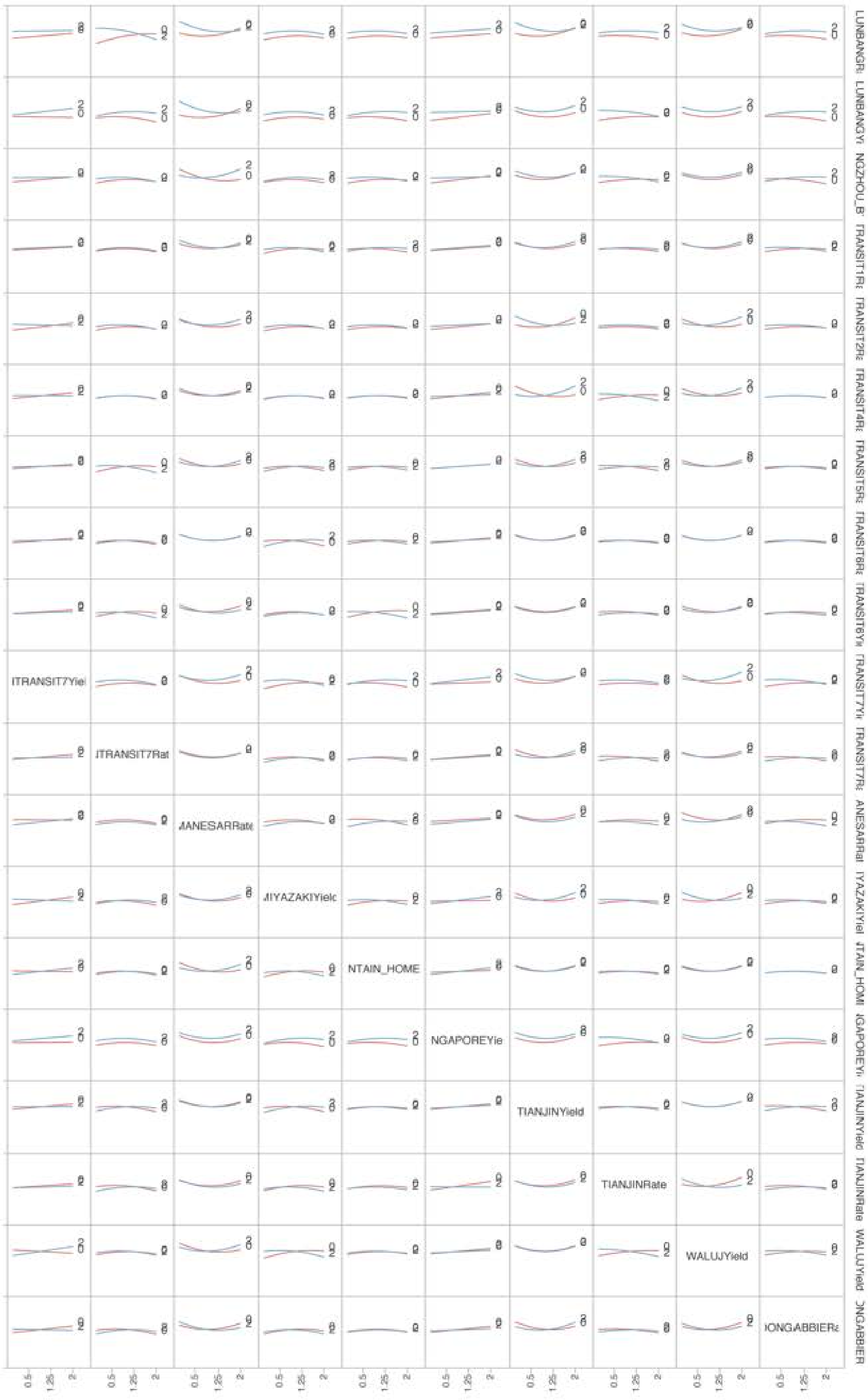


Figure 97: Interaction Profiles for OUTPUT (scales redacted).

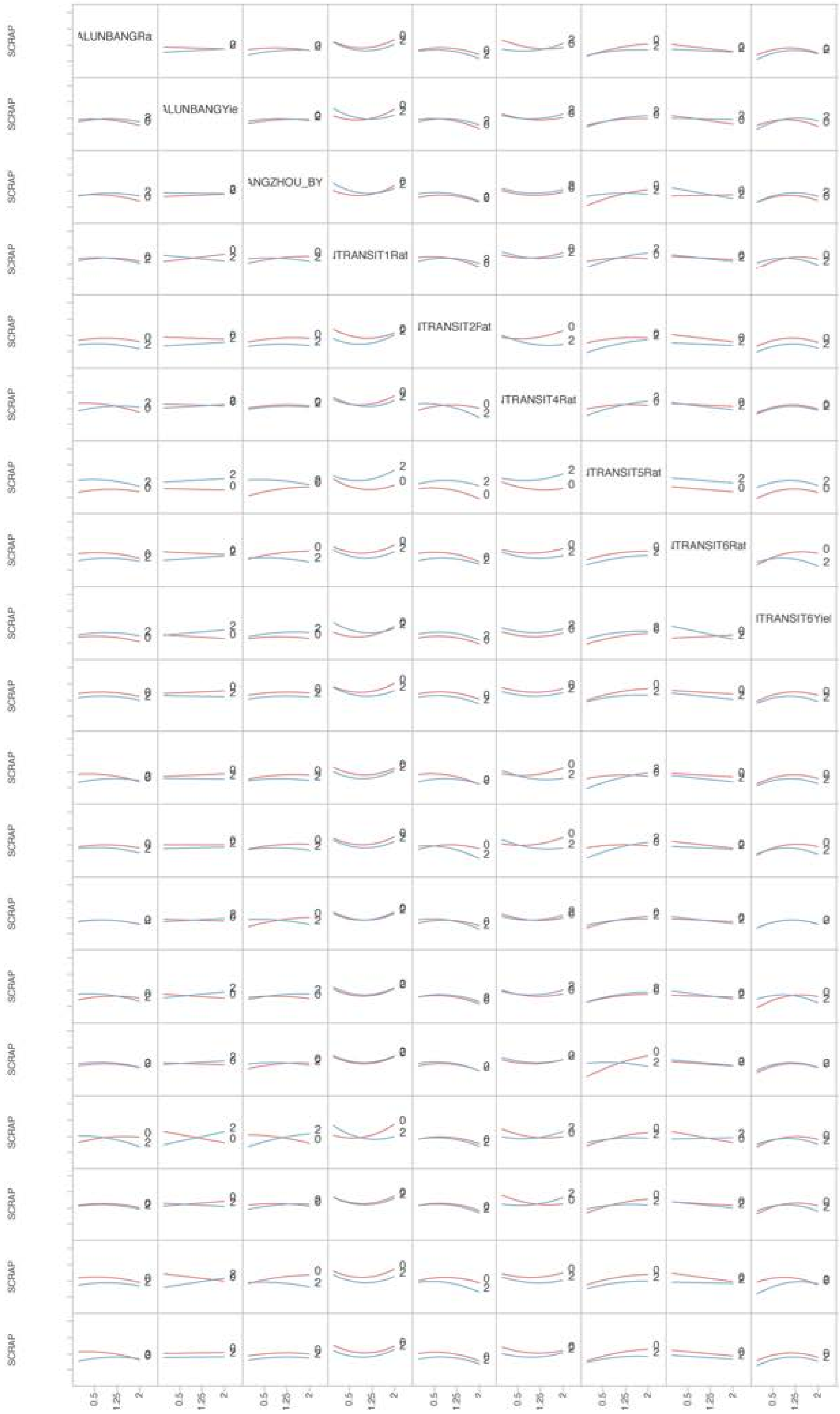


Figure 98: Interaction Profiles for LOSSES (scales redacted).

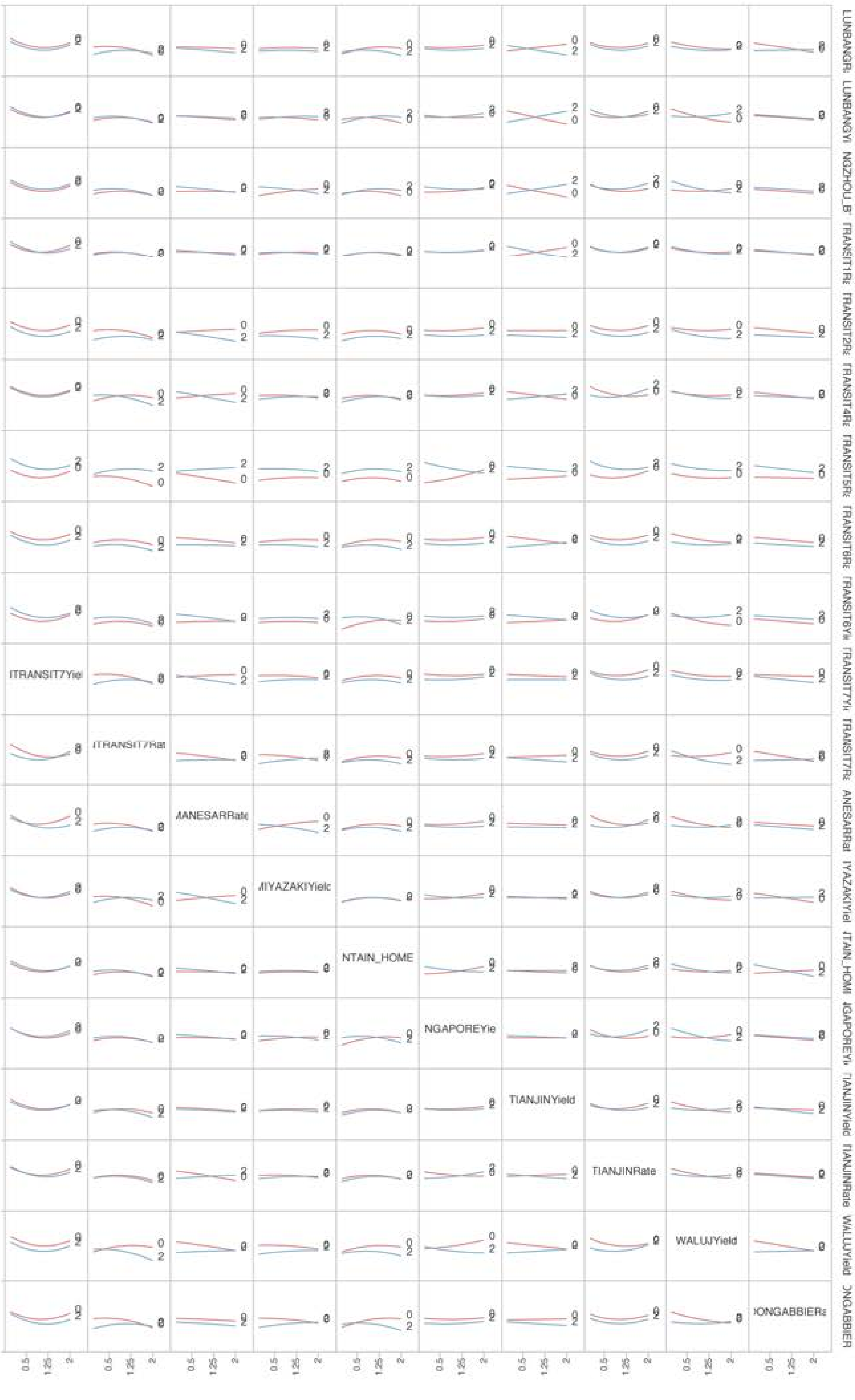


Figure 99: Interaction Profiles for LOSSES (scales redacted).

Project Portfolios

The regional fitness landscape was somewhat more rugged than we had seen with individual factories and the performance of the region sat in an area of relatively low output and losses but moderate WIP, as shown by the white reference marker in Figure 100.

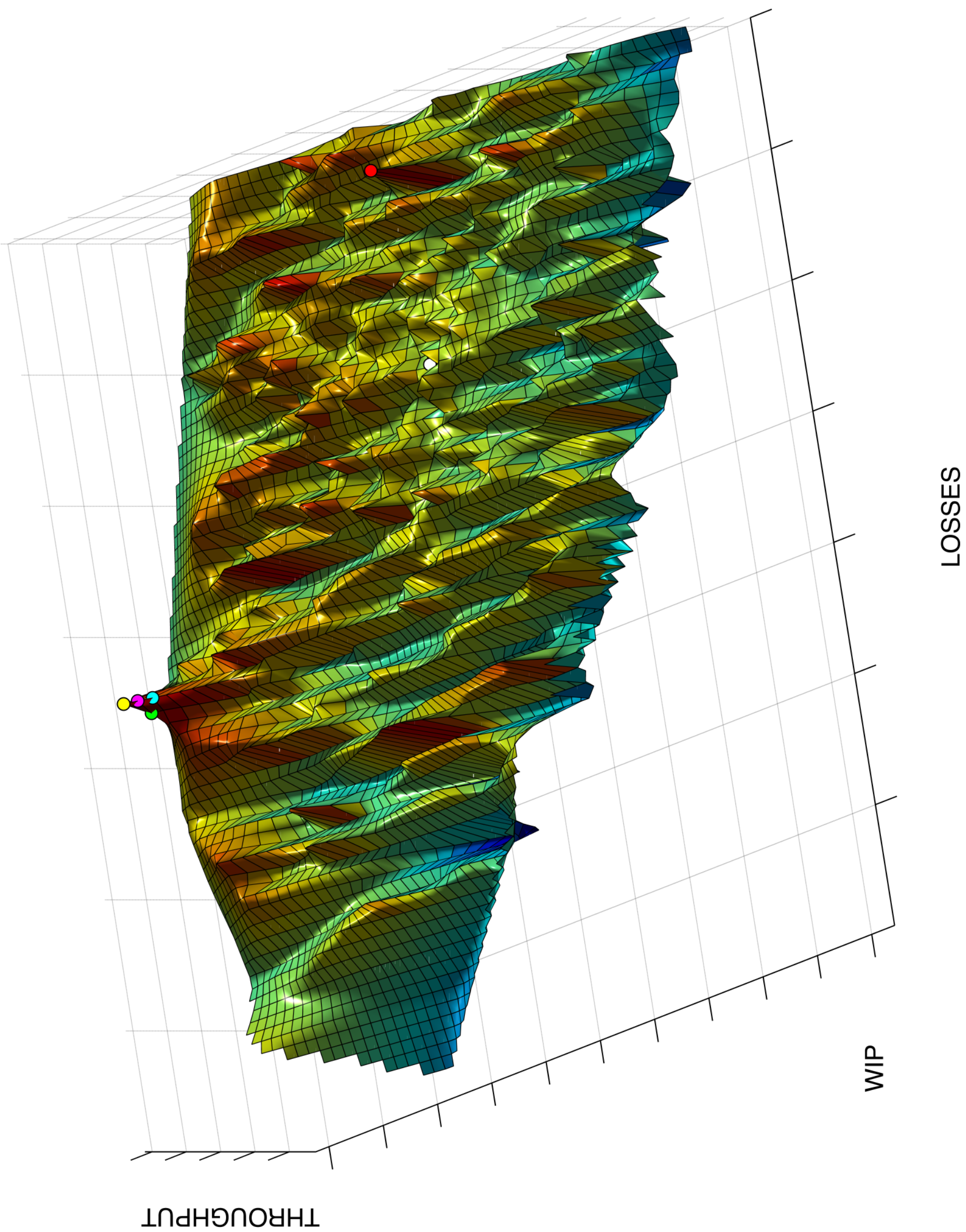


Figure 100: Fitness Landscape for Case Study Enterprise (Scales Redacted)

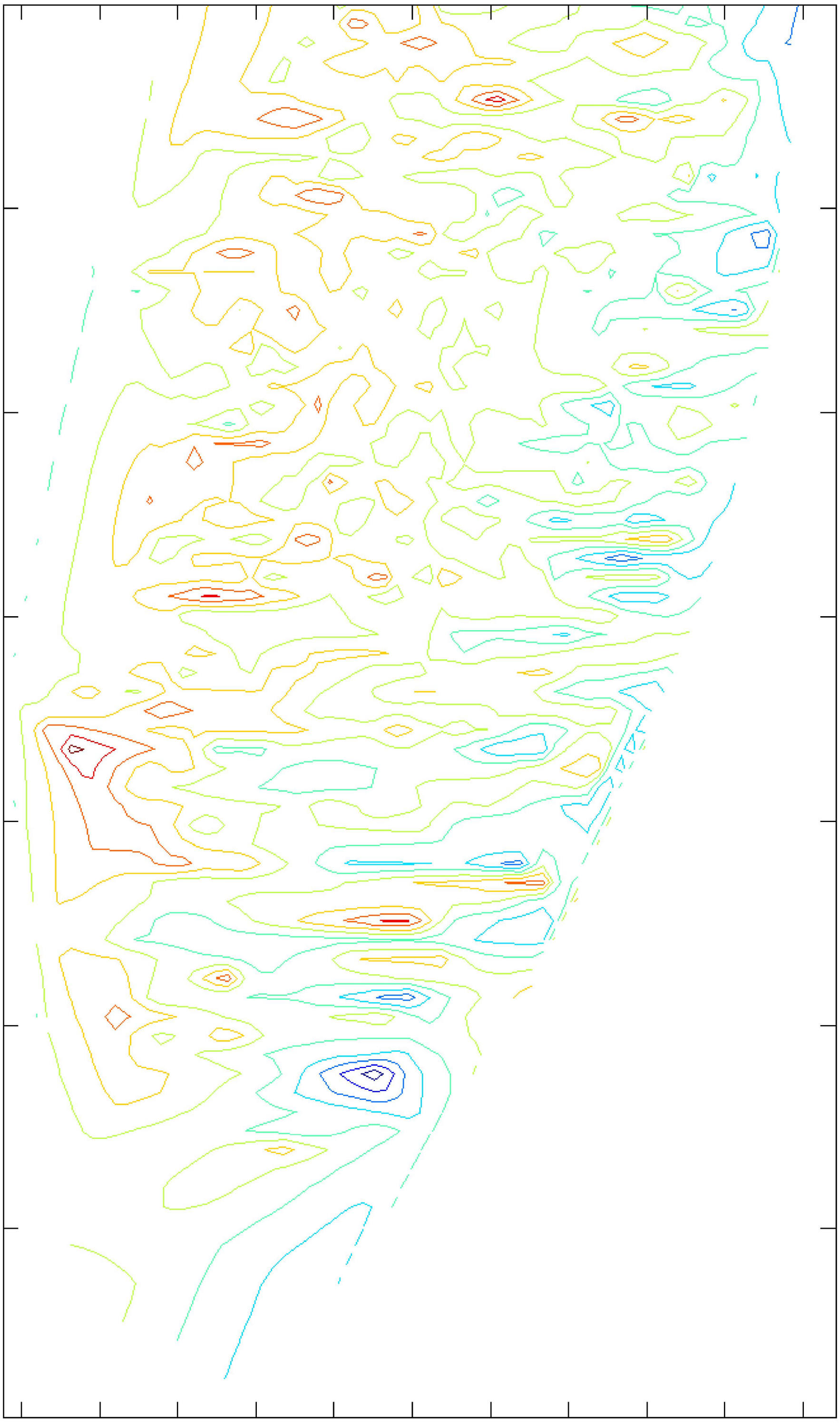


Figure 101: Contour Plot of Fitness Landscape for Case Study Enterprise (Scales Redacted)

Until recently, the facilities had been managed more or less independently, even though they were considered to be part of the one Asia-Pacific region. Two years prior to this study, the manufacturing sites fell under a new management paradigm that saw an alignment of metrics, reporting and improvement activities, along with the harmonization of site approaches to Lean Manufacturing. This was reflected on their approaches to improvement – initially site by site and more recently with regional sharing and cooperation. Nevertheless differences still existed and capacity was not yet fully managed on a regional basis.

The Region's Supply Chain was not brought under common management with Operations until 2014. At that time the organizational leadership began to consider the Total Delivered Cost of production. Cheaper, slower global logistics lanes increased the organization's total inventory increasing its total product cost and reducing its overall cash flow. Our study demonstrated that stock in-transit represented eight of the twenty most important factors affecting business outcomes and this was therefore a significant insight from our screening and response surface DoEs.

The impact of a hypothetical improvement portfolio that would minimise in-transit steps 1, 4, 5, and 7 is demonstrated in Figure 102. In this example, halving these lead-times could bring about a 25% increase in overall throughput and a 6% reduction in the overall WIP. Since the total lead-time for freight lanes is comprised of container loading, transfer to port, vessel loading, the sea-lane selected (including transits and transfers) and the priority of the vessel and container for unloading, it would be possible to achieve shorter lead times even without changing the mode of transport and so in-transit lead time reduction was achievable. In some instances it may also have been possible for the organization to achieve such outcomes by identifying alternative suppliers in closer proximity to the end use.

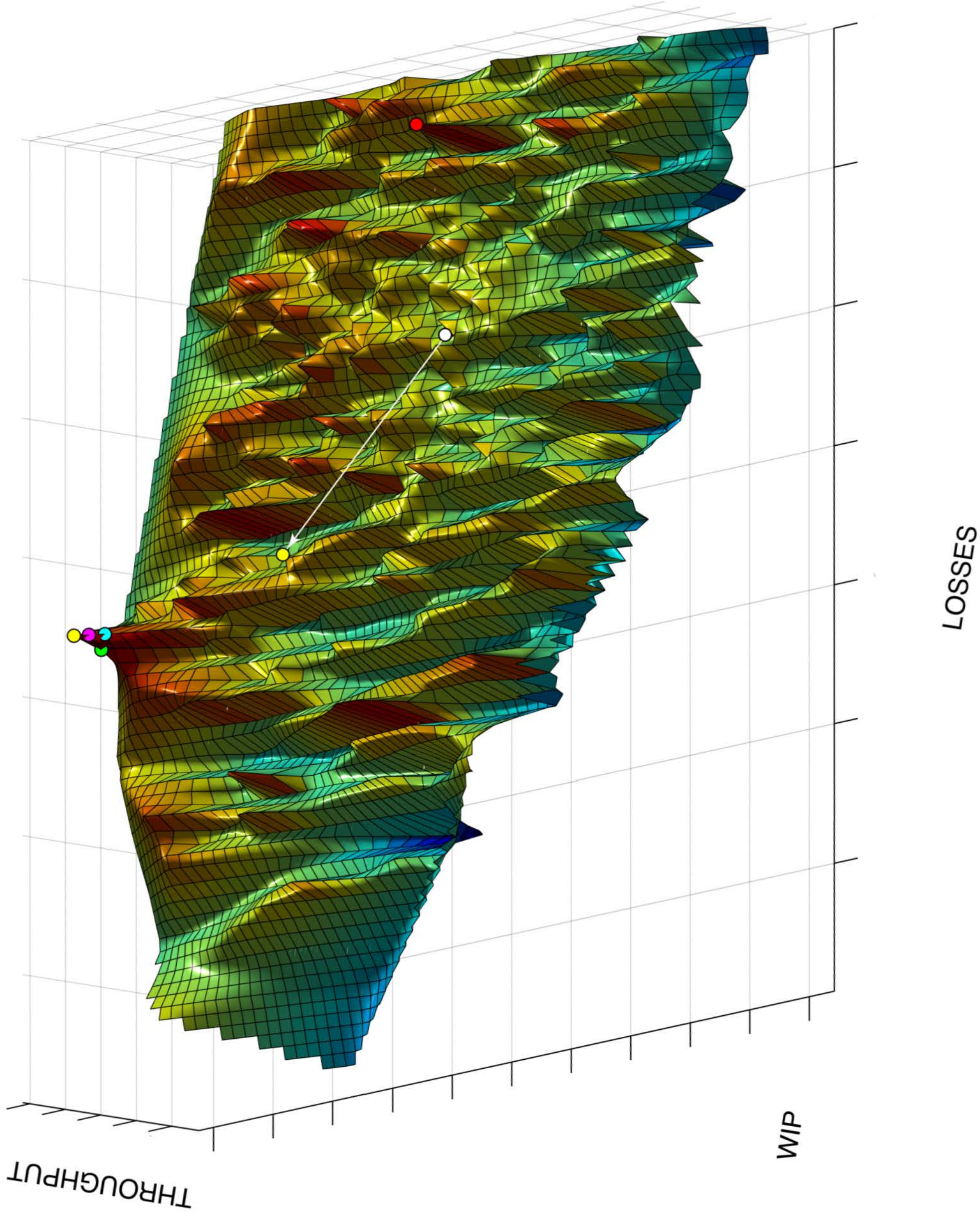


Figure 102: Enterprise Performance and Potential Improvement Portfolio

Discussion

The first two case studies demonstrated that our methodology could be applied to single factories as stand alone entities. In each case, we were able to model a factory and visualize the feasible decision space, showing Pareto Optimal outcomes as well as the rugged and varied landscape of suboptimal outcomes that were possible. Nevertheless, in the same way that a factory might optimize the output for a single machine at the cost of the overall optimization of the factory, so too is it possible to optimize a single factory at the cost of the optimization of the overall enterprise. It was therefore essential that we complete this research by conducting this third case study in order to determine whether or not the methodology could be used to model an enterprise and identify Pareto Optimal outcomes.

In this final case, we examined a more complex system, the entire Asia Pacific regional manufacturing value chain of a global MNE, composed of 13 factory elements, 7 in-transit elements, 20 process elements and 27 WIP elements. For factory and process elements we once again considered rate, yield and changeover times, whereas only rate and yield were relevant for in-transit elements. The model was therefore comprised of 80 (39 + 14 + 27) production factors that could be controlled and studied.

This case demonstrated the scalability of the methodology by modelling a complex enterprise with factory elements and, through the use of recursion, factory elements such as individual machines in the same model. In addition, the enterprise case demonstrated the methodology's broadly applicability across different process types – machines, factories and stock in-transit supply chain elements.

Like the earlier cases, the Fitness Landscape for this organisation was rugged with many peaks and valleys. In this case, however, we found that four of the five highest points were clustered in one area (see Figure 102 above). Although this peak represented a tremendous opportunity by comparison with much of the landscape, it also posed a potential problem for the organisation in that it reduced the number of potential available paths for improvement. The nature of this surface led us to consider the question of quality of the solution space - what characteristics make a response surface more or less attractive to an organisation? We identified three areas for consideration, these being:

i. The scale of potential: This aspect refers to the relative height of the Pareto Optimal peaks above the current state. A landscape with high peaks represents opportunity for an organisation to improve.

ii. The number of opportunities: This refers to the number of choices an organization has for improving its current state. More peaks reflect greater choice and this is important, particularly when some choices may be more difficult to attain or might be less organisationally desirable.

iii. Peak location: The z-axis in our example is a maximization objective and we therefore want to find high peaks of opportunity. However the x- and y- axes are minimization objectives and so we would prefer the peaks to be located in the low corner (the Northeastern corner of our example in Figure 102 above. Thus the location of peaks is also an important measure of the quality of the Fitness Landscape.

iv. The robustness of the solution space: The grade of the peaks represents how much the objective changes with respect to changes in the production parameters.

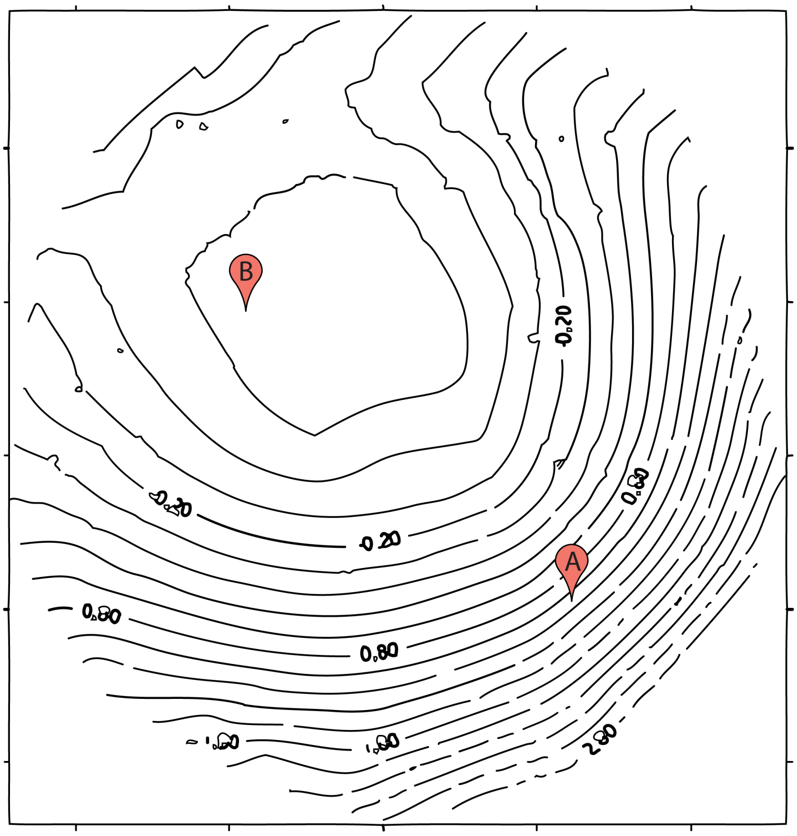


Figure 103: An Exemplar Contour Map [233]

> Steep peaks or gradients (point 'A' in Figure 103 above) are not robust to change, so even small shifts in a production parameter could result in large reductions in performance. Alternatively, plateaux are quite robust (point 'B' in Figure 103 above) as they can tolerate large changes in parameters with little or no change in performance.

Finally, we were again able to demonstrate reliability of the methodology since it was able to deliver internally consistent results across a number of factories, countries and currencies.

Conclusions

In this third case study we demonstrated the use of multiscale modelling in order to simulate an enterprise VSM. The VSM was modelled at subsystem (machine), system (line and factory) and supersystem (region) levels as described earlier in Figure 18. Preparation of a model at this scale proved to be no more difficult than the complex single factory case in Chapter 6. Although data once again proved difficult to obtain, the methodology was robust, given consistent assumptions. This case demonstrated that the methodology is capable and provides a structured and objective approach for optimal project portfolio selection that links strategy to targeted improvement efforts.

8: Discussion

Research Questions

The hypotheses that motivated this research were:

i. That continuous improvement methodologies, such as Lean Manufacturing and Six Sigma lack structured objective approaches for optimal project portfolio selection that link strategy to targeted improvement efforts.

ii. That, as a consequence of (i), opportunities may be lost, scarce resources would be inappropriately allocated and that improvement activities would result in local optimality with sub-optimal outcomes for the business system as a whole.

iii. That it is possible to develop approaches to bridge the gaps posited in (i) and thereby fulfil the business needs expressed in (ii).

Research Objectives

According to the aforementioned problem statement and hypotheses, the overall objective of this research is to develop a reliable methodology for identifying optimal portfolios of improvement projects within existing design constraints. Such a methodology will require consideration of business strategies, business processes and will involve the preparation of accurate models in order to describe and predict business outcomes that would arise as the result of changes to business process parameters. Therefore such a methodology ought to be:

- Generic: The methodology should be broadly applicable across different processes, across different industries and to companies following different strategies.

- Scalable: The methodology ought to be capable of identifying portfolios of improvement projects at different levels of an organisation – whether this is a manager operating an individual factory or one responsible for many factories.

- Reliable: Since the research objective is to find improvements within an existing process design, our definition will require internally consistent results rather than absolute results that could be compared to external benchmarks.

We review these objectives in the subsequent sections of the discussion.

Project and Portfolio Selection Frameworks

Although at the time of writing there were a great many published papers covering methods for project selection, we found that there was surprisingly little structure offered to businesses to assist them in defining overall portfolios of improvement projects. In our estimation, much of what did exist was insufficient for dealing with real world complexity. Moreover, we found little evidence that these were in common use in industry settings.

As we sought to characterise the literature, we found that much of the research was concentrated towards the application of MADM techniques for project selection. This was of concern, since MADM approaches assume that an appropriately informed and optimised set of projects already exists [169] and yet these papers did not provide guidance to direct the ideation of such project sets. Indeed MADM is only suitable for choice decisions and it would seem that the project sets they consider are frequently generated on the basis of managerial experience alone. Therefore, although MADM may assist in reducing a project set based on relative project merit; it is unlikely that the initial project set is either optimal or complete. We suggest that the literature must therefore be extended to provide guidance on the creation of project portfolios.

Furthermore, MADM techniques have applicability to discrete problems but not to continuous problems. Here again, MADM reveals its utility for dealing with choice problems but not for design problems. We argued previously that one should not therefore infer that MADM fits well with continuous improvement since MADM limits itself to the a priori definition of alternatives and only an implicit definition of objectives. Instead we argue that improvement portfolio selection should begin with a definition of strategic goals and that these goals should lead the ideation of project alternatives. Only then should discrete approaches be used to select a subset of actions to implement.

Our investigation into the state of the art convinced us of the need to examine the practice of project and portfolio selection in industry to determine whether the gaps in the literature impacted negatively upon industry practice. There was, however, a dearth of peer reviewed research into industry practices and what did exist was limited by small data sets [48,63] or did not address the question of project selection [176]. We therefore examined the state of practice in industry and our results revealed a considerable dissatisfaction with project and portfolio selection amongst practitioners [6]. It also confirmed our initial hypotheses, revealing that an implicit connection or in many cases no connection was made between business strategy and project selection. Such a misalignment would very likely reduce the chances that project outcomes would have the desired impact on the business. In addition, poor selection would most likely result, leading to inefficiently deployed resources. Moreover, we identified that organizations do not use the most appropriate structured tools to select their project portfolios. Tools such as brainstorming, which have been advocated by the popular press, are not appropriate for project selection and prioritization. Instead, there are a number of multi-attribute decision-making tools, such as AHP, which are better suited and their application is well described in the literature.

Although projects may be considered to be the ultimate expression of business strategy we found gaps in industry practice that could result in a failure to execute strategy appropriately. A critical step - linking the strategy to projects – has been skipped and instead practitioners have tried to find implicit links using informal and subjective methods focused on near term and activity-based requirements. In our view, inefficiently deployed resources working on a suboptimal set of projects that may or may not be directed towards strategy could quite possibly be worse than no activity at all.

To address this issue, we therefore prepared a normative construct to direct the translation of strategy to projects (Figure 104). Our model begins with strategy informing an optimization process to enable the creation of an optimal future state (1 in Figure 104). Portfolio generation then occurs to select a subset portfolio of projects (2 in Figure 104). Finally, small groups of projects may be selected (4 in Figure 104) for eventual implementation and project management (5 in Figure 104). The process should provide feedback to the business strategy so that progress towards the future state may be monitored (6 in Figure 104).

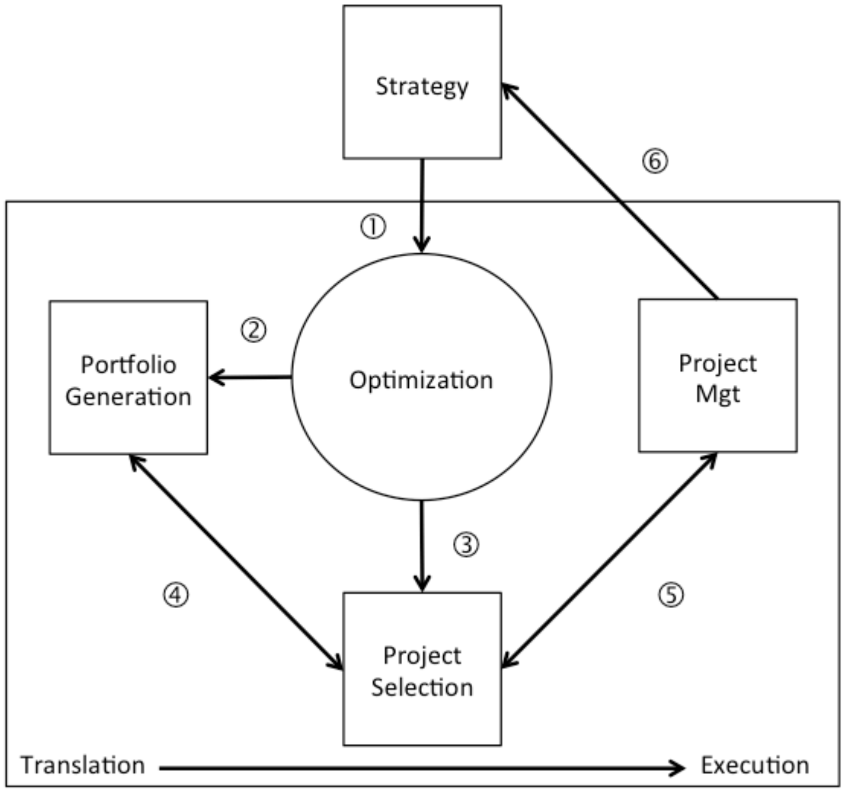


Figure 104: Framework for Linking Strategy to Process Improvement Implementation (Normative Model) [1]

Since there already is a great body of literature and practice surrounding strategy formulation, project execution and project management, we decided to attend to the gaps that we had observed. Thus the bulk of this research concentrated on defining optimal states that align with strategy and the subsequent generation of continuous improvement portfolios, as illustrated in Figure 105 below.

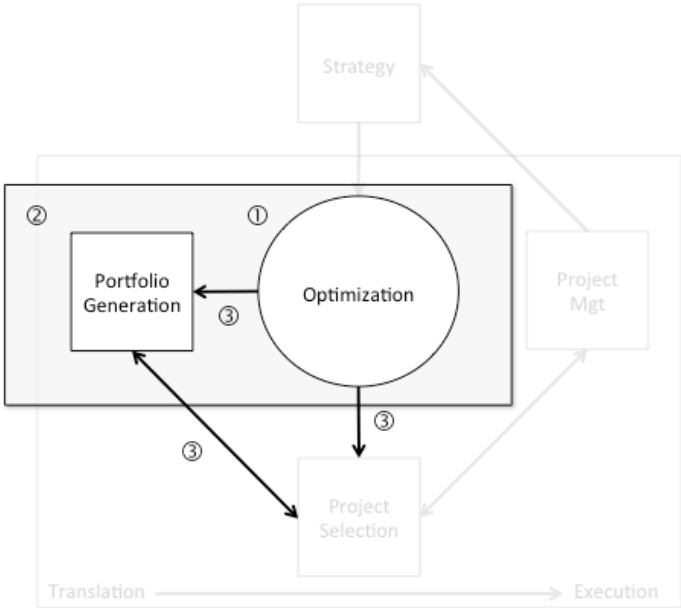


Figure 105: Focal Areas for this Research [1]

Fitness Landscapes

Our research was founded upon the axiom that there is a positive nexus between strategic alignment and business performance [1]. On this foundation, we have asserted that projects represent the eventual implementation vehicle for strategy and that they must therefore be directed by that strategy. We therefore proposed a mediating process to translate strategy into projects. The most critical steps in this process are the identification of an optimal state from within the strategic framework and the generation of a portfolio, which is informed by this optimal state.

If one is to create an optimal state from strategy, we reasoned that one must first comprehend the strategic intent. Thus we outlined a simple process and framework, based on sound practices from the literature, which could be used to determine the completeness of process improvement project portfolios [9]. When applied in an SME, its use highlighted a number of potential gaps and areas of too much focus, some of which went beyond the portfolio itself.

We can summarize the foregoing discussion by remarking that the selection of efficient improvement portfolios plays a critical role in the realization of strategy and that this is generally conducted without foreknowledge of Pareto Optimal solutions and without adequate guidance from the literature.

We therefore set out to develop a methodology for constructing Pareto Optimal portfolios of improvement projects. The methodology drew from biology in applying the concepts of meronomic classification, fitness landscapes and scale separation maps to help clarify and categorise the components of complex multiscale manufacturing systems. We also developed an original approach to simulation and modelling for multiobjective and multiscale problems, which provided us with both the capability to visualize the PF as a decision reference map as well as to deliver the requisite precursor information needed to prepare improvement portfolios.

By employing these techniques, we were able to produce 3 dimensional Fitness Landscapes and contour maps for each of the three case studies. These revealed the complex nature of the feasible solution spaces and provided support to our proposition that solution space would be too complex to permit selection of Pareto Optimal improvement portfolios from first principles. For example, the contour map in Figure 106 (below) reveals a convex surface marked with numerous local optima. Moreover, most of these are very steep peaks, indicating that they are not robust solutions. Thus if one of these was chosen, portfolios and their outcomes must be finely tuned if the outcome is to be maintained over time. This is clearly evident in Figure 107 (below), which shows a narrow ridgeline of local optimality that drops away to regions of lower opportunity. The white marker represents the performance of the studied company and an opportunity lay close by as indicated by the cyan marker. Once again, it is clear that uninformed decisions regarding project selection might easily result in negative impacts to the business overall.

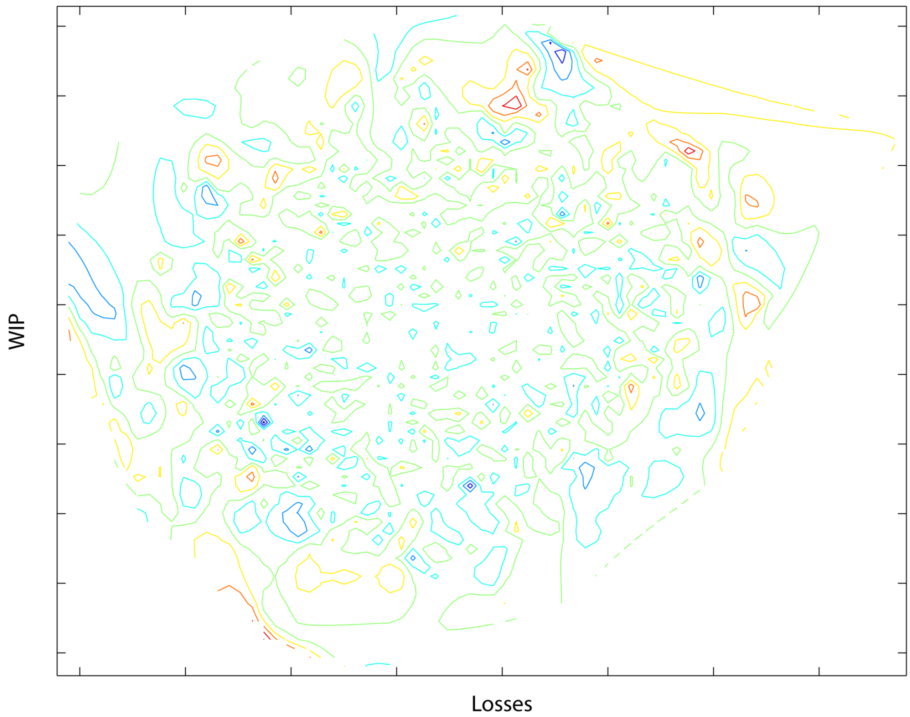


Figure 106: Contour Plot of Fitness Landscape (Case Study Two)

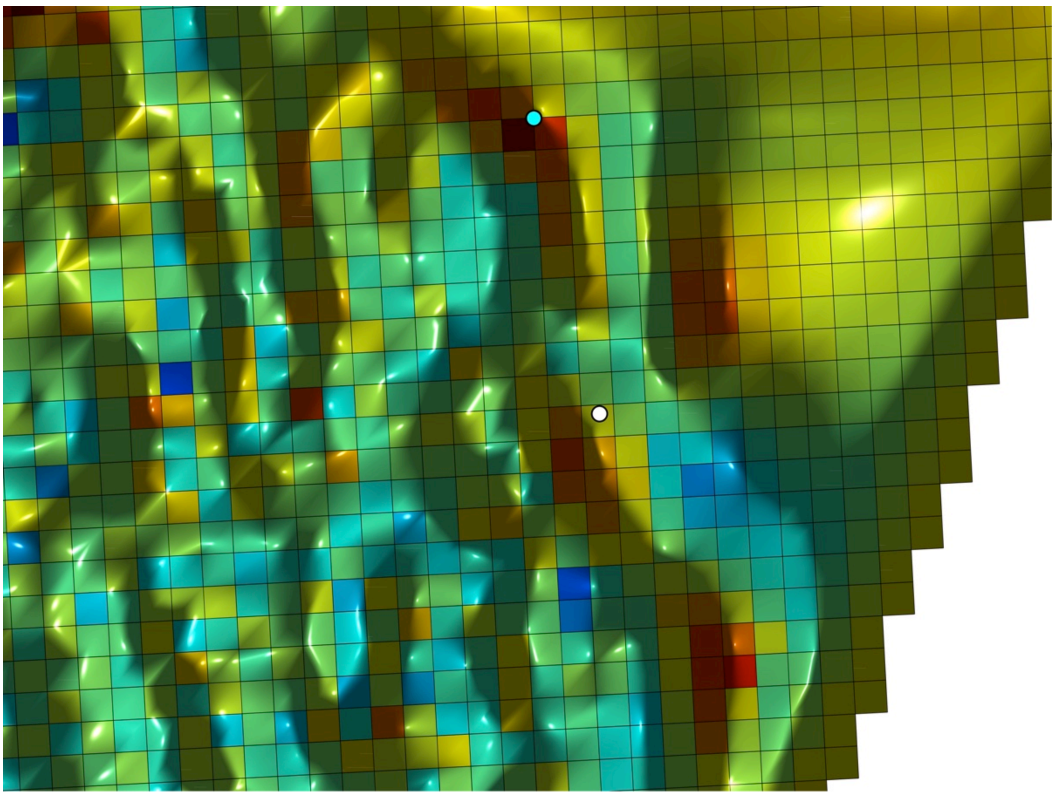


Figure 107: Fitness Landscape Showing Ridge of Local Optimality (Case Study Two)

We have presented three case studies in which we utilized multiscale simulation and DoE to prepare Pareto production frontiers. In each case we were able to examine alternative positions on the frontier and feasible improvement strategies and outcomes. As far as we can ascertain, this research is the first example of its kind.

Our results demonstrate preferences between various improvement strategies, based on their relative potential impact on factory performance. We have not yet however demonstrated preference based on their relative feasibility. We are currently examining ways in which we might also include resources, time and so on into this analysis. This work includes examination of heuristic and discrete optimization approaches to portfolio selection.

As presented here, the landscapes are only two- and three-dimensional and higher dimensionality would be needed for organizations pursuing $n > 3$ strategic outcomes. We have dealt with this issue in our studies by collapsing similar dimensions (such as scrap and yield losses) where possible, but we recognize that there will be circumstances where strategic dimensions will be orthogonal and this will therefore not be possible. Future work needs to extend this methodology to cope with $n > 3$ dimensional decision spaces.

Pareto Optimal Solutions

Our research has focused on the construction of Pareto Optimal solutions, that is, decision vectors that are defined in terms of their dominance or management preference over other decision vectors. In the course of this research, we concentrated on factors effecting the basic economic survival of several firms. This led us to emphasise a certain dimensionality (Output, WIP and Losses) and the need for certain commensurate dollar scales. For example, we have concentrated on tangible outcomes such as throughput or conversion losses. Yet there are a great many alternative business outcome measures that are not tangible or easily measurable. For example agility (the ability to respond to changes in product mix or volume), quality (in its broadest sense as the ability to satisfy stated or implied needs), safety (for example no lost time injuries) or staff satisfaction measures are all important strategic goals that are nonetheless difficult to measure and do not lend themselves to financial or even commensurate measures.

We therefore feel obliged to emphasise that the dimensions of the Pareto Frontier do not need to be commensurate, only the measures that are considered in each dimension need be. For example, it would be possible to apply the methodology to create a surface of dimension throughput (measured in dollars), agility (measured in part commonality) and quality (measured in DPMO). What may thus appear as a shortcoming is therefore not inherent in the methodology, but rather in a broader ability to define and measure what is important to the business in a meaningful and consistent manner. Furthermore, our case studies demonstrated the need for relative rather than absolute measures. Since the frontier reflects relative preference, absolute measures are unnecessary and this may simplify the creation of frontiers.

The frontier itself may be a little misleading in so far as it is suggestive of a real landscape and therefore of the effort required to get from one point to another. In fact the landscape shows the robustness of positions (for example a plateau may be robust in that small changes will not impact outcomes, whereas a ridgeline might be very susceptible to change). We recognise that a Pareto Optimal solution might better be defined in terms that include not only the desirability of the outcome, but also the attainability of that outcome. Therefore, further work will need to be done to consider how one might be able to include information regarding the relative difficulty of achieving various positions on the landscape. When considering the difficulty of attaining a position, one should consider the technical (does the organization posses the skills required) management (does it have the resource to sustain the effort), financial (is the outcome worth the investment, what are the opportunity costs) and cultural (is an outcome or lack of outcome managerially unacceptable) difficulties involved.

9: Conclusions

Conclusions

Manufacturing organisations must routinely deliver efficiencies in order to remain competitive. Many have embraced continuous improvement methodologies, such as Lean manufacturing and Six Sigma in order to achieve these goals. However their ability to realise sustainable competitive advantage from continuous improvement is hampered by the lack of structured objective approaches for optimal project portfolio selection that link strategy to targeted improvement efforts. As a consequence, scarce resources are inappropriately allocated, opportunities are lost and there is sub-optimisation of the system as a whole.

We set out to address this issue and to develop a generic, scalable and reliable methodology to improve project portfolio selection. In the course of this research we have made several contributions to the state of the art and we have also identified a number of opportunities for future research. In this concluding chapter, we outline our research contributions and our recommendations for future research.

Research Contributions

This research made the following contributions:

- Developed a framework for linking strategy to process improvement implementation.
- Developed a methodology for developing portfolios of improvements projects in manufacturing that are related to strategy.
- Advanced the understanding of industry practice in improvement project selection.
- Established a meronomic approach to categorising and mapping factory systems using Scale Separation Maps.

- Presented the use of Fitness Landscapes as reference frames for determining Pareto Optimality.
- Developed an object-oriented methodology for modelling and simulating multiscale systems.
- Evaluated the feasible performance space of two individual factories and one region of 13 factories.
- Presented ways in which portfolios of projects may be constructed to move from the current state to a Pareto Optimal state.

Recommendations for Future Research

As business competition intensifies, structured continuous improvement methodologies will become increasingly important to businesses. Whether that need is filled by existing methodologies or new approaches, it is certain that managers will always be faced with the challenge of choosing between various potential projects that will compete for scarce resources to satisfy numerous stakeholders and accomplish multiple objectives under conditions of uncertainty. Therefore it will also be necessary to have a means of optimal project portfolio selection that links strategy to targeted improvement efforts.

While this research has provided frameworks for portfolio selection as well as a means for identifying optimal projects and portfolios, it also represents a starting point for many lines of further research as outlined in theses concluding paragraphs:

i. Intangible outcomes: The current research has demonstrated the creation of three Pareto Frontiers for businesses with traditional cost leadership strategies. In these cases, all of the outcomes were tangible and could readily be dollarized. Companies may seek to achieve are many other outcomes that are intangible. This is not a shortcoming in the methodology as much as a limitation in our ability to quantify things that matter, as we frequently observe when intangibles are considered as externalities such that prices do not reflect the full social costs or benefits of an activity. Further research is needed to understand how more fully represent the intangible elements of strategy.

ii. $n \geq 4$ dimensions: Each example in this thesis was represented in 3-dimensional objective space. This was not by accident, for in order for us to demonstrate the concept of a fitness landscape, we needed to visualize the concept. While it is true that many organisations will only require a 3-dimensional objective space, many strategies will call for a higher dimensionality. Indeed, in our examples we collapsed dimensions where they were not orthogonal. Higher dimensionality is not easy to represent and also will require the development of more sophisticated approaches to project and portfolio selection. We suggest that the problem will be amenable to discrete optimisation techniques. Nevertheless, there is no theoretical constraint to the dimensionality of problems that can be tackled with our approach, nor is it essential that the dimensions have commensurate metrics.

iii. Other strategies: As stated above, the examples considered all involved companies that followed traditional cost leadership strategies. It is therefore important to explore the application of this approach to other strategic patterns. Once again, whilst there is no theoretical constraint preventing such analyses, one must duly consider how to measure outcomes (such as agility or differentiation).

iv. Effort driven analysis: We caution that the fitness landscapes are representative of the relative desirability and robustness of solutions in the objective space. It would be a mistake to assume that a steep peak represents an outcome that is difficult to obtain. Nevertheless, managers do need to consider the difficulty of attaining a position on the objective space. Here we could define 'difficulty' in terms of (i) technical difficulty (are the available skills or tools sufficient or is the problem amenable to an implementable solution), (ii) management difficulty (does management have the appetite to tackle the obstacles to achieve a position on the objective space), (iii) cultural difficulty (can the change be addressed in a manner that is culturally acceptable to the organisation) and (iv) resource difficulty (does the organisation have the requisite financial, people or temporal resources required to realise a position on the objective space).

v. Automated discrete optimization portfolio selection: Earlier we mentioned the difficulty managers would have understanding ≥ 4 dimensional objective space. Such higher dimensionality would preclude managers from using simpler heuristic models for project and portfolio selection as we have used in this research. Moreover, multi-year portfolios or portfolios designed across a large-scale enterprise would be difficult to prepare and analyse by hand. Therefore future research ought to explore software-driven discrete optimization portfolio selection methods.

vi. Application to service industries: Although there is no theoretical constraint to the application of this methodology to industries beyond manufacturing, it is important to demonstrate its use more broadly including, though not limited to, service industries such as banking and insurance.

vii. Software improvements: The software developed for this research combines elements from many different applications. Ideally all of this functionality should reside in a single application for ease of use. For example, it would simplify the use of this approach if the DOE and its analysis were automated. Moreover, the Java® code that was developed during the course of this research could be optimised and potentially ported to another, faster implementation language.

viii. Network redesign: We have remained within the bounds of existing factory and network design in this research. This is because typically decision makers make operational level improvement decisions rather than network design decisions. Yet such strategic design decisions are made by businesses and so it would be of interest to extend the methodology to compare alternative network and factory designs. This would require the introduction of speculative or design-based parameters as well as a means for comparing two or more objective spaces. Moreover, such research would need to address the question of objective space optimality – that is, how does one quantify the overall quality of an objective space?

ix. Design of robust surfaces: In point (iv) above, we noted that the objective space reflects the desirability and robustness of various feasible solutions. We further note that the cases studied were quite rugged, with many sharp peaks and abrupt changes in the landscape. Ideally a landscape should not only have Pareto Optimal outcomes that benefit the company, these Pareto Optimal outcomes should be very robust. A robust surface will have broad Pareto Optimal plateaux so that Pareto Optimal solutions are robust to changes in production parameters. Further research into what constitutes robustness and how this can be designed into a process would be of great interest for future research.

x. Energy and resource efficiency frontiers: We have demonstrated traditional business outcomes related to material flow, such as throughput, WIP and scrap. Energy and resource efficiency are becoming more widely discussed aspects of manufacturing outcomes and we believe that the methodology described herein could quite easily be utilised to measure these alongside the traditional measures. Indeed, the software was designed with this in mind, so that energy and resource consumption models could be included as parametrically controlled behaviours of a process unit.

xi. Selection of Improvement Methods: This research has provided frameworks for portfolio selection as well as a means for identifying optimal projects and portfolios. Future research should extend this through detailed investigation of improvement methods and their combination(s) to best match the identified improvement paths.

Concluding Remarks

In this thesis we have introduced a new approach to developing and assessing portfolios of continuous improvement projects. We believe that this methodology has great scope for extension and for application across industries.

Appendix 1: Survey Instrument

Selecting Continuous Improvement Projects

1. Participant Information Statement and Consent Form

THE UNIVERSITY OF NEW SOUTH WALES

Continuous Improvement Project Selection: Industry Practice

[Participant selection and purpose of study]
You (i.e. the research participant) are invited to participate in a study of how continuous improvement projects are selected in industry. We (i.e. the investigators) hope to learn more about current practice. You were selected as a possible participant in this study because of your business' potential use of continuous improvement methods.

[Description of study and risks]
Participation involves completion of a simple survey that should take approximately 15 - 20 minutes to complete on-line

[Confidentiality and disclosure of information]
Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission, except as required by law. If you give us your permission by checking the box below, your responses will be included in a publication in a peer reviewed journal. In any publication, information will be provided in such a way that you cannot be identified.

[Recompense to participants]
No payments will be made to participants.

Complaints may be directed to the Ethics Secretariat, The University of New South Wales, SYDNEY 2052 AUSTRALIA (phone 9385 4234, fax 9385 6648, email ethics.sec@unsw.edu.au). Any complaint you make will be investigated promptly and you will be informed out the outcome.

[Feedback to participants]
If you would like to receive the study results please complete the section below.

[Your consent]
Your decision whether or not to participate will not prejudice your future relations with the University of New South Wales. If you decide to participate, you are free to withdraw your consent and to discontinue participation at any time without prejudice.

If you have any questions, please feel free to ask us. If you have any additional questions later we will be happy to answer them.

Thank you

*** I agree to the terms and conditions laid out in the aforementioned consent statement.**

- ○ Yes
- ○ No

Would you like to receive further information about the results of this survey?

- ○ Yes
- ○ No

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Figure 108: Survey Consent Form

Selecting Continuous Improvement Projects

Please complete the following if you would like to be kept informed of the survey results.

Name:
Company:
Address:
Address 2:
City/Town:
State:
ZIP/Postal Code:
Country:
Email Address:
Phone Number:

2. About Your Organization

Please tell us about your organization

a) Where is your organization headquartered?

Select a country

b) What is your organization's primary activity?

Select an industry

c) What was your organization's total revenue for the last 12 months?

Estimate revenue | Currency

d) How many people are employed in your organization?

Select from drop down menu

e) What is the ownership of your organization?

Select from drop down menu

3. About You

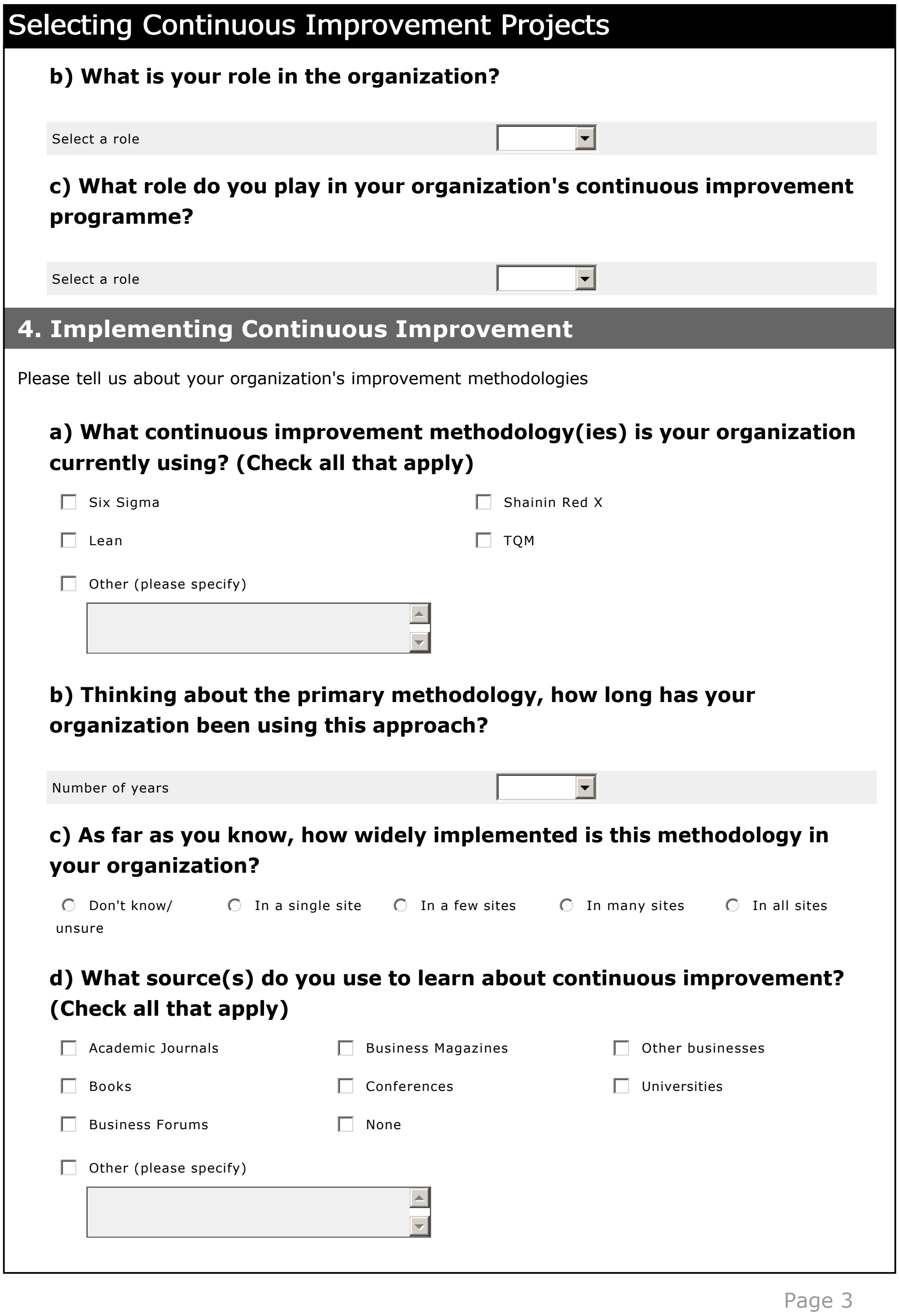
Please tell us about yourself

a) Where are you located?

Select a country

Page 2

Figure 109: Demographics



Selecting Continuous Improvement Projects

b) What is your role in the organization?

Select a role

c) What role do you play in your organization's continuous improvement programme?

Select a role

4. Implementing Continuous Improvement

Please tell us about your organization's improvement methodologies

a) What continuous improvement methodology(ies) is your organization currently using? (Check all that apply)

- Six Sigma
- Shainin Red X
- Lean
- TQM
- Other (please specify)

b) Thinking about the primary methodology, how long has your organization been using this approach?

Number of years

c) As far as you know, how widely implemented is this methodology in your organization?

- Don't know/ unsure
- In a single site
- In a few sites
- In many sites
- In all sites

d) What source(s) do you use to learn about continuous improvement? (Check all that apply)

- Academic Journals
- Business Magazines
- Other businesses
- Books
- Conferences
- Universities
- Business Forums
- None
- Other (please specify)

Page 3

Figure 110: Implementation

Selecting Continuous Improvement Projects

e) What is the source(s) of your current methodology? (Check all that apply)

- [ ] Don't know/ unsure
- [ ] Consultant
- [ ] Parent Company
- [ ] Developed in house
- [ ] Other (please specify)

e) What is the main factor(s) influencing the adoption of new manufacturing methods in your business? (Check all that apply)

- [ ] Don't know/ unsure
- [ ] External pressures (e.g. competition, customers)
- [ ] Compatibility with existing organizational culture
- [ ] Management and organizational support
- [ ] Perceived operational benefits
- [ ] Cost of acquiring new equipment and training
- [ ] Other (please specify)

5. Value Stream Maps

Thinking about your business:

a) Value streams are defined for all strategic value creation activities.

○ Strongly disagree ○ Disagree ○ Neither agree nor disagree ○ Agree ○ Strongly agree

b) Value stream improvement objectives are determined from, and aligned with, the organization's strategy.

○ Strongly disagree ○ Disagree ○ Neither agree nor disagree ○ Agree ○ Strongly agree

c) Value streams include metrics that are linked to the outcomes determined in the organization's strategy.

○ Strongly disagree ○ Disagree ○ Neither agree nor disagree ○ Agree ○ Strongly agree

d) Value stream improvement objectives are linked to key customer outcomes.

○ Strongly disagree ○ Disagree ○ Neither agree nor disagree ○ Agree ○ Strongly agree

Page 4

Figure 111: Value Stream Maps

Selecting Continuous Improvement Projects

e) Improvement objectives are directed at optimising the value stream.

○ Strongly disagree ○ Disagree ○ Neither agree nor disagree ○ Agree ○ Strongly agree

f) Project outcomes are assessed and corrections are made to the portfolio to deliver the intended outcome(s).

○ Strongly disagree ○ Disagree ○ Neither agree nor disagree ○ Agree ○ Strongly agree

6. Project Selection

Please tell us how your organisation selects improvement projects

a) What is your opinion of your current method for selecting projects?

○ Very dissatisfied ○ Dissatisfied ○ Neutral ○ Satisfied ○ Very satisfied

b) Which best describes the perspective your organization takes in selecting projects?

○ Single product ○ Whole of site ○ Two or more sites integrated ○ Whole of the enterprise ○ Supply chain

c) What time horizon does your organization take in selecting projects?

○ 6 months or less ○ 1 year ○ 2 years ○ 3 years ○ More than 3 years

d) Who determines the majority of your improvement opportunities?

○ Shop floor staff ○ Technical staff ○ Production management ○ Site management ○ Corporate or Executives

e) Which best describes your scope in identifying opportunities?

○ Opportunistic- open to any changes ○ Continuous Improvement- small changes within existing processes ○ Process Improvement- changes to the design of whole processes ○ Optimisation- within a value stream ○ Optimisation- across value streams

Page 5

Figure 112: Project Selection

Selecting Continuous Improvement Projects

f) What measure(s) do you consider in selecting projects? (Check all that apply)

- [ ] Inventory
- [ ] Throughput
- [ ] Cycle time
- [ ] Resource availability
- [ ] Project timing
- [ ] Product cost
- [ ] Absorption
- [ ] Other financial measures (please specify)
- [ ] Current workload
- [ ] Other (please specify)

g) Which tool(s) do you use to identify and prioritise project opportunities? (Check all that apply)

- [ ] None
- [ ] Cause and effect matrix
- [ ] Pareto chart
- [ ] Unweighted scoring
- [ ] Resource availability
- [ ] Simulation*
- [ ] Consensus
- [ ] Brainstorming
- [ ] Cost- benefit analysis
- [ ] Business benefits
- [ ] Pareto priority index
- [ ] Theory of constraints*
- [ ] Analytic hierarchy process*
- [ ] PROMETHEE*
- [ ] Other (please specify)

h) If you ticked any box marked with an asterisk in the previous question, please elaborate on the approach used.

7. Thank You

Thank you very much for your involvement

Page 6

Figure 113: Project Selection – Measurement and Tools

Appendix 2: Survey Sample Characteristics and Detail Results

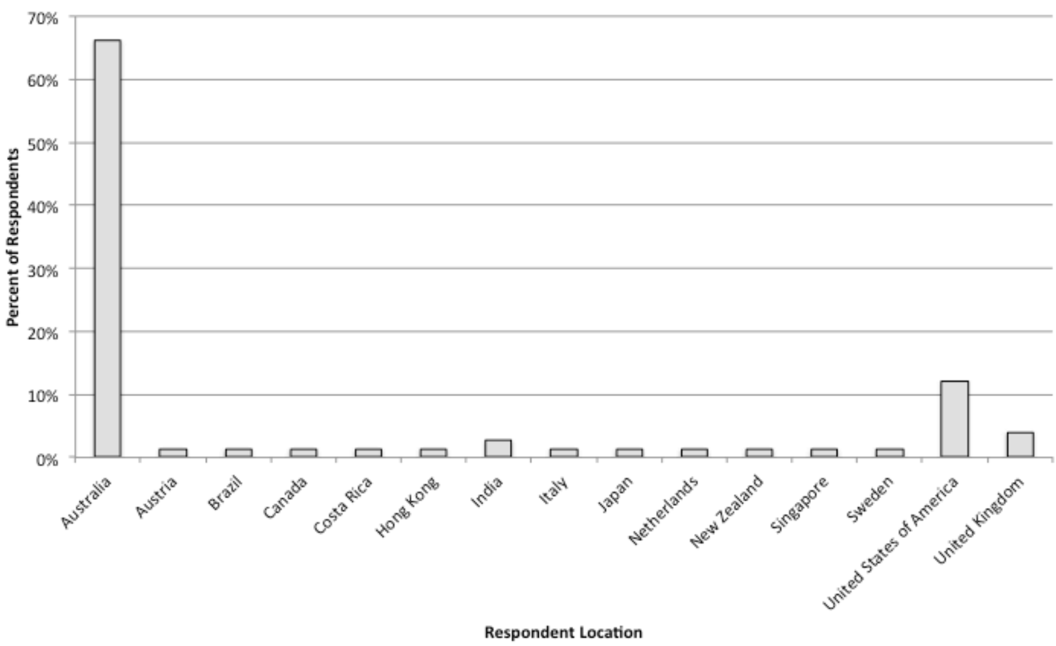


Figure 114: Respondent Location

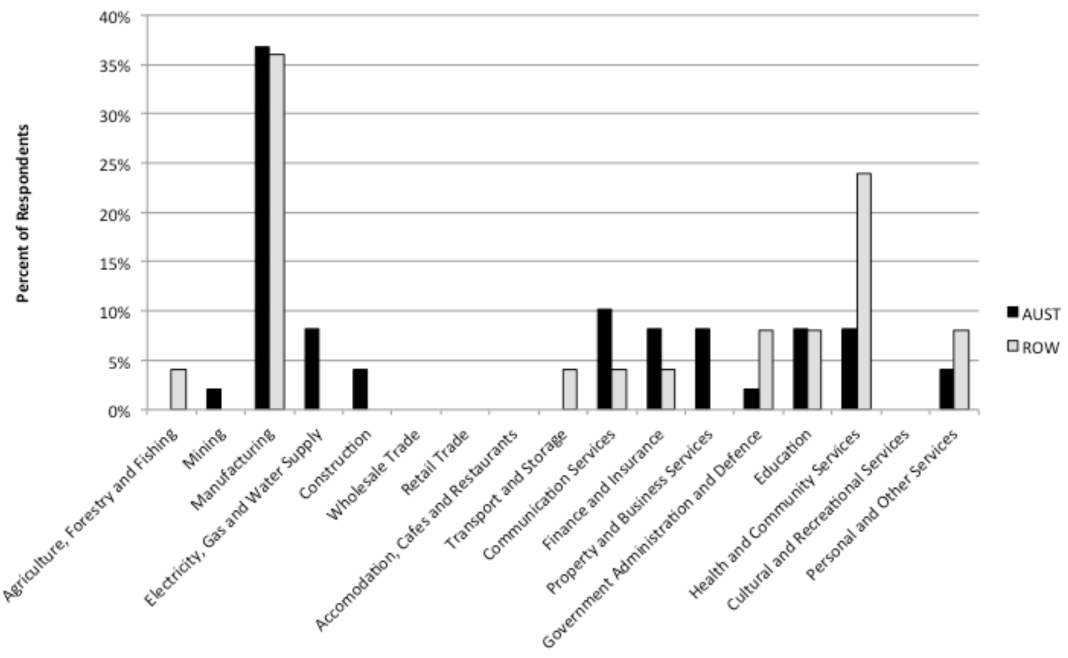


Figure 115: Respondent Industry by ANZSIC Code [234]

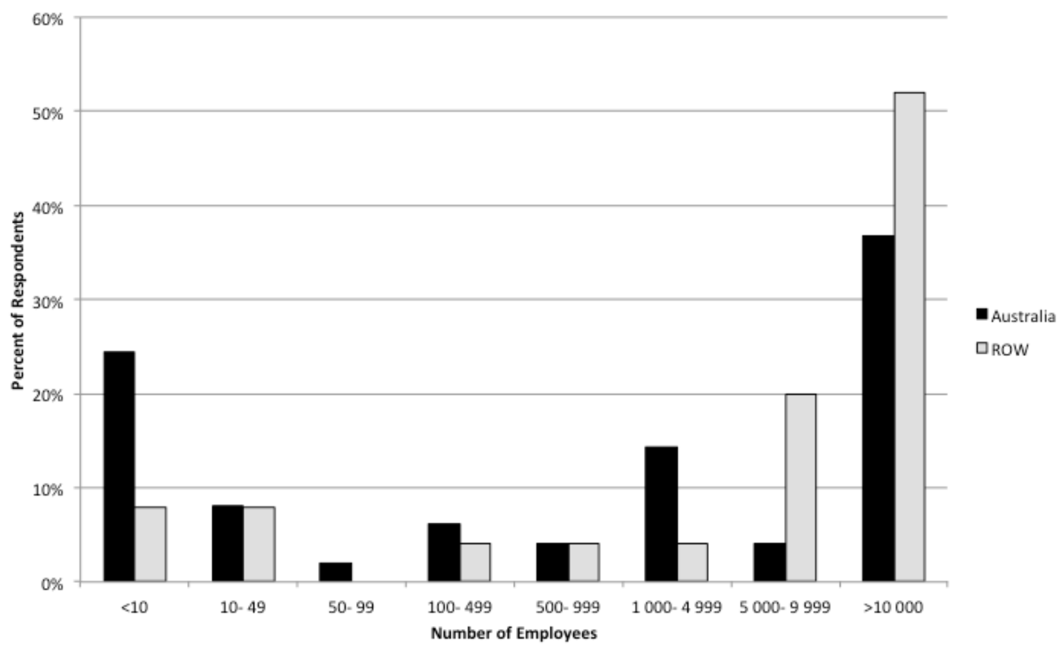


Figure 116: Number of Employees in Organisation

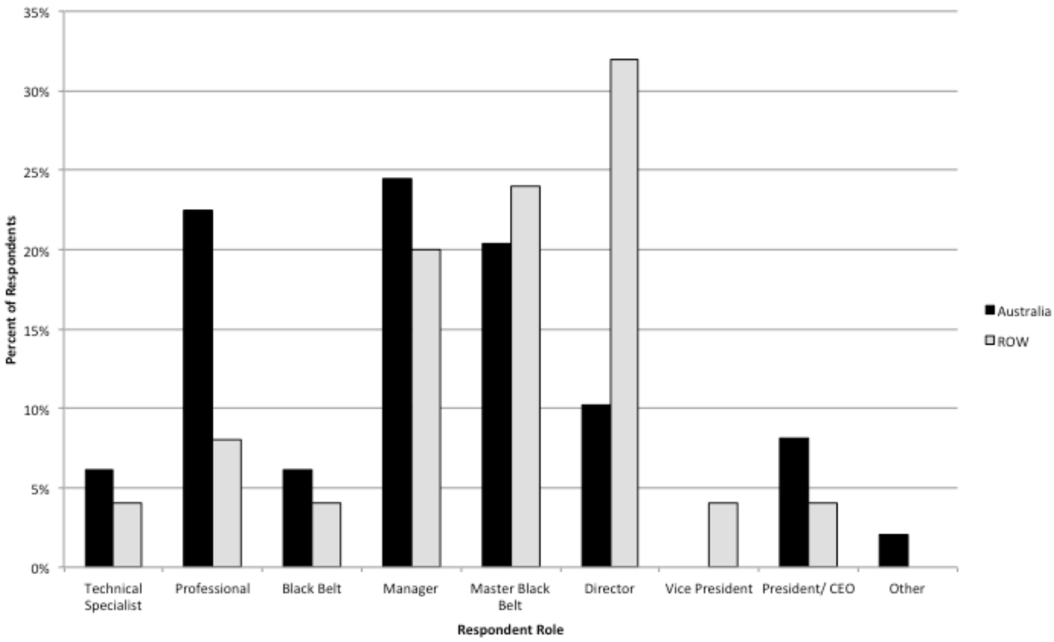


Figure 117: Respondent Role in Organisation

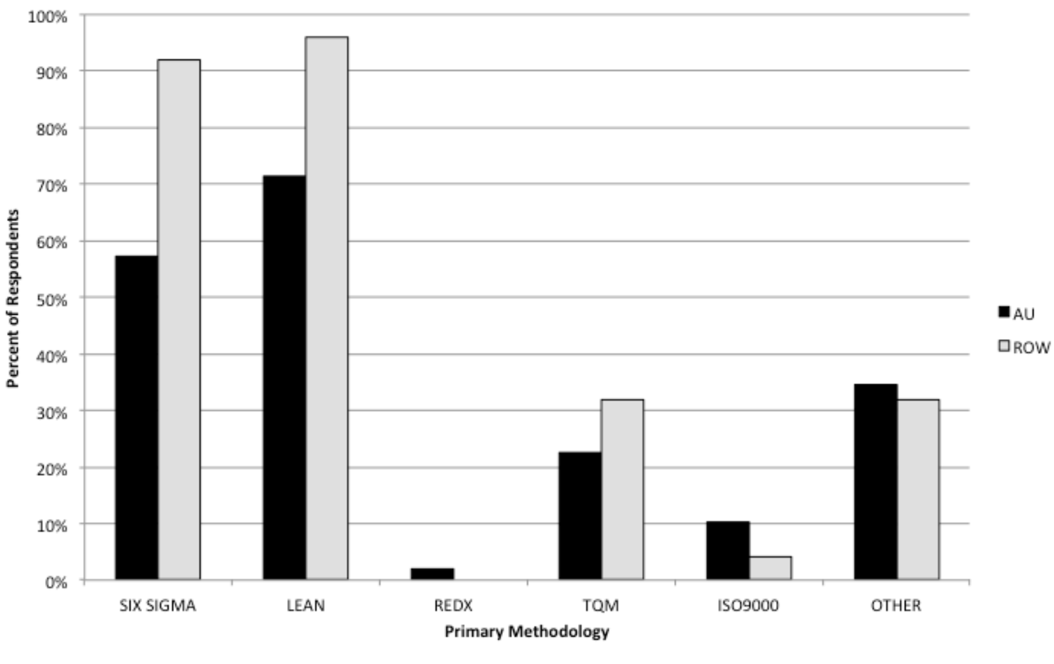


Figure 118: Primary Methodology used in Organisation

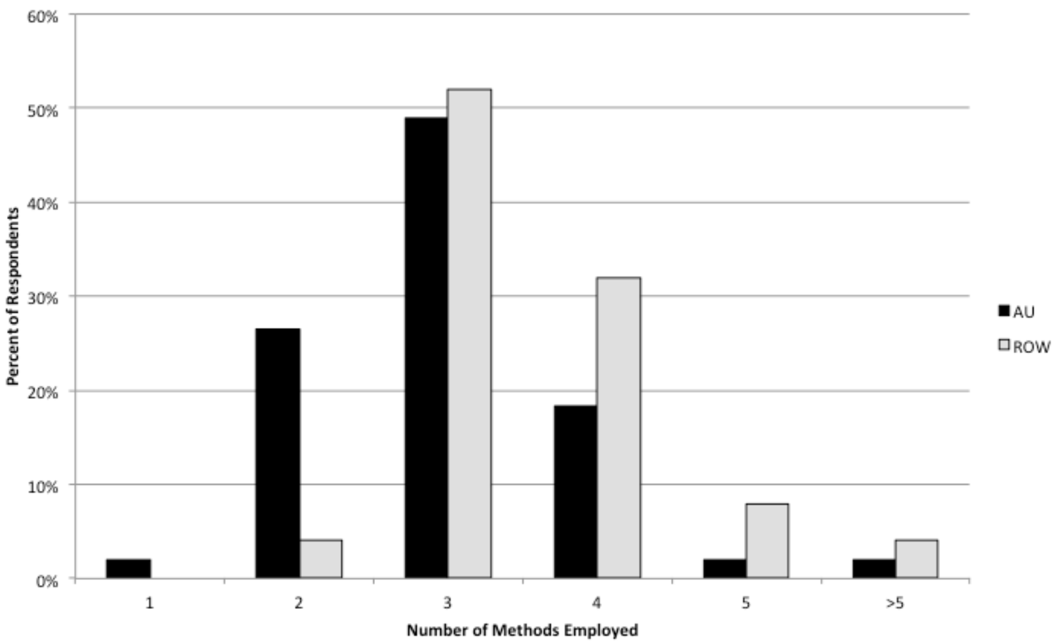


Figure 119: Number of Methods Employed by the Organisation

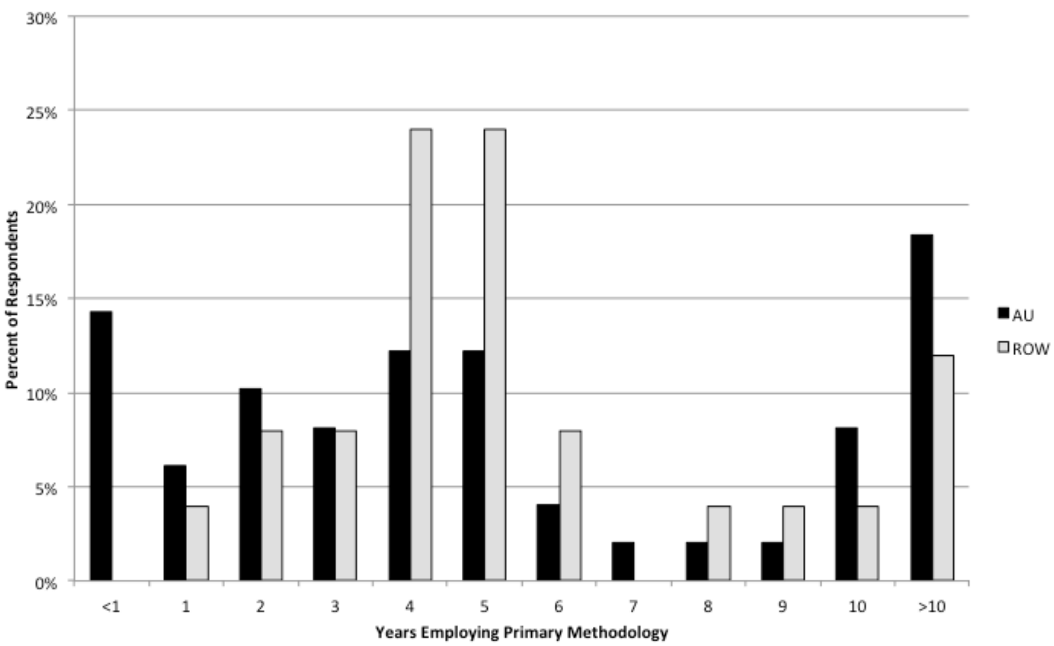


Figure 120: Number of Years the Organisation has Employed its Primary Methodology

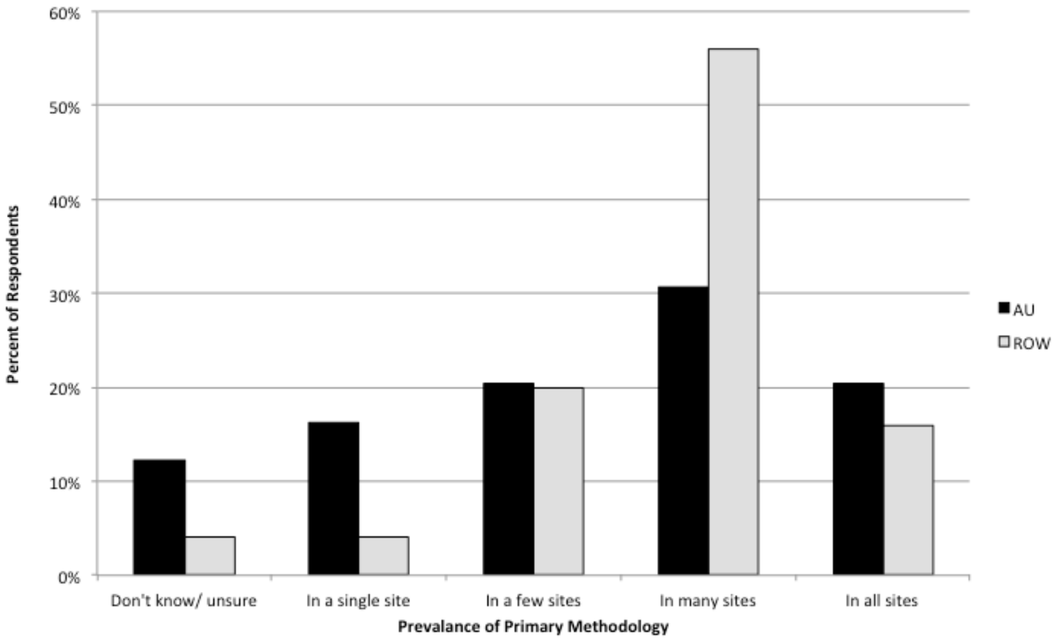


Figure 121: Prevalence of Primary Methodology (Number of Sites Employing)

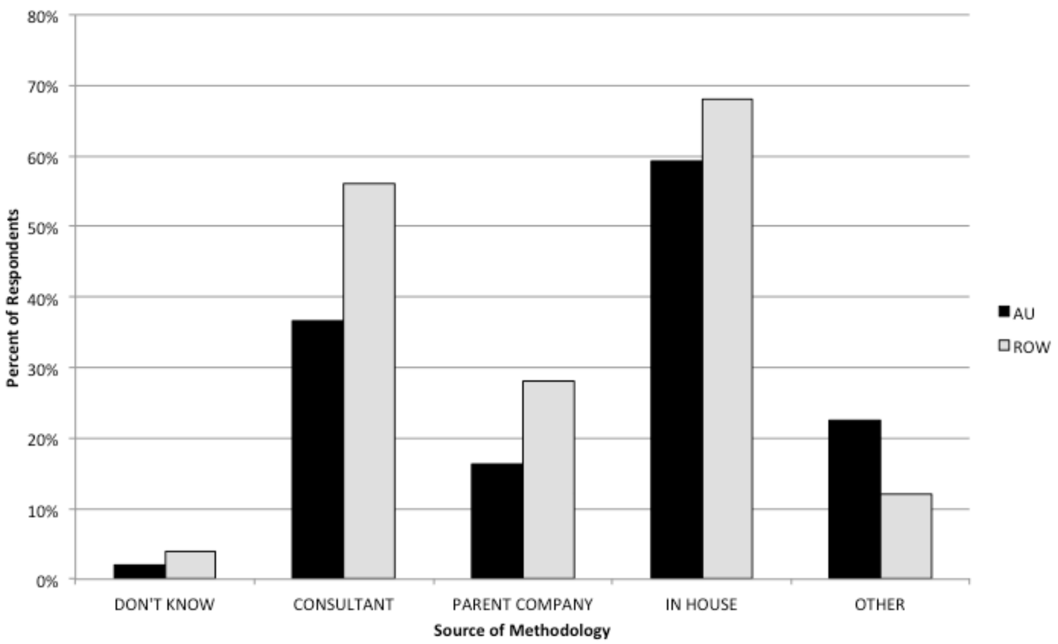


Figure 122: Source of Methodology to Respondent Site

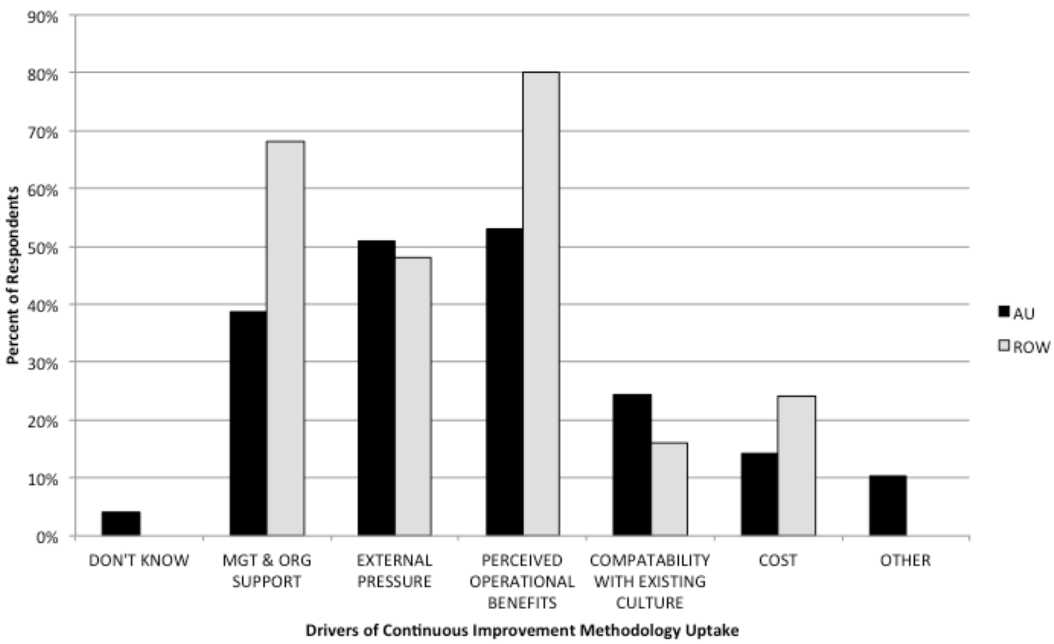


Figure 123: Rationale (Drivers) for Selection and Uptake of Methodology

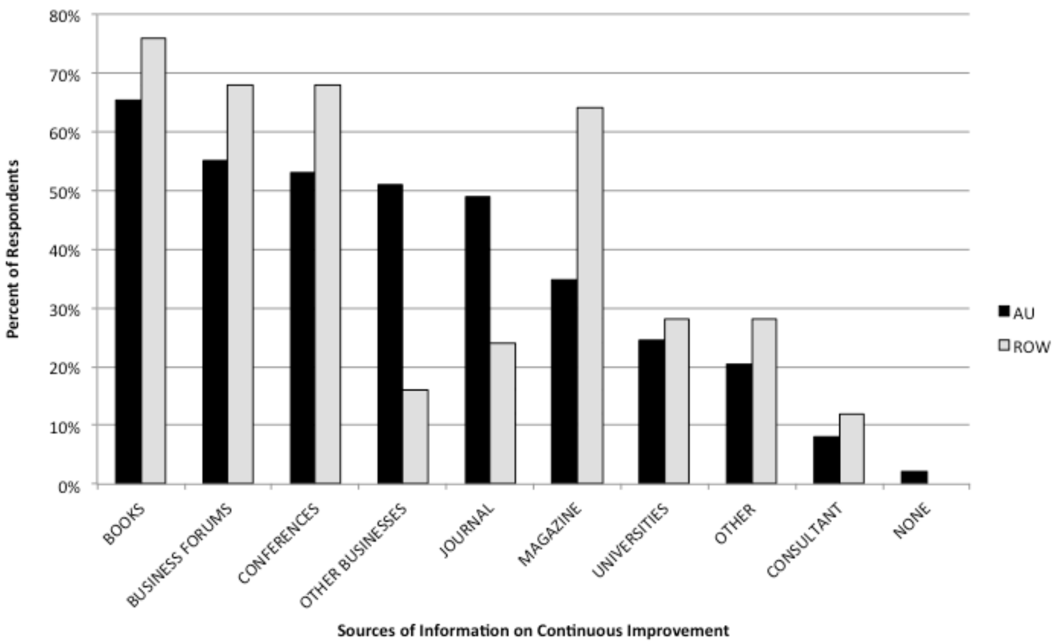


Figure 124: Information Sources Consulted for Continuous Improvement

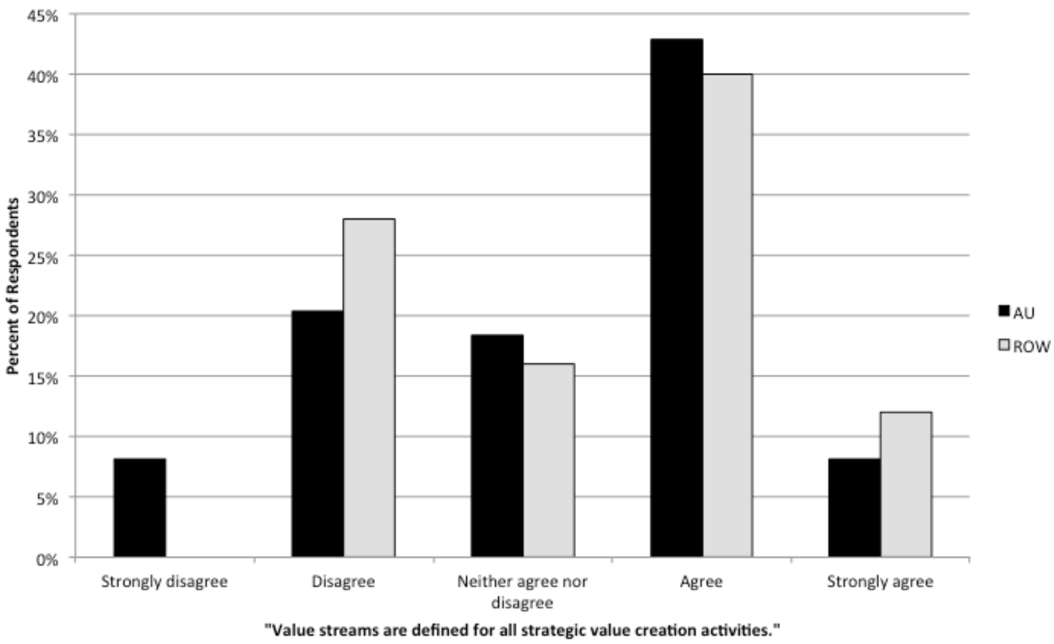


Figure 125: Link between Strategic Value Creation Activities and Value Stream Maps

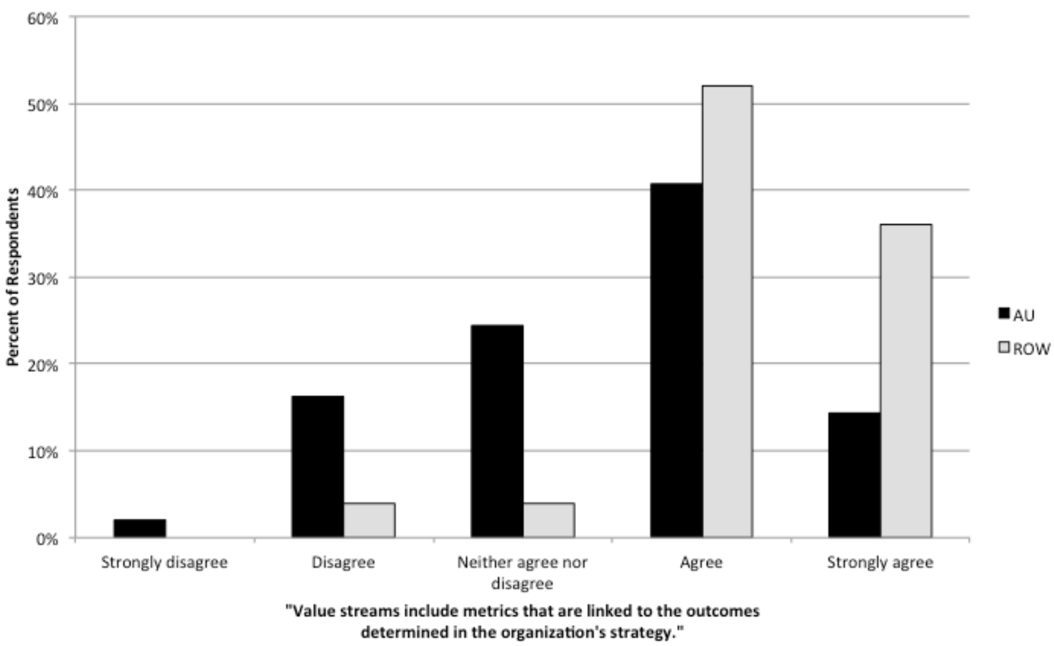


Figure 126: Alignment between Strategic Metrics and Value Stream Metrics

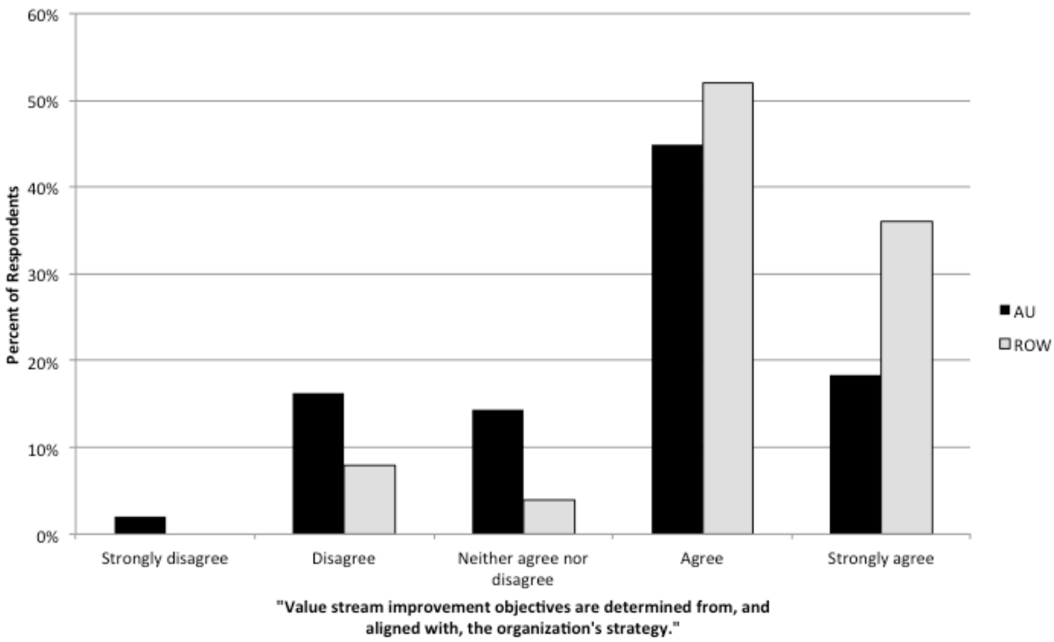


Figure 127: Alignment between Strategy and Value Stream Improvement Objectives

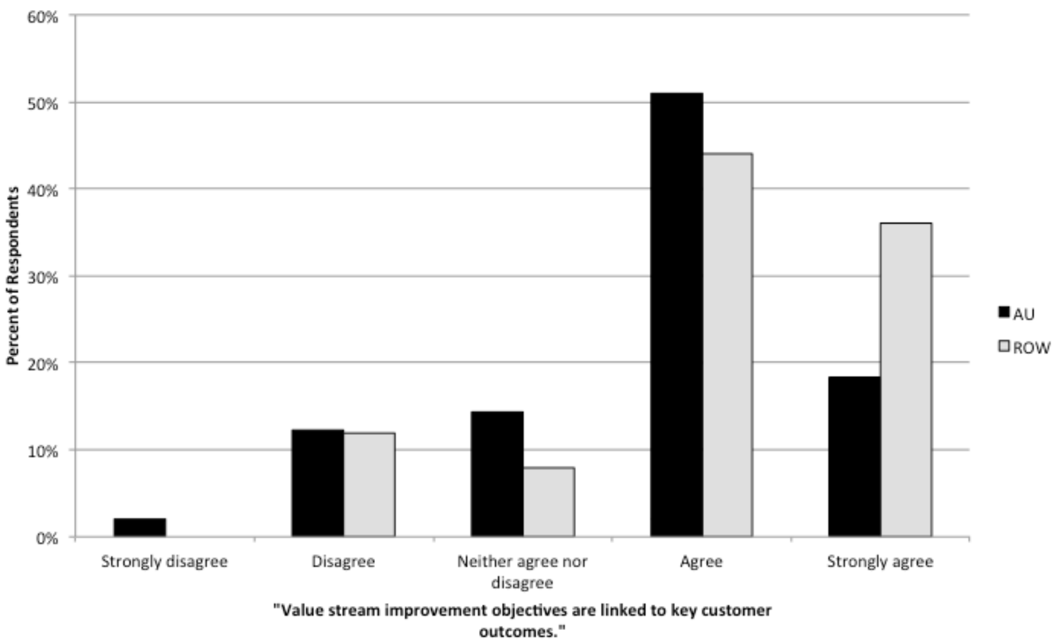


Figure 128: Link between Key Customer Outcomes and Value Stream Improvement Objectives

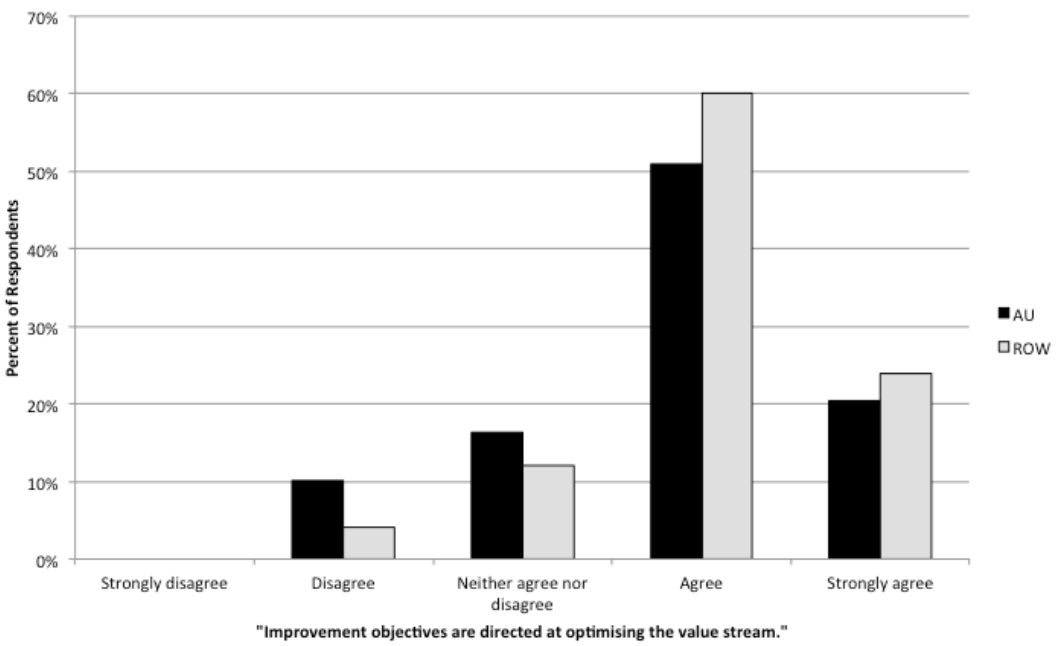


Figure 129: Degree to which Improvement Objectives are Directed Towards Value Stream Optimisation

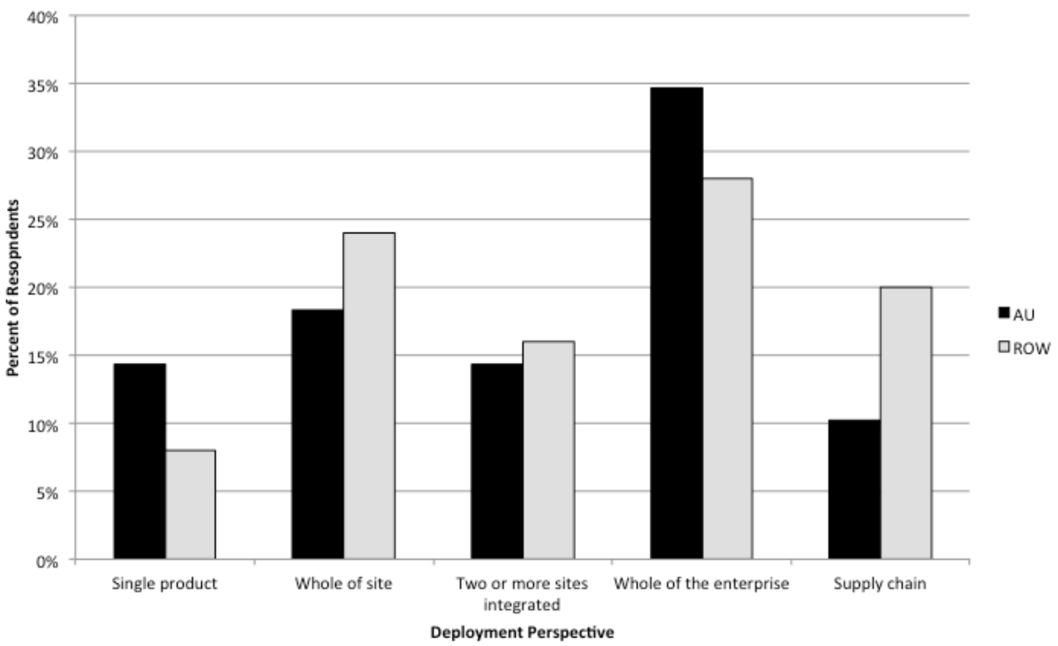


Figure 130: Number of Sites in Deployment Perspective

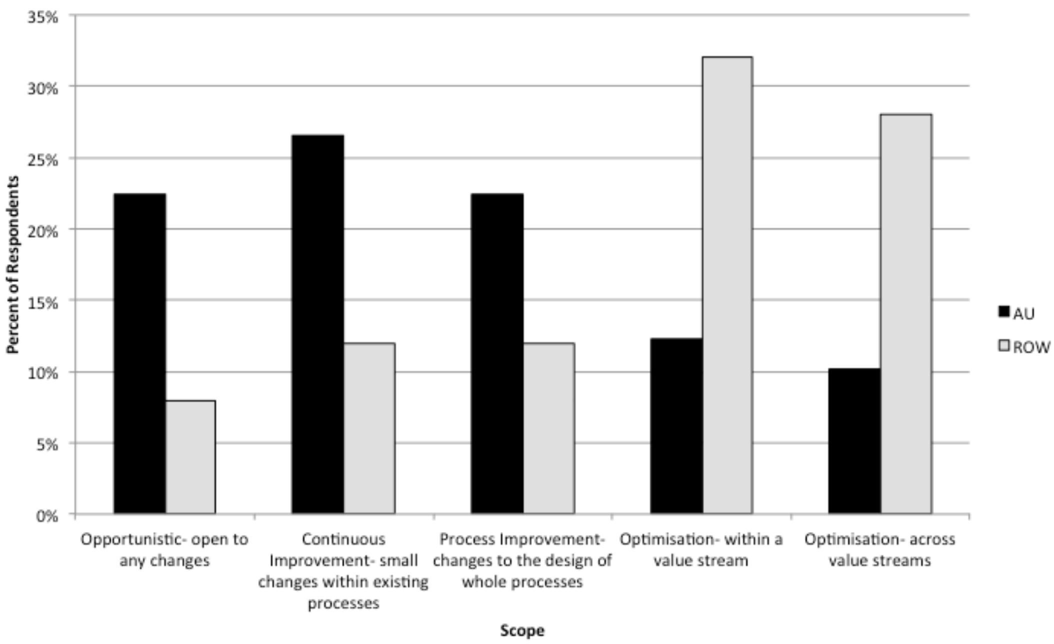


Figure 131: Intended Scope of Improvement Programme

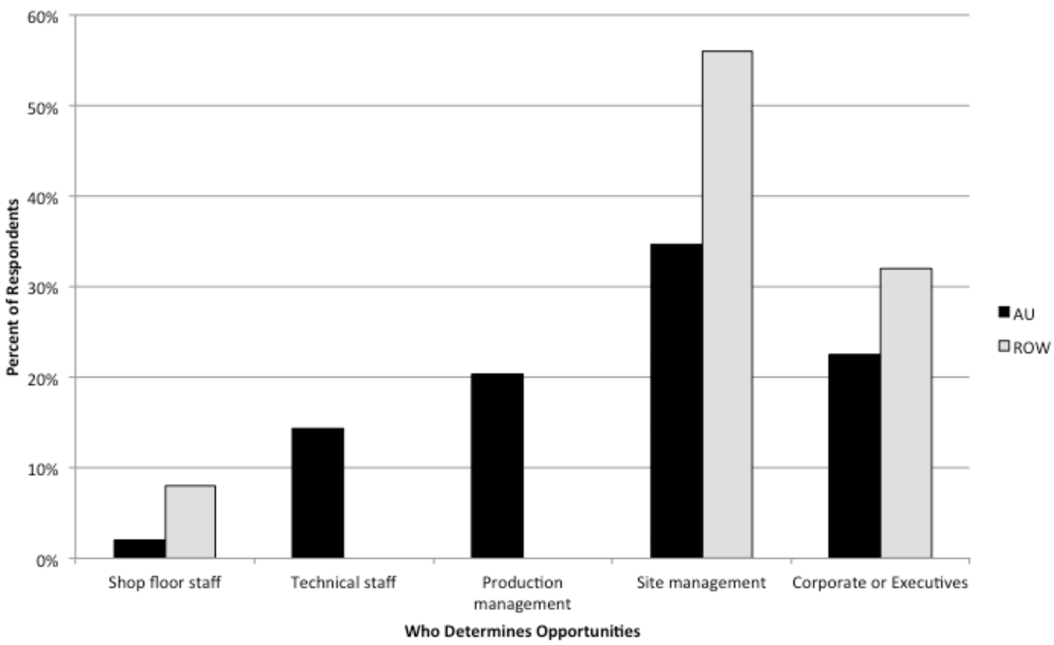


Figure 132: Determination of Opportunities

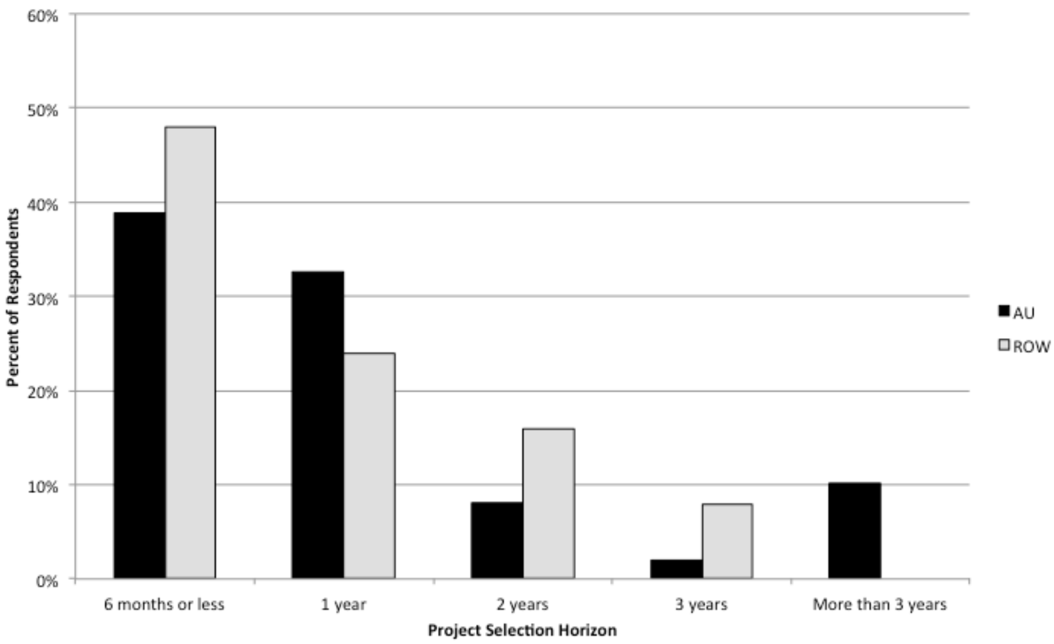


Figure 133: Project Selection Horizon

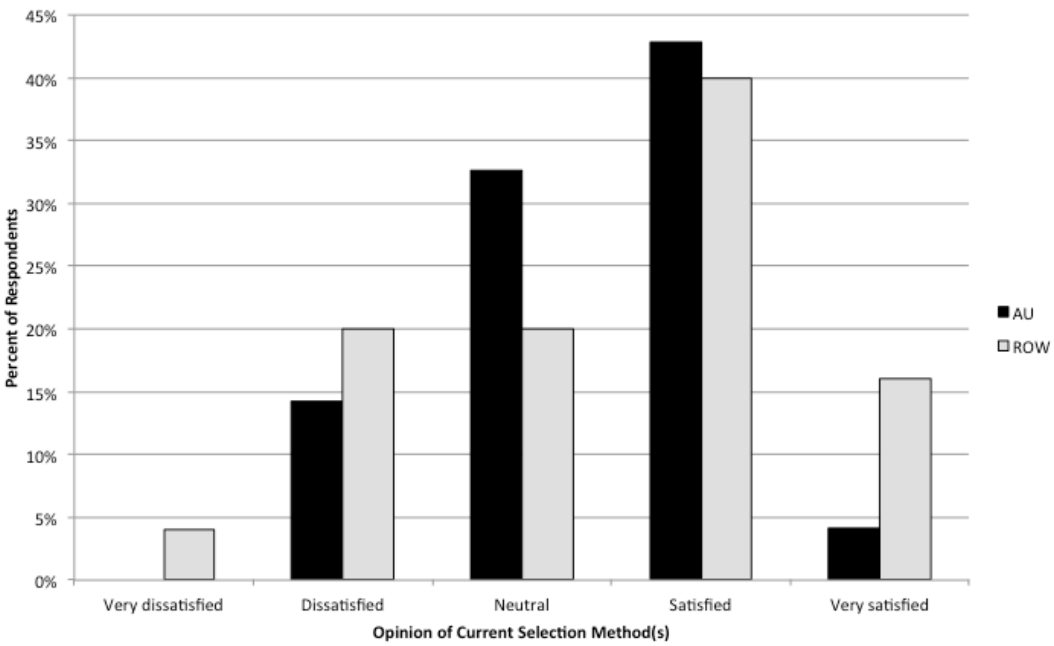


Figure 134: Respondent Opinion of Current Improvement Methods

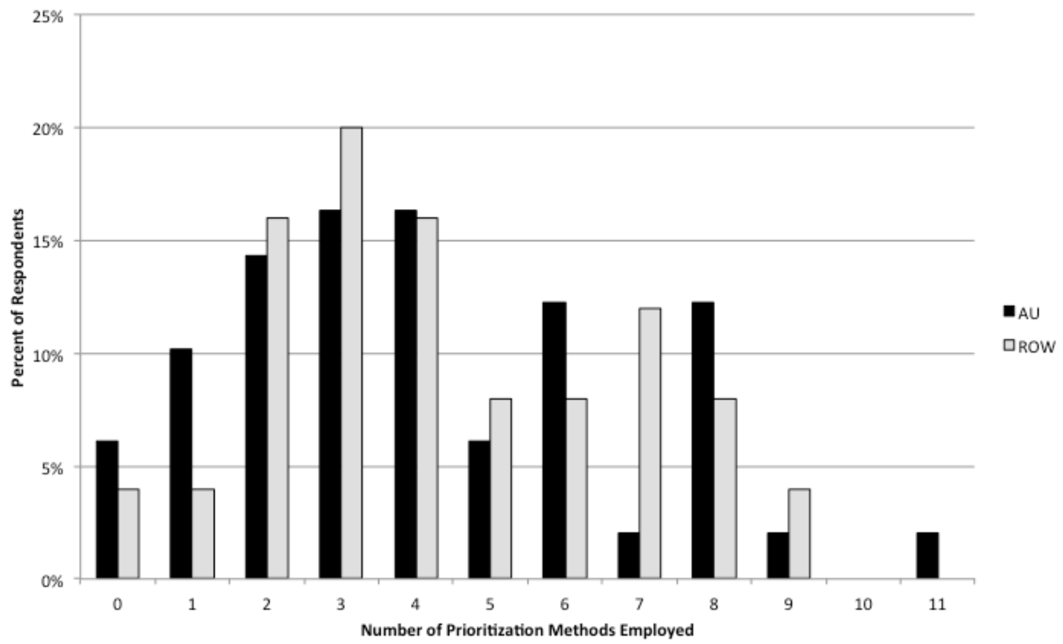


Figure 135: Number of Prioritisation Methods Employed

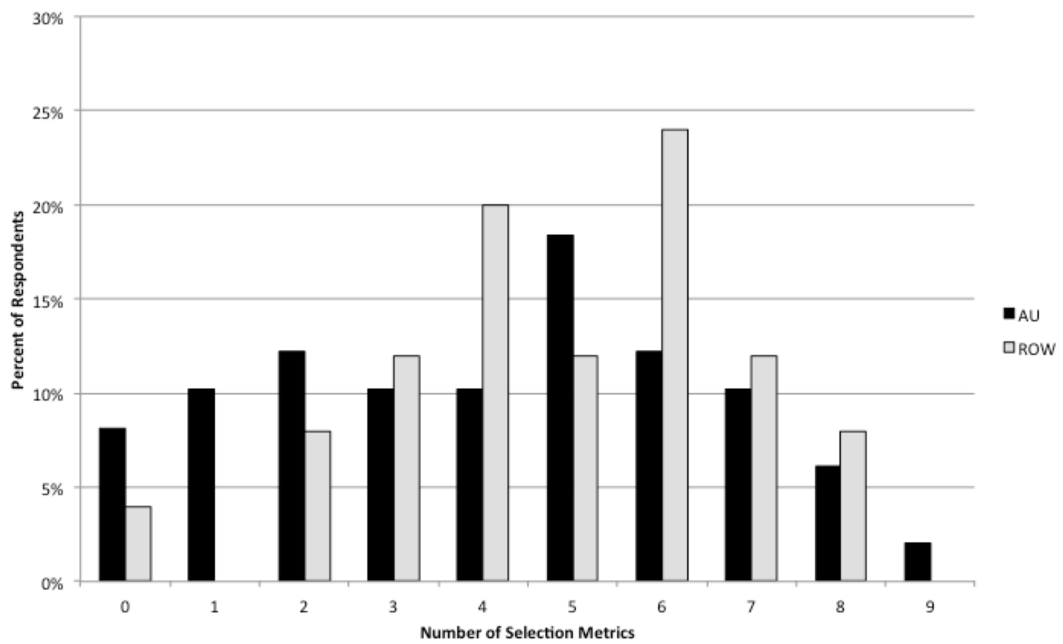


Figure 136: Number of Selection Metrics Employed

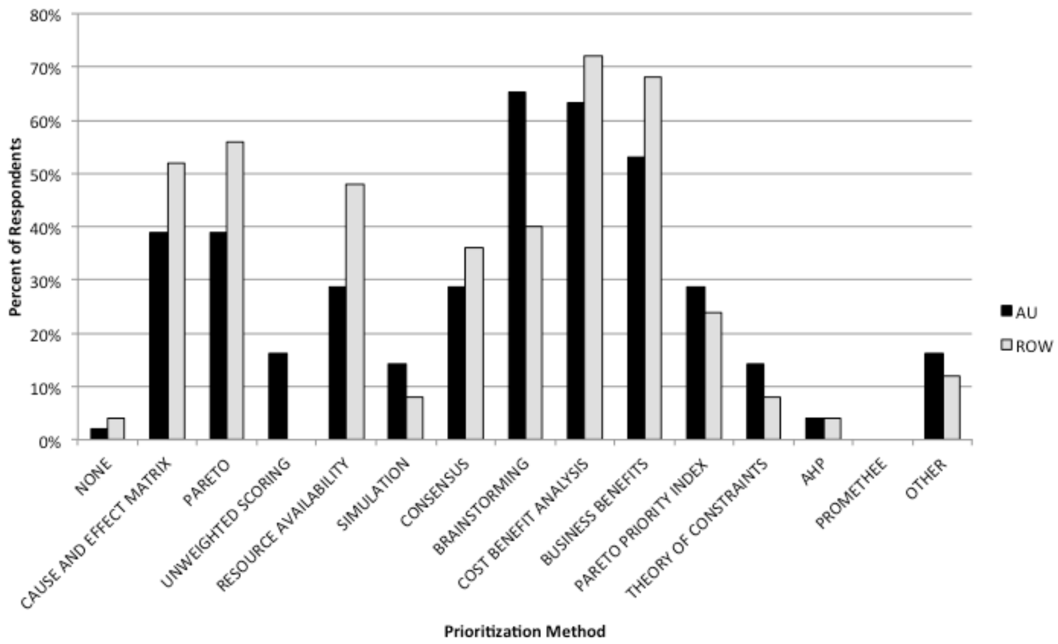


Figure 137: Prioritisation Methods Employed

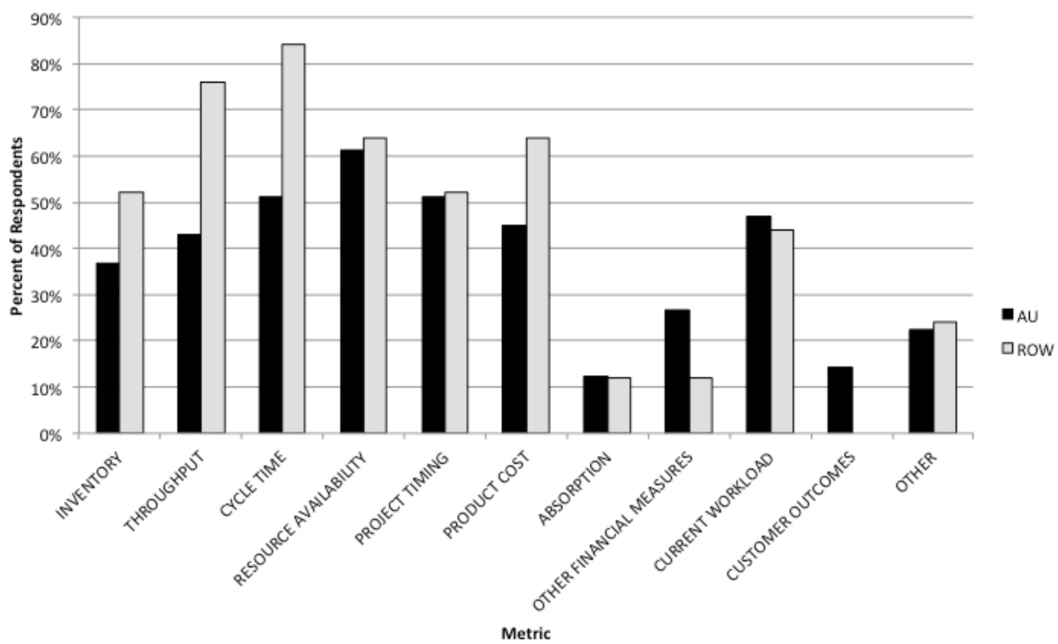


Figure 138: Prioritisation Metrics Employed

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