Optimizing Integrated Municipal Solid Waste Management System under Multiple Uncertainties

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Optimizing Integrated Municipal Solid Waste Management System under Multiple Uncertainties

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Abstract

To define a holistic and systematic approach to municipal waste management, an integrated municipal solid waste management (IMSWM) system is proposed. This system includes functional elements of waste generation, source handling, and processing, waste collection, waste processing at facilities, transfer, and disposal. Multi-objective optimization algorithms are used to develop an optimum IMSWM that can satisfy all main pillars of sustainable development, aiming to minimize the total cost of the system (economic), and minimize the total greenhouse gas emissions (environmental), while maximizing the total social suitability of the system (social). For the social objective, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method is used to identify the main parameters that affect the social suitability of the system.

This research focuses on developing an optimized holistic model that considers all four main components of a modern IMSWM namely transfer, recycling, treatment, and disposal.

The model is formulated as a mixed-integer linear programming (MILP) problem and solved using the epsilon constraint handling method. A metaheuristic method is developed using non dominated sorting genetic algorithm (NSGA) to deal with larger problems. A solution repair function is developed to handle several equality constraints included in the proposed IMSWM model. Sensitivity analyses are conducted to identify the effect of changes in parameters on the objective functions. Based on the results, the proposed metaheuristic algorithm based on NSGA-II performed better than other algorithms. The interval-parameter programming (IPP) methods are used to consider various uncertainties that exist in the system.

The model is applied to the case study of the Australian capital territory (ACT). The data is gathered from several resources including Australian national waste reports, and ACT government transport Canberra and city services (TCCS). Based on the waste characteristic and city map several feasible scenarios are recommended.

Several non-dominated solutions are identified for the model that the decision-maker can choose the most desirable solution based on the preferences. Based on the importance of any objective function at any time the decision-maker can choose a solution to suit the needs.

Keywords

Integrated Municipal solid waste management

Mathematical programming

Mixed-integer linear programing

Uncertain demands

Robust optimization

Waste composition

Waste management technologies

Waste to energy

Evolutionary algorithms

Stochastic optimization

Exact approach

Solution repair

Constraint handling

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List of abbreviations

Abbreviation	Definition
ABC	Artificial bee colony
ACT	Australian capital territory
ACO	Ant colony optimization
AHP	Analytic Hierarchy Process
ALS	Alternating Least Square
ANP	Analytic network process
APM	Agile project management
AR	Autoregressive
EPA	Environment Protection Authority
ETA	Estimated time of arrival
EV	Electric vehicle
FWGP	Fuzzy weighted goal programing
GA	Genetic algorithm
GHG	Greenhouse Gas
IGD	Inverted generational distance
IMSWM	Integrated municipal solid waste management
IPCC	Intergovernmental Panel on Climate Change
ISO	International Standardization Organization
MCDA	multiple-criteria decision analysis
MCDM	Multiple-criteria decision-making
MILP	Mixed-Integer Linear Programming
NIMBY	Not In My Backyard
NSGA	Non-dominated sorting genetic algorithm
NSW	New South Wales
PSO	Particle swarm optimization
SA	Simulated Annealing
TS	Tabu search
VNS	Variable neighborhood search

Chapter 1 :Introduction

1.1 Motivation and Background

The environment is heading towards a potential risk due to unsustainable waste disposal (United Nations, 2006). Dealing with waste has been a problem from the earliest days of humanity's existence on Earth. The increasing population of societies and generated waste forced people to develop ideas to better deal with waste to safeguard public health (Van Engeland *et al.*, 2020). These ideas led to the introduction of the first incineration plants called destructors in the late 19th century (Herbert, 2002). Later in the early 20th century, the sanitary landfill concept was introduced to eliminate open dumps of waste and was developed in a practical effort to prevent leachate from entering the environment (Letcher & Vallero, 2019).

United Nations (2006) defines waste as "materials that are not prime products (that is, products produced for the market) for which the generators have no further use in terms of their purposes of production, transformation or consumption, and of which they want to dispose of". Waste can be generated during the extraction of raw materials, the processing of raw materials into intermediate and final products, the consumption of final products, and other human activities while residuals, recycled or reused at the place of generation are excluded (United Nations, 2006). Later, it was realized that a part of waste could be converted into energy and new materials. Nowadays, even private companies (*Apple*, *Dell, UPS*) introduce several routines to make the best use of waste management systems in their companies.

Municipal solid waste (MSW) consists of several types of waste, including rubbish, food, institutional, commercial, industrial, construction, and sanitation wastes (Sharholy *et al.*, 2008). In 2018, 2.01 billion tons of MSW were generated globally, and at least 33% of that waste was not managed in a safe way for the environment (Kaza *et al.*, 2018). Kaza *et al.* (2018) also it is predicted that the world will be generating 3.40 billion tons of MSW in the year 2050. This massive increase in the MSW generation is one of the growing problems that both industrial and developing countries face (Ghiani *et al.*, 2014). Based on the amount of the generated waste, MSW management consumes about 20% – 50 % of the total budget of municipalities (Lohri *et al.*, 2017). However, to decrease the cost and environmental impacts the WM system should be integrated, market-oriented, and flexible (McDougall *et al.*, 2001).

In the 1970s, the hierarchy of MSW management was developed with the main aim of reducing, reusing, recycling, recovery, and final disposal of waste (Tan *et al.*, 2014). To define a holistic and systematic approach for MSW management, an extension of the waste management hierarchy was suggested as integrated municipal solid waste management (IMSWM). Raisinghani and Idemudia (2016) explained IMSWM as “the selection and application of suitable techniques, technologies, and management programs to achieve waste management objectives and goals”. IMSWM prioritizes waste processing methods in the order of reduction, reuse, recycling, and disposal of waste. Each of these steps includes different decision making such as the location of waste facilities and the technologies that are being used (Ghiani *et al.*, 2014). According to Ghiani *et al.* (2014), several strategic, tactical, and operational decisions are involved in IMSWM, like the location of waste management facilities, selection of different waste treatment policies, and allocation of waste to waste processing plants. The IMSWM aims to integrate WM processes to gain an efficient WM system (Marshall & Farahbakhsh, 2013). However, for a WM system to be efficient, other than economic efficiency, the environmental and social criteria should also be satisfied (Tan *et al.*, 2014). IMSWM incorporates several criteria, including economic, environmental, social, and technical, some of which conflict with each other, and this makes the task of developing an optimum IMSWM a complex task (Ghiani *et al.*, 2014; Soltani *et al.*, 2015).

Kaza *et al.* (2018) indicated that the cost of MSW management usually exceeds $100 per ton of waste while low-income countries only spend $35 per ton, including collection, transport, treatment, and disposal. Despite the authorities' effort to provide adequate services for the whole population, especially in low- and middle-income countries, it often covers less than 50% of the population (Kaza *et al.*, 2018).

1.2 Current Challenges and Research Gaps

Several waste management (WM) facilities and technologies such as incineration, sanitary landfill, composting, and material recovery have been used in industries (Hannan *et al.*, 2020) that should be considered in the IMSWM. The site selection of these WM facilities and technologies and the allocation of waste should be considered wisely to reduce the total cost and environmental footprint of the whole IMSWM system while simultaneously considering the social acceptance of such technologies. Mies and Gold (2021) identified several factors involved in the social acceptance of a WM facility or technology and classified them into affected groups such as workers, organizations, customers, the local community, and society. Identifying these parameters and quantifying them is an essential and challenging task in any IMSWM. However, social acceptance of SWM facilities and technologies has gotten less attention in the literature than economic and environmental considerations. In most of the studies, only one or very few indicators are used to calculate the social acceptance of the system. However, As several indicators affect the social acceptance of waste management facilities, considering all of these indicators is an important step towards developing a more realistic model of the system. One of the main focuses of this study is to address this gap in the literature by including a comprehensive list of social acceptance factors.

Furthermore, the waste composition is an important factor in identifying material recovery potential, facilitating processing equipment design, and assessing waste's chemical and environmental properties regarding local regulations and laws (Gidarakos *et al.*, 2006). However, this decision should be taken considering all three sustainability objectives, i.e., economic, environmental, and social. To the best of our knowledge, there has not been a study that considered both waste composition and a comprehensive list of social objective indicators at the same time. For example, Hosseinalizadeh *et al.* (2021) considered waste composition as a proxy for economic and environmental objectives discarding social factors, while Ghannadpour *et al.* (2021), Rabbani *et al.* (2021), and Chen *et al.* (2022) considered all three sustainability objectives but ignored waste composition.

In real-world scenarios, the value of all the different parameters in a WM system is not always known. Numerous factors can affect many parameters in the model like a waste generation which is affected by several socioeconomic factors or transportation cost which is dependent on fuel and labor costs and can vary day to day. Several parameters in an SWM system are subject to several uncertainties. Hence, creating a robust solution for any SWM system requires considering these uncertainties and assessing their effect on the model solutions. These uncertainties usually occur together it is important to consider multiple uncertainties simultaneously to identify their combined effect of them.

The review of the literature indicates that several studies have considered multi-objective models for WM, however, there is a gap in developing a comprehensive method to evaluate the social acceptance of the system and optimize the acceptance along with other sustainability objectives. Also, considering the waste composition in multi-objective models has not been given enough attention in multi-objective models. In addition, although several studies have considered uncertainties in their model, the considered uncertain parameters usually belong to one group and are closely related to each other. Therefore, there is a need for creating a model that considers uncertainty in different aspects of the system like generation, transportation, and selling products.

1.3 Research Objective and Research Questions

This research aims to address the above gaps by developing a holistic optimization model for the IMSWM to satisfy the sustainability objectives based on the known constraints. The optimization process intends to minimize the system's total cost and greenhouse gas (GHG) emissions while maximizing social acceptance. The project aimed to identify the most suitable waste management technologies considering the waste composition. Another objective of this research is to develop a comprehensive formula to assess the social acceptance of the whole system to be used in the optimization model. This research also aims to identify the most important sources of uncertainty in the model and evaluate the effects of those uncertainties on the model objectives.

These research aims are investigated by answering the following research questions:

1- How can the waste composition affect the selection of appropriate waste management technologies?
2- What is the effect of having transfer stations in the system compared to the mixed collection of waste?
3- What are the main indicators of social acceptance for a waste management system and how considering them can affect the decisions in the system?
4- How to improve the decision-making process by considering uncertainties in the SM systems?

The main contributions of this study are as follows:

(i) Developing a holistic IMSWM system covering the waste streams from generation points to final markets, including all main components: transfer stations, treatment facilities, material recycling facilities, and disposal facilities;

(ii) Considering all three main objectives of SWM, including financial, environmental, and social objectives in a multi-objective optimization problem while considering waste composition simultaneously;

(iii) Considering 11 separate social acceptance indicators for social sustainability objectives and using the TOPSIS method as a multi-criteria decision-making tool to identify the most important indicators;

(iv) Developing a modified solution method based on evolutionary algorithms that can deal with very large instances of the model;

(v) Considering multiple uncertainties of the model parameters and assessing the combined effect on the model.

1.4 The Organization of the Thesis

This thesis has 5 Chapters and is organized as follows:

In Chapter 1, an introduction of the thesis topic is presented. Integrated solid waste management is introduced and the importance of proper waste management is discussed. The motivation and scope of the are then presented followed by the research questions and gaps. The last section in this Chapter indicates the organization of this thesis.

In Chapter 2, a comprehensive literature review of the research topic is presented. Several Waste management modeling techniques are reviewed and discussed along with optimization objectives and constraints. Several solutions to approach the waste management problems with or without uncertainty are also discussed in this Chapter.

Chapter 3 presents a holistic IMSWM system model considering all components of the system and all three sustainability objectives. The model is solved using the MILP methods and a modified method based on evolutionary algorithms is developed and used to solve the model in the case study of ACT, Australia.

Chapter 4 extends the model developed to consider several uncertainties in the system and solved them with the developed evolutionary algorithm based on NSGA-II. At first, the most important parameters with uncertainty are identified and the model is solved for uncertain scenarios.

The Final Chapter, Chapter 5, presents a summary of the conducted research in this thesis. The results of the model are discussed and several managerial recommendations are made. Future research directions are also presented in this Chapter.

Chapter 2 :[1] Background Study and Literature Review

In this Chapter, a literature review is presented on the topic of optimizing Integrated municipal solid waste management (IMSWM) systems. Several methods of modelling IMSWM systems are reviewed and the main components of the models including the optimization objectives and optimization constraints are assessed. As a main part of the study, the history of considering uncertainty in IMSWM modeling is also reviewed in this Chapter. Finally, research gaps are summarized after an exhaustive review, as the base of work in this thesis.

2.1 Optimization Objectives

The main objectives of developing an optimum IMSWM are to simultaneously reduce the costs and environmental impacts of the IMSWM while considering the social impacts and acceptance of the system (Ghiani *et al.*,2014). Considering these main optimization objectives for waste management, researchers have tried to optimize the waste management system according to several objective functions. According to Hannan *et al.* (2020), the most frequently used objective functions in literature are as follows:

- Cost minimization (Hosseinalizadeh *et al.*, 2021; Rabbani, *et al.*, 2021)
- Environmental hazard minimization(Mofid-Nakhaee *et al.*, 2020; Pishvaee *et al.*, 2011)
- Social acceptance maximization (Ghannadpour *et al.*, 2021; Tsydenova *et al.*, 2018)
- Risk minimization (Martín-Gamboa *et al.*, 2021; Ziaei & Jabbarzadeh, 2021)
- Route optimization(Salavati-Khoshghalb *et al.*, 2019; Schiffer *et al.*, 2019)
- Time optimization (Eshtehadi *et al.*, 2020; Shao *et al.*, 2020)
- Allocation of waste bins(Rossit *et al.*, 2020; Toutouh *et al.*, 2019)
- Transfer stations (Asefi et al., 2019; Yadav & Karmakar, 2020)

These objectives can be classified into three main groups based on the main objectives of sustainability namely economic, environmental and social objectives.

2.2 Optimization Constraints

Based on the characteristics of the place that the optimization is trying to optimize the system for, several criteria enforce several restrictions on the model. These restrictions are called constraints of the model. Based on Hannan *et al.* (2020), the more constraints a model considers,

[1] These following article has been submitted based on this Chapter and Chapter 3:
Ansari, M, Abbasi , A., and Chakrabortty, R.K., “An Integrated Municipal Waste Management System to identify the optimum technologies for waste composition using MILP and evolutionary algorithms”, Waste Management, under review, 2022. [sections 2.1, 2.2, 2.3,2.4, 2.5, 3.1, 3.2, 3.3, 3.4 and 3.5]

the more it becomes realistic and practical. Several groups of constraints have been used in the literature for waste management models. Some of these constraints are as follows:

- Capacity constraints (Erfani *et al.*, 2019; Rathore & Sarmah, 2019)
- Mass-balance constraints (Hossein Asefi & Lim, 2017; Santibañez-Aguilar *et al.*, 2013; Yadav *et al.*, 2017)
- Time constraints (Faccio, Persona, and Zanin, 2011; Son and Louati, 2016; Yadav *et al.*, 2018; Mukherjee Basu and Punjabi, 2020)
- Waste type constraints (Asefi et al., 2019; Hemmelmayr *et al.*, 2013; M. Rabbani *et al.*, 2019)
- Labor constraints (Muneeb *et al.*, 2018; M. Rabbani *et al.*, 2019)
- Environmental constraints (Edalatpour *et al.*, 2018; Mohammadi *et al.*, 2019; Vonolfen *et al.*, 2011; Walmsley *et al.*, 2018)
- Regulatory constraints (Fan & Liu, 2010; Vonolfen *et al.*, 2011)
- Political constraints (Marshall & Farahbakhsh, 2013; Plata-Díaz *et al.*, 2014; Wee *et al.*, 2017; Yukalang *et al.*, 2017)
- Social constraints (Jones *et al.*, 2010; Kamaruddin *et al.*, 2013; Noche *et al.*, 2010)

2.3 Modeling Approaches of IMSWM

2.3.1 Deterministic Approach

Several studies have tried to model the waste management system as a mathematical problem and optimized it using different operation research techniques. Table 2.1 shows the analysis of the reviewed literature in the field of MSWM optimization. The categorization of the literature for reviewing is based on the classification of the MSWM studies introduced by Asefi *et al.* (2020).

However, the majority of these studies have only considered one aspect of a sustainable system, mainly Financial criteria (EPA, 2002), and tried to solve a single objective mathematical model representing the decision framework of MSW to optimize the cost of the MSWM system (Eiselt, 2007; Önüt & Soner, 2008; Sadeghian Sharif *et al.*, 2018; Šomplák *et al.*, 2014; Tavares *et al.*, 2009; Vidović *et al.*, 2016). The related studies are reviews considering several categorizations including model type, method, system components, objectives, WM system, and type of waste. As shown, most of these studies have only considered one aspect of a sustainable system, mainly financial criteria (EPA, 2002), and considered a single objective mathematical model optimizing the cost of the MSWM system.

Table 2.1: Classification of the literature in IMSWM modeling

Author and Publication Year	Model type	Method				System components				Objectives					WM system						Type of waste		
										Economic		Environmental		Social									
		system assessment	multi-criteria decision making	operation research	hybrid	transfer station	treatment facilities	recycling facilities	disposal facilities	Transport cost	Infrastructure	Emission	Visual pollution	Equity in services	Generation	proceeding	Collection	transfer and transport	transformation	Disposal	Municipal	Residue	hazardous
Wanichpongpan and Gheewala	LCA	*					*		*		*	*				*	*	*	*	*	*	*	
Hung *et al.*(2007)	Fuzzy AHP+CAM		*				*		*		*	*		*					*	*			
Eiselt (2007)	MILP			*					*	*							*			*	*		
Liamsanguan & Gheewala (2008)	LCA	*				*	*	*	*			*					*	*		*	*		
Önüt and Soner (2008)	Fuzzy AHP+TOPSIS		*			*			*	*	*									*			
Minciardi *et al.* (2008)	Reference point			*		*	*	*	*		*	*				*			*	*	*		
Guo *et al.* (2008)	SP+ILP			*					*		*												
Erkut *et al.* (2008)	MILP-Lexicographic			*		*	*	*	*		*	*					*		*	*	*		
Tseng and Tseng (2009)	ANP+DEMATEL		*				*	*	*		*	*		*					*	*	*		
Guo *et al.* (2008)	FP+ILP			*			*		*		*								*	*	*		
Mitropoulos *et al.* (2009)	MILP +			*		*	*		*		*								*	*	*		
Abbasi & El Hanandeh (2016)	Stochastic ELECTRE		*				*	*	*			*											
Tavares *et al.* (2011)	AHP		*							*	*	*		*						*	*		
Li and Chen (2011)	FP+SP+ILP			*							*					*			*	*	*		
Dai *et al.* (2011)	SVR+MILP				*	*	*	*	*		*				*				*	*	*		
Agostinho *et al.* (2013)	ERA	*				*	*	*	*		*	*											*
Othman *et al.* (2013)	LCA	*				*	*	*	*			*					*	*	*	*	*	*	*
Oyoo *et al.* (2013)	WLC		*								*	*		*			*			*	*		
Isalou *et al.* (2013)	Fuzzy ANP		*					*	*		*	*		*						*	*		
Santibañez-Aguilar *et al.* (2013)	MILP			*		*	*	*	*		*	*				*	*		*	*	*		
Herva *et al.* (2014)	ERA+MFA	*				*	*	*	*			*									*		
Arena and Di Gregorio (2014)	MFA+LCA	*				*	*	*	*			*				*	*			*	*		
Vinodh *et al.* (2014)	Fuzzy AHP+TOPSIS		*						*		*	*		*					*		*		
Šomplák *et al.* (2014)	MILP + Monte Carlo			*			*		*	*	*										*		
Tan *et al.* (2014)	MILP			*		*	*	*	*		*	*			*	*			*	*	*		
Asefi *et al.* (2015)	MILP			*		*	*	*	*		*					*	*	*	*	*	*		
Hanine *et al.* (2016)	Fuzzy AHP+TOPSIS		*						*		*	*		*						*	*		
Chauhan & Singh (2016)	Fuzzy AHP+TOPSIS		*						*	*		*		*						*			
Vidović *et al.* (2016)	MILP + Heuristic			*		*			*	*	*						*	*			*		
Hariz *et al.* (2017)	AHP+VIKOR+PROMETH		*						*		*	*		*						*			
Silva *et al.* (2017)	MILP			*						*	*			*			*		*	*	*		
Habibi *et al.* (2017)	Robust MILP			*		*	*	*	*	*	*	*	*	*			*	*		*	*		
Mirdar Harijani *et al.* (2017)	MILP +				*	*	*	*	*		*	*		*	*		*	*		*	*		
Asefi and Lim (2017)	Delphi-TOPSIS+ MILP				*	*	*	*	*	*	*	*		*	*		*	*	*	*	*	*	
Edalatpour *et al.* (2018)	SP(LP)			*		*	*	*	*		*	*			*	*			*	*	*		
Sadeghian Sharif *et al.* (2018)	Bi-level programming			*			*	*	*		*										*		
Asefi *et al.* (2019)	MILP+VRP				*	*	*	*	*	*	*						*	*			*		
Rathore and Sarmah (2019)	MILP+GIS			*		*			*	*	*					*	*			*	*	*	
Mofid-Nakhaee *et al.* (2020)	MILP			*		*	*	*	*	*	*	*		*		*	*	*	*	*	*		
Batur *et al.* (2020)	MILP			*		*	*	*	*	*	*				*	*	*	*	*	*	*		
Rabbani *et al.* (2021)	MILP			*		*	*			*	*	*			*	*	*	*	*		*		
Ghannadpour *et al.* (2021)	MILP				*		*		*	*				*	*		*			*			*
Hosseinalizadeh *et al.* (2021)	MILP			*			*	*	*	*	*	*				*	*		*	*	*		
This study	MILP				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*		

Hung *et al.* (2007) and Tan *et al.* (2014) developed a bi-objective decision-making model for MSWM considering only economic and environmental criteria, while Agostinho *et al.* (2013) considered ecological and social criteria to propose an alternative system for recovering materials. Tan *et al.* (2014) developed a bi-objective MILP considering both economic and environmental criteria. Habibi *et al.* (2017) were one of the few studies considering a multi-objective decision model for MSWM using visual pollution as a social acceptance constraint alongside cost and GHG emissions. Social criteria are also considered in the form of public awareness and education by Mofid-Nakhaee *et al.* (2020) in their model of sustainable MSWM. In one of the most comprehensive studies that consider all three sustainability criteria, Asefi and Lim (2017) proposed a location routing problem (LP) in the form of a multi-objective MSWM model that considers economic, environmental, and social criteria simultaneously while considering all the main components of MSWM in a holistic decision framework. However, in their study, the main objective is again based on economic criteria that have been classified into two objectives of infrastructure cost and transportation cost of the system. Environmental and social criteria are considered only in the site selection phase.

In the past few years, researchers have been trying to model the SWM model as close to real-world problems as they can. The main steps for developing such a model are:

- Considering multiple objective functions
- Considering a comprehensive waste management system including all four main components of transfer, recycling, treatment, and landfill facilities.
- Considering all the constraints that affect the system.
- Considering uncertainty in every parameter that can be uncertain.

However, considering all these parameters in a model might make the model large and complex. Habibi *et al.* (2017) developed a multi-objective model to optimize the three main objectives in SWM, including costs, GHG emissions, and visual pollution. However, in their model, only waste generation is considered an uncertain parameter.

Zarrinpoor and Pishvaee (2021) proposed a solid waste management system in the presence of random disruptions as uncertainties in the system. Considering multiple uncertainties in the system makes the problem very complex. The problem is very complex, and the regular MILP solvers like CPLEX cannot solve the model. Therefore, the authors proposed an L-shaped method with several enhancement strategies to be able to deal with the size of the problem. However, the only financial objective was considered in that model. Financial and environmental objectives were considered in Homayouni *et al.* (2021) in their bi-objective model. However, they have not considered all components of the SWM, and only one uncertain parameter is considered in their model. The advantage of their study was the usage of a heuristic method that can manage large-size problems better.

2.3.2 Stochastic Approach

While some of the parameters that are used in MSWM modeling are determined, usually in real-life scenarios, some of the parameters are uncertain or completely unknown. These parameters include but are not limited to waste generation rate, waste treatment cost, site suitability, transportation cost, consumer preferences, weather situations, legislation, etc. (Baetz, 1990; Thomas *et al.*, 1990; Xi *et al.*, 2010). Rakas *et al.* (2004) conducted one of the first studies that considered uncertainty directly in their model to find locations for undesirable facilities. Li and Chen (2011) referred to uncertainty as one of the major challenges that can reduce the efficiency of the MSWM system, make it harder to achieve an optimized solution, and impair confidence in decisions. Cai *et al.* (2009) also emphasized that these uncertainties introduce some complications to the decision-making process. The use of system analysis techniques under uncertainty helps to gain optimal decisions and make balanced trade-offs. Yadav *et al.* (2017) also demonstrated that several parameters in the MSWM system are associated with uncertainty and list them as waste-generation rate, functioning cost of facilities, and transportation cost. They tried to apply these uncertainties in their previously proposed model. The following table shows some of the more frequently considered uncertain parameters in waste management models. Table 2.2 indicates the uncertain parameters used most frequently in the literature.

Table 2.2: uncertain parameters in the solid waste management system

	Articles	Waste	Emissions	Transportation	Processing	Fixed costs	Purchasing	Facility	Waste quality	Delay	Risk	Selling price
1	(Hong *et al.*, 2006)							*				
2	(M. S. Pishvaee & Torabi, 2010)			*	*	*		*		*		
3	(Fonseca *et al.*, 2010)			*								
4	(C. Dai *et al.*, 2011)			*	*			*				
5	(Pishvaee *et al.*, 2011)			*								
6	(Vahdani *et al.*, 2012)			*	*	*		*				
7	(Zeballos *et al.*, 2012)								*			
8	(Lieckens & Vandaele, 2012)	*								*		

9	(Vahdani *et al.*, 2012)			*		*		*		
10	(J. Xu & Wei, 2012)			*		*		*		
11	(Lieckens & Vandaele, 2012)									*
12	(Phuc *et al.*, 2012)			*	*	*	*	*		
13	(Mir Saman Pishvaee & Razmi, 2012)	*		*						
14	(Özkir & Başligil, 2013)						*			
15	(Soleimani & Govindan, 2014)						*			
16	(Vahdani & Naderi-Beni, 2014)			*	*	*		*		
17	(Hatefi & Jolai, 2014)	*							*	
18	(Hatefi & Jolai, 2014)			*	*	*		*		
19	(Jindal & Sangwan, 2014)			*		*	*	*		
20	(Ramezani *et al.*, 2014)			*	*	*		*		*
21	(Vahdani & Naderi-Beni, 2014)			*	*	*		*		*
24	(Ene & Öztürk, 2015)				*					
26	(Hasani *et al.*, 2015)						*			
27	(W. Chen *et al.*, 2015)								*	
28	(Subulan *et al.*, 2015)			*		*		*		
29	(Ayvaz *et al.*, 2015)	*							*	
30	(Zhalechian *et al.*, 2016)	*		*	*	*		*		*
31	(Z. Dai & Dai, 2016)				*			*		
32	(Talaei *et al.*, 2016)				*					
33	(Hatefi *et al.*, 2016)					*		*		
34	(Shafiei Kisomi *et al.*, 2016)			*	*					
35	(Yu & Solvang, 2016)						*			
36	(Özceylan, 2016)							*		
37	(MA *et al.*, 2016)			*	*					
38	(Hamidieh *et al.*, 2017)	*		*	*	*				
39	(Phuc, Yu, and Tsao, 2017)			*	*	*	*	*		
40	(Z. Xu *et al.*, 2017)			*						
41	(Ameknassi *et al.*, 2017)			*	*			*	*	
42	(Temur & Yanık, 2017)	*		*	*	*				
43	(Z. Dai & Li, 2017)						*	*		
44	(Keshavarz Ghorabaee *et al.*, 2017)	*	*					*		
46	(Pedram *et al.*, 2017)	*							*	
47	(Heidari *et al.*, 2019)	*			*					
48	(Asefi et al., 2019)	*		*						

49	(Gambella *et al.*, 2019)	*							
50	(Tirkolaee *et al.*, 2020)	*					*		
51	(Ziaei & Jabbarzadeh, 2021)		*		*			*	
52	(Das *et al.*, 2021)		*						
	This study	*		*		*			*

Dantzig (1955) was the first that introduced the concept of uncertainty in mathematical modelling in the shape of stochastic programming, and the topic has attracted lots of interest since then. Birge and Louveaux (2011) indicated that these problems need a set of decisions that are affected by the outcome that evolves and will gradually be revealed. Bakker *et al.* (2020) indicated that, regarding the fact that in optimization under uncertainty, some of the parameters are not known from the beginning. The concepts of feasibility and optimality that were defined for a deterministic problem are no longer valid in optimization under uncertainty. Bakker also demonstrates that the use of multi-stage models helps the decision-maker to adapt each decision in each stage to the uncertain parameters revealed in previous stages. Berglund and Kwon (2014) developed a robust facility location problem for hazardous waste transportation under demand and risk uncertainty. They only considered cost as an objective in their model. They proposed an exact method to solve relatively small problems, whereas, for the larger problems, the authors implemented a genetic algorithm. Biswas and De (2016) implemented a fuzzy chance constraint programming approach to minimize total SWM cost under multiple uncertainties. Habibi *et al.* (2017) extended the modelling to the multi-objective model, considering minimizing the system's total cost and GHG emission and visual pollution as objectives of the model. Uncertainty in generated waste was considered in their model, and a linear programming approach was used to solve that model. Edalatpour *et al.* (2018) also considered waste generation as an uncertain parameter in their model and proposed a multi-objective supply chain network to minimize the total cost and GHG emissions of the system. They classified the waste into dry and wet waste and used sun-drying as the only option for dealing with wet waste. Safaei *et al.* (2017) also proposed a MILP model under demand uncertainty. The model was single objective and considered a special type of waste only (i.e., cardboard and paper) to study the recycling options. They used a robust optimization method to deal with the uncertainty. Pouriani *et al.* (2019) also formulated a bi-level mathematical model that considers waste generation an uncertain parameter. The proposed model was a single objective and only considered financial objective and solved only for a small area. The authors recommend using heuristic methods for larger problems. Tirkolaee *et al.* (2020)

implemented a robust optimization approach to deal with uncertainty in waste generation in a single objective problem trying to minimize total system cost.

Also, the uncertainty in parameters of waste management has been addressed in the literature. However, there still exist some shortcomings in considering multiple uncertainties and all three sustainable development objectives. In most related studies, either only one uncertain parameter is considered, or in a few studies that consider multiple uncertainties, the selected parameters are all related to a specific effect in the system. Considering multiple uncertainties of different nature and related to different system components like generation, transportation, waste facilities, and waste markets is an essential step in assessing the combined effect of multiple uncertainties on the model. As the social acceptance of the model is highly related to several parameters in the model, the effect of uncertainties on social acceptance of the IMSWM system should be studied deeper alongside the economic and environmental objectives.

2.4 Solution Approaches

Hannan *et al.* (2020) classified the solution approaches for solving solid waste management models into three main categories:

2.4.1 Conventional Approaches

The conventional methods usually deal with multiple objectives by transforming them into a single objective using the weighted sum method. These methods have been widely used in the literature, especially in the deterministic modeling approaches. Yousefloo and Babazadeh (2020) developed a multi-objective MILP considering economic and environmental objectives. Bavaghar Zaeimi & Abbas Rassafi (2021), tried to solve their MILP model of waste management system using the Fuzzy weighted goal programming(FWGP) method. Another popular method to deal with multi-objective MILP problems is the epsilon constraint method introduced by Becerra & Coello (2006). In this method, the model is transformed into a single-objective problem and solved using exact methods. Azadeh *et al.* (2019) used the weighted sum method for selecting the optimum size of a waste management system. In this method, the objective functions are summed up with different weights and the aim is to optimize this sum. However, the conventional solution methods are not very practical in multi-objective problems with uncertainties considered in the model. Hannan *et al.* (2020) also indicated that the conventional methods, especially MILP have weaknesses in dealing with large-scale problems requiring large computational effort.

2.4.2 Heuristic Approaches

Heuristic approaches tackle these weaknesses of conventional methods. It is very hard to find an exact solution to very large problems. Heuristic methods can find acceptable solutions in reasonable times by sacrificing a level of optimality, accuracy, precision, or completeness. To tackle this problem inexact methods were introduced. In these methods, the algorithm starts from one solution and moves to neighbor solutions until the final solution is found. The local search can be done by several methods including Luus – Jaakola, random optimization, random search, and pattern search. Mostafayi Darmian *et al.* (2020) used the local search heuristic to solve a multi-objective location-districting optimization model. Perron *et al.* (2010) introduced a heuristic method named variable neighborhood search (VNS) to deal with the aforementioned problem of the exact solution. This method has been used by several researchers in waste management studies (Asefi et al., 2019; Barbucha, 2019; Tayebi Araghi *et al.*, 2021).

2.4.3 Meta-Heuristic Approaches

Metaheuristics have become very popular in waste management modelling recently. When there is a lack of complete information about the model, the metaheuristic methods tend to perform better as they are usually problem-independent. Several metaheuristic methods have been used in IMSWM modelling.

Akhtar *et al.* (2016) applied Particle swarm optimization (PSO) to solve an optimization problem for waste collection systems with constraints. Akhtar *et al.* (2016) also indicated that this method requires fewer tuning parameters. Hannan *et al.* (2018) implemented the PSO in a capacitated vehicle routing problem to optimize the waste collection routes. Although PSO is easy to implement and requires few parameters to control, Hannan *et al.* (2020) explained that this method can be trapped in a local minimum, and assigning the proper initial parameters is sometimes hard.

Another famous metaheuristic method is ant colony optimization (ACO) which is inspired by the movement of ant colonies that is directed by the pheromones left by the previous ants (Dorigo, 2006). Babaee Tirkolaee *et al.* (2020) proposed a hybrid augmented ACO algorithm to solve a capacitated arc routing problem for SWM. The main advantage of ACO is that the convergence in this method is guaranteed. However, the theoretical analyses are complex and harder to implement. Abdmouleh *et al.* (2017) also indicated that the probability distribution in this method could change for each iteration and the convergence time is uncertain.

An artificial bee colony (ABC) is inspired by the natural foraging act of honey bees. Le Dinh *et al.* (2013) demonstrated that the main advantage of ABC over other methods is the simplicity of this method, and it is more flexible and robust. Wei *et al.* (2019) developed a hybrid approach based on ABC to reduce the carbon emission of solid waste management. Against all the advantages, Hannan *et al.* (2020) indicated that this method has limited local searchability.

A genetic algorithm (GA) is one of the most utilized metaheuristic methods. The main algorithm consists of three stages: reproduction, crossover, and mutation. In a recent study, Pourreza Movahed *et al.* (2020) developed a multi-objective optimization model based on GA to minimize the energy consumption and emission of SWM. GA is relatively easy to implement, however, it is sometimes time-consuming and sometimes does not provide an exact solution.

Babaee Tirkolaee *et al.* (2019) proposed an efficient Simulated Annealing (SA) to solve the problem of multi-trip vehicle routing problems for urban waste collection. The method reduces the total costs by 13%. The SA method is flexible and can find the global optimum. But because it is a random search-based method, the convergence is usually small, and if the problem does not have too many local minimums, the use of this method cannot be justified. Also, this method needs more parameter tuning compared to other techniques.

Connor and Shea (2016) described the tabu search (TS) method as a concept that can help other methods not to be stuck in a local minimum. Shao *et al.* (2020) used the TS method alongside the variable neighborhood search to optimize the waste collection synchronization and find the best vehicle routes. TS usually gives precise solutions, but the convergence is usually slow.

From the literature review on optimization of IMSWM, it is identified that there is a lack of a comprehensive model that s all components of the system and considers a real-life situation where there are several uncertainties in the parameters of the IMSWM system.

Most of the revied models have tried to solve their problem using the exact method so the problem size should be limited. To be able to solve real-life instances of the solid waste optimization problem, heuristic and meta-heuristic methods are encouraged to be used in the literature. However, very few studies have tried to develop a heuristic method to solve the problem. (Mahmoudsoltani *et al.*, 2018; Rabbani *et al.*, 2019; Delgado-Antequera *et al.*, 2020)

Considering uncertainties in the IMSWM is a topic that has received a lot of interest lately. The types of uncertainties that have been considered in the literature are reviewed earlier in the uncertainties section. In most of these studies, the fuzzy chance constraint method is used to deal with the uncertainties in the system (Bui *et al.*, 2020; Bavaghar *et al.*, 2021; Mamashli and Javadian, 2021; Tirkolaee, *et al.*, 2021). As mentioned before, very few studies have used evolutionary algorithms in IMSWM problems. To the best of our knowledge, no study in IMSWM has considered using robust evolutionary optimization to deal with uncertainties in the system.

2.5 Summary and Conclusion

This Chapter reviewed several modeling methods for IMSWM systems and the various solutions methods of the models. The models are discussed in two major categories of deterministic and uncertain models.

In the existing literature on deterministic modeling of IMSWM systems, despite having a great amount of research, most studies have considered economic and environmental objectives in their model and the social objective has gotten much less attention. Although some researchers have used social objectives in their model, the numerous parameters that affect the social acceptance of the model are usually ignored and just a few social acceptance indicators are used. The composition of the generated waste is also one of the important parameters that is crucial for proper decision making especially in selecting the types of used technologies.

Several parameters in an IMSWM model are subject to uncertainty meaning that the exact value of these parameters cannot be identified. Several studies have considered uncertainty in their models. however, there is usually more than one parameter in the uncertain model, while many studies only consider demand or waste generation as an uncertain parameter. Some studies that have considered multiple uncertainties in their model are reviewed in this Chapter. The review indicated that most of these studies usually consider uncertainty in parameters that are related to one component or level of the system. While to have a proper assessment of the effect of uncertainties on the model, the important parameters subject to uncertainty should be identified in each component of the system like generation, transportation, and waste markets.

Chapter 3 :Integrated Solid Waste Management System: Modelling and Solving Deterministic IMSWM Model

In this Chapter, based on the literature review conducted in Chapter 2 an IMSWM model is developed as a mathematical programming model and then solved using MILP methods and evolutionary algorithms.

3.1 Model Description

A schematic view of the developed model for this study is demonstrated in Figure 3.1: Components of the proposed solid WM system. Each generation point is considered to produce two kinds of waste: mixed waste and recyclable waste. To identify the effect of establishing transfer stations, mixed waste can either be transferred to transfer stations or directly to disposal facilities. Recyclable waste can be taken directly to the appropriate recycling facility or transferred to a transfer station first. Transfer stations act as sorting facilities that sort the input waste regardless of its origin and send the waste to suitable facilities between recycling, treatment, and disposal facilities. The waste is processed in each recycling and treatment facility, and the products are sent to compatible markets. The residue waste from the process is sent directly to disposal facilities, where a part of the waste is transferred into energy, and the rest is disposed of using different techniques.

The location of the candidate facilities is given to the model as input data. The distance between any two locations on the network is calculated using the spatial data from the open street map database using Dijkstra's shortest path algorithm (Dijkstra, 1959).

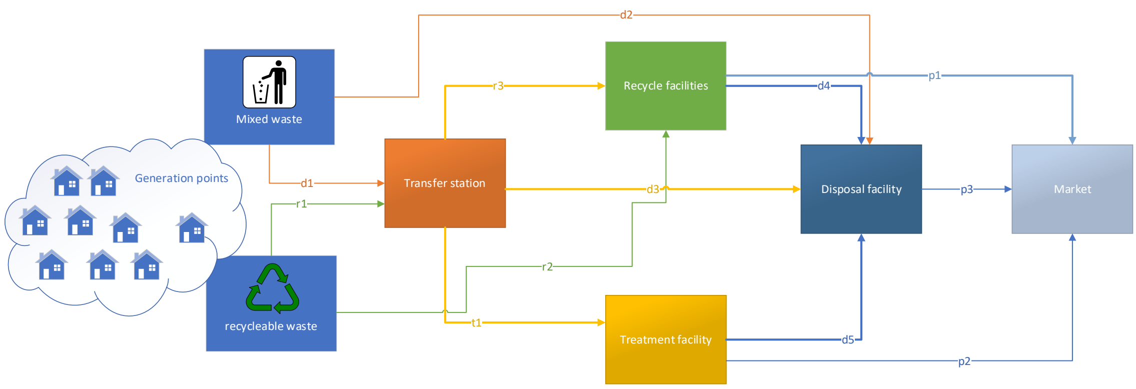


Figure 3.1: Components of the proposed solid WM system

In Figure 3.1 the waste travel passes are shown as follows:

r1 is the amount of source-separated recyclable waste which is transferred to transfer stations for sorting and transportation.

r2 is the amount of source-separated recyclable waste which is transferred directly to the compatible recycling facility.

r3 is the amount of recyclable waste sorted at transfer stations that is sent to a compatible recycling facility.

d1 is the amount of mixed waste generated at generation points that are transferred to transfer stations for sorting and transportation.

d2 is the amount of mixed waste generated at generation points that are transferred directly to landfill facilities for disposal.

d3 is the amount of mixed waste sorted in transfer stations, that is transferred to landfills for disposal

d4 is the amount of mixed waste residue in recycling facilities, that is transferred to landfills for disposal

d5 is the amount of mixed waste residue in treatment facilities, that is transferred to landfills for disposal

t1 is the amount of treatable waste sorted at transfer stations, that is transferred to treatment facilities.

P1 is the amount of recycled materials from recycling facilities, that are transferred to waste markets.

P2 is the amount of treated waste from treatment facilities, that is transferred to waste markets.

P3 is the total energy recovery of landfills.

Nomenclature for the model

3.1.1 Model Sets

$g \in G$ waste generation nodes

$k \in K$ potential transfer station nodes

r∈R potential recycling nodes

$t \in T$ potential treatment nodes

l∈L potential landfill nodes

m∈M potential waste market nodes

3.1.2 Variable Sets

Waste amount variables cannot be negative numbers. Therefore, each of the defined variables is a continuous variable with a lower bound of 0. The facility establishment variables are defined as binary variables: 1 when the facility is established and 0 otherwise.

Disposal waste variables:

$d1_{i,j}$: disposal waste amount from generation point i to transfer stations j, $i \in G, j \in K$

$d2_{i,j}$: disposal waste amount from generation point i directly to landfill j, $i \in G, j \in L$

$d3_{i,j}$: disposal waste amount from transfer station i to landfill j , $i \in k, j \in L$

$d4_{i,j}$: disposal waste amount from recycling facility i to landfill j , $i \in R, j \in L$

$d5_{i,j}$: disposal waste amount from treatment facility i to landfill j , $i \in T, j \in L$

d6j: disposal waste amount that has been disposed of in landfill i, $j \in L$

Recyclable waste variables:

$r1_{i,j}$: recyclable waste amount from generation point i to transfer station j, $i \in G, j \in K$

$r2_{i,j}$: recyclable waste amount from generation point i directly to recycle facility j, $i \in G, j \in R$

$r3_{i,j}$: recyclable waste amount from transfer station i to recycle facility j, $i \in k, j \in R$

Treatable waste variables:

$t1_{i,j}$: treatable waste amount from transfer station i to treatment facility j , $i \in k, j \in T$

Product variables:

$p1_{i,j}$: recycled product amount from recycling facility i to market j , $i \in R, j \in M$

$p2_{i,j}$: treated products amount from treatment facility i to market j, $i \in T, j \in M$

$p3_{i,j}$: products amount from landfill i to market j, $i \in L, j \in M$

Facility establishment variables

transfer_e_i: is 1 when the transfer facility is established at node i and 0 otherwise, $i \in K$

recycle_e_i: is 1 when recycle facility is established at node i and 0 otherwise, $i \in R$

treatment_e_i: is 1 when treatment facility is established at node i and 0 otherwise, $i \in T$

landfill_e_i: is 1 when the transfer facility is established at node i and 0 otherwise, $i \in L$

market_e_i: is 1 when the market is established at node i and 0 otherwise, $i \in M$

3.1.3 Model Parameters

Waste amounts:

node: G

mixed_$waste_i$: is the amount of mixed waste generated at generation node $i \in G$

recyclable_$waste_i$: is the amount of recyclable waste generated at generation node $i \in G$

Transportation cost:

node: G

c_{ij}: is the cost of transferring one unit of mixed waste on the link $(i,j) \in A$, $i \in G,K,R,T,L$, $j \in K, R,T,L,M$

Infrastructure cost

transfer_f_i is the fixed cost of opening a transfer station at node $i \in K$

recycle_f_i is the fixed cost of opening a recycling facility at node $i \in R$

treatment_f_i is the fixed cost of opening a treatment facility at node $i \in T$

landfill_f_i is the fixed cost of opening a landfill center at node $i \in L$

market_f_i is the fixed cost of selling at one unit of waste at the market at node $i \in M$

Variable processing cost

$transfer\_v_i$ is the variable cost of processing one unit of waste at the transfer station at node $i \in K$

$recycle\_v_i$ is the variable cost of processing one unit of waste at a recycling facility at node $i \in R$

$treatment\_v_i$ is the variable cost of processing one unit of waste at the treatment facility at node $i \in T$

$landfill\_v_i$ is the variable cost of processing one unit of waste at the landfill center at node $i \in L$

$market\_v_i$ is the variable cost of processing one unit of waste at the market at node $i \in M$

Facility capacities

$transfer\_c_i$ is the capacity of the transfer station at node $i \in k$

$treatment\_c_i$ is the capacity of the treatment technology $q \in Q$ at node $i \in T$

$recycle\_c_i$ is the capacity of the recycling technology $l \in L$ at node $i \in R$

$landfill\_c_i$ is the capacity of the landfill facility at node $i \in L$

$market\_c_i$ is the capacity of the market facility at node $i \in M$

Minimum amounts for opening new facilities.

$transfer\_m_i$: is the minimum amount of mixed waste required to establish a transfer station at node $i \in K$

$recycle\_m_i$: is the minimum amount of recyclable waste required to establish a recycling facility at node $i \in R$

$treatment\_m_i$: is the minimum amount of treatable waste required to establish a treatment facility at node $i \in T$

$landfill\_m_i$: is the minimum amount of disposal waste required to establish a landfill facility at node $i \in L$

$market\_m_i$: is the minimum amount of product required to establish a market facility at node $i \in M$

Final price of waste

$Sell\_price_i$: is the price of one unit of product at node $i \in M$

GHG emissions

GHG_mixed_{ij}: is the total GHG emissions produced in the process of collection and transportation of mixed waste from node i to node j

$GHG\_recycle_{ij}$: is the total GHG emissions produced in the process of collection and transportation of processed waste from node i to node j

$GHG\_transfer_i$: is the total GHG emission from processing one ton of waste in the transfer station i

GHG_recyle_i: is the total GHG emission from recycling one ton of waste in the recycling station i

$GHG\_treatment_i$: is the total GHG emission from the treatment of one ton of waste in the treatment facility i

$GHG\_landfill_i$: is the total GHG emission from the disposal of one ton of waste in the landfill facility i

Compatibility of waste types

Compatibility i,j: is 1 when the waste type from the facility I is compatible to be transferred to facility j and is 0 otherwise

3.1.4 Objective Function

A sustainable SWM system aims to minimize the total system cost, minimize the environmental hazards of the system, and maximize the social acceptance of the system. Based on these three strategies, three main groups of objective functions are defined for the WM model.

3.1.4.1 Economic Objective

The first objective function is to minimize the total cost of the system. Equation (1) calculates the total cost of collection and transportation of waste from generation points to system facilities, fixed establishment cost of the system facilities, process cost of the system based on the amount of waste that is being processed at each facility, and system's total revenue by selling waste products in the compatible markets. Based on these equations, the first objective function is calculated.

$$
\begin{aligned}
\text{Minimize f1(x)} = & \left\{\sum_{i\in G}\sum_{j\in K} c_{i,j}d1_{i,j} + \sum_{i\in G}\sum_{j\in L} c_{i,j}d2_{i,j} + \sum_{i\in K}\sum_{j\in L} c_{i,j}d3_{i,j} + \sum_{i\in R}\sum_{j\in L} c_{i,j}d4_{i,j}\right. \\
& + \sum_{i\in T}\sum_{j\in L} c_{i,j}d5_{i,j} + \sum_{i\in G}\sum_{j\in K} c_{i,j}r1_{i,j} + \sum_{i\in G}\sum_{j\in R} c_{i,j}r2_{i,j} + \sum_{i\in K}\sum_{j\in R} c_{i,j}\, r3_{i,j} \\
& \left. + \sum_{i\in K}\sum_{j\in T} c_{i,j}\, t1_{i,j} + \sum_{i\in R}\sum_{j\in M} c_{i,j}\, p1_{i,j} + \sum_{i\in T}\sum_{j\in M} c_{i,j}\, p2_{i,j} + \sum_{i\in l}\sum_{j\in M} c_{i,j}\, p3_{i,j}\right\} \\
& + \left\{\sum_{i\in K} transfer_{f_i} transfer_{e_i} + \sum_{i\in R} recycle_{f_i} recycle_{e_i} + \sum_{i\in T} treatment_{f_i} treatment_{e_i}\right. \\
& \left. + \sum_{i\in L} landfill_{f_i} landfill_{e_i} + \sum_{i\in M} market_{f_i} market_{e_i}\right\} \\
& + \left\{\left(\sum_{i\in G}\sum_{j\in K} d1_{i,j} + \sum_{i\in G}\sum_{j\in K} r1_{i,j}\right) transfer_{v_j}\right. \\
& + \left(\sum_{i\in G}\sum_{j\in R} r2_{i,j} + \sum_{i\in K}\sum_{j\in R} r3_{i,j}\right) recycle_{v_j} + \left(\sum_{i\in K}\sum_{j\in T} t1_{i,j}\right) treatment_{v_j} \\
& + \left(\sum_{i\in G}\sum_{j\in L} d2_{i,j} + \sum_{i\in K}\sum_{j\in L} d3_{i,j} + \sum_{i\in R}\sum_{j\in L} d4_{i,j} + \sum_{i\in T}\sum_{j\in L} d5_{i,j}\right) landfill_{v_l} \\
& \left. + \left(\sum_{i\in R}\sum_{j\in M} p1_{i,j} + \sum_{i\in T}\sum_{j\in M} p2_{i,j} + \sum_{i\in L}\sum_{j\in M} p3_{i,j}\right) market_{v_m}\right\} \\
& - \left\{\sum_{i\in R}\sum_{j\in M} p1_{i,j}\, sellprice_j + \sum_{i\in T}\sum_{j\in M} p2_{i,j}\, sellprice_j + \sum_{i\in L}\sum_{j\in M} p3_{i,j}\, sellprice_j\right\}
\end{aligned}
\tag{1}
$$

3.1.4.2 Environmental objective

Greenhouse gasses (GHG) increase the planet's temperature by tarping the heat. EPA (2014) indicated that Human activities are entirely responsible for the increase in the past 150 years. The most important sector responsible for GHG emissions is the Transportation sector based on the EPA. As transportation is an important element of the IMSWM system, along with different facilities and activities that have GHG emissions, assessing the environmental efficiency of the system can be achieved by calculating and minimizing the GHG emissions of the whole system (Edalatpour *et al.*, 2018; Mohsenizadeh *et al.*, 2020; Wang *et al.*, 2020).

3.1.4.2.1 GHG emissions

It has been proven that greenhouse gas (GHG) is the reason for huge climate change worldwide (Thanh & Matsui, 2013). Solid waste management consists of several functional elements each as a source of GHG production (Edalatpour *et al.*, 2018; Kristanto & Koven, 2019; Mohsenizadeh *et al.*, 2020; Walmsley *et al.*, 2018; Wang *et al.*, 2020). According to EPA (2014), carbon dioxide (CO2) with 76 percent is the main part of GHG, and following that is methane(CH4) with 16 percent and nitrous oxide (N2O) with 6%. Fluorinated gases (F-gases) are also 2 percent of GHG. According to AR6 Synthesis Report: Climate Change 2022 — IPCC (2019), the waste management industry contributes 3 to 4 percent of total world GHG production. Chen *et al.* (2010) indicated that the rapid growth in solid waste generation in societies resulting from population growth and economic development had become a major challenge in both economic and environmental aspects.

Landfilling is the main strategy of waste disposal in most countries, which is one of the main sources of producing methane (CH4) as one of the main parts of GHG (Scheutz *et al.*, 2014). However, the CO2 generation in landfills is not considered very high. A huge part of CO2 production in the waste management system relates to the transportation sector. The main source of GHG in waste transportation is the consumption of fossil fuels. Total GHG emissions of vehicles include the emission caused by burning fossil fuels plus the emissions from the exhaust purification process of vehicles. Because the nature of the waste collection process includes several stops and the operation and longer idle time, and since the GHG emission of vehicles is different in different working loads, calculating the GHG emissions of waste collection is challenging. Several studies have tried to estimate the GHG emission of the waste collection and transportation process (Eisted *et al.*, 2009; Gilardino *et al.*, 2017; Korkut *et al.*, 2018; Nguyen & Wilson, 2010; Pérez *et al.*, 2017)

In this model, two types of collection vehicles are used to collect solid waste generated in the city based on the type of generated waste. We are using the GHG estimation method developed by Chen and Lo (2016) to estimate the GHG emissions from several components of the waste management system. Table 3.1 shows the estimated GHG emission from waste management activities in our model.

Table 3.1: GHG emissions from waste management activities and facilities

sector	GHG Gas	Emission	Unit	Reference
Mixed waste transfer	CO_2	0.0191	kg CO_2/km/ton	(Kristanto & Koven, 2019)
recyclable waste transfer	N_2O	0.0497	kg $CO_{2\text{-}eq}$/km/ton	(Kristanto & Koven, 2019)
Recycled product transfer	CO_2	0.0226	kg CO_2/km/ton	(Korkut *et al.*, 2018)
Recycled product transfer	N_2O	0.051	kg $CO_{2\text{-}eq}$/km/ton	(Korkut *et al.*, 2018)
Transfer station facility	CO_2	0.032	kg $CO_{2\text{-}eq}$ /ton	(Environmental Protection Agency, 2002)
Waste recycle facility	CO_2	0.05	kg CO_2 /ton	(Y. C. Chen & Lo, 2016)
Waste treatment facility	CH_4	125	kg $CO_{2\text{-}eq}$ /ton	(Pipatti *et al.*, 2006)
Sanitary landfill	CH_4	300	kg $CO_{2\text{-}eq}$ /ton	(Belanger*et al.* , 2009)

The environmental objective function has two main parts: the total GHG emission of transporting waste and products between facilities of the system and the total GHG emission of processing waste inside each facility

$$\text{Minimize f2(x)} = \Bigg\{\sum_{i\in G}\sum_{j\in K} d1_{i,j}GHGmixed_{i,j} + \sum_{i\in G}\sum_{j\in L} d2_{i,j}GHGmixed_{i,j} + \sum_{i\in G}\sum_{j\in K} r1_{i,j}GHGrecycle_{i,j}$$
$$+ \sum_{i\in G}\sum_{j\in R} r2_{i,j}GHGrecycle_{i,j} + \sum_{i\in K}\sum_{j\in R} r3_{i,j}GHGrecycle_{i,j} + \sum_{i\in K}\sum_{j\in T} t1_{i,j}GHGrecycle_{i,j}$$
$$+ \sum_{i\in K}\sum_{j\in L} d3_{i,j}GHGrecycle_{i,j} + \sum_{i\in R}\sum_{j\in L} d4_{i,j}GHGrecycle_{i,j} + \sum_{i\in R}\sum_{j\in M} p1_{i,j}\,GHGrecycle_{i,j}$$
$$+ \sum_{i\in T}\sum_{j\in L} d5_{i,j}GHGrecycle_{i,j} + \sum_{i\in T}\sum_{j\in M} p2_{i,j}\,GHGrecycle_{i,j} + \sum_{i\in l}\sum_{j\in M} p3_{i,j}\,GHGrecycle_{i,j}\Bigg\} \tag{2}$$
$$+ \Bigg\{\left(\sum_{i\in G}\sum_{j\in K} d1_{i,j} + \sum_{i\in G}\sum_{j\in K} r1_{i,j}\right)GHGtransfer_j$$
$$+ \left(\sum_{i\in G}\sum_{j\in R} r2_{i,j} + \sum_{i\in K}\sum_{j\in R} r3_{i,j}\right)GHGrecycle_j + \left(\sum_{i\in K}\sum_{j\in T} t1_{i,j}\right)GHGtreatment_j$$
$$+ \left(\sum_{i\in G}\sum_{j\in L} d2_{i,j} + \sum_{i\in K}\sum_{j\in L} d3_{i,j} + \sum_{i\in R}\sum_{j\in L} d4_{i,j} + \sum_{i\in T}\sum_{j\in L} d5_{i,j}\right)GHGlandfill_j\Bigg\}$$

3.1.4.3 Social sustainability objectives

Hosseinijou *et al.* (2013) demonstrated that due to the high number of stakeholders with diverse backgrounds, quantifying and controlling the social effects of a system requires considering several attributes. Due to this large number of attributes, Andrews (2009) published the guidelines for the Social Life Cycle Assessment of Products to simplify the measurement and implementation of social responsibility. Several other publications have also suggested other guidelines on social responsibility (Compact, 2007; Hemphill, 2013; SAI, 2014). Table 3.2 shows five groups of stakeholders and 31 impact subcategories in social sustainability introduced by Andrews (2009).

Table 3.2: social sustainability impact factors

Stakeholders	*Impact subcategories*
Worker	*Freedom of association and collective bargaining*
	Child labor
	Fair salary
	Working hours

	Forced labor
	Equal opportunities/discrimination
Consumer	Health and safety
	Social benefits/social security
	Health and safety
	Feedback mechanism
	Consumer privacy
	Transparency
	End-of-life responsibility
	Access to material resources
Local community	Access to immaterial resources
	Delocalization and migration
	Cultural heritage
	Safe and healthy living conditions
	Respect for indigenous rights
	Community engagement
	Local employment
	Secure living conditions
Society	*Public commitments to sustainability issues*
	Contribution to economic development
	Prevention and mitigation of armed conflicts
	Technology development
	Corruption
Value chain actors* (not including consumers)	Fair competition
	Promoting social responsibility
	Supplier relationships

Respect for intellectual property rights

According to Mirdar Harijani *et al.* (2017), the most important attributes that have been used in these guidelines are human rights, labor practices, fair operating practices, consumer issues, and community involvement and development. Mirdar Harijani *et al.* (2017) presented a proposed social sustainability measure with complete guidelines for stakeholders and impact categories to a panel that consists of managers, engineers, and other stakeholders to identify the most influential impact subcategories in the waste management field. Figure 3.2 shows The selected impact subcategories and the developed inventory indicators by Mirdar Harijani *et al.* (2017).

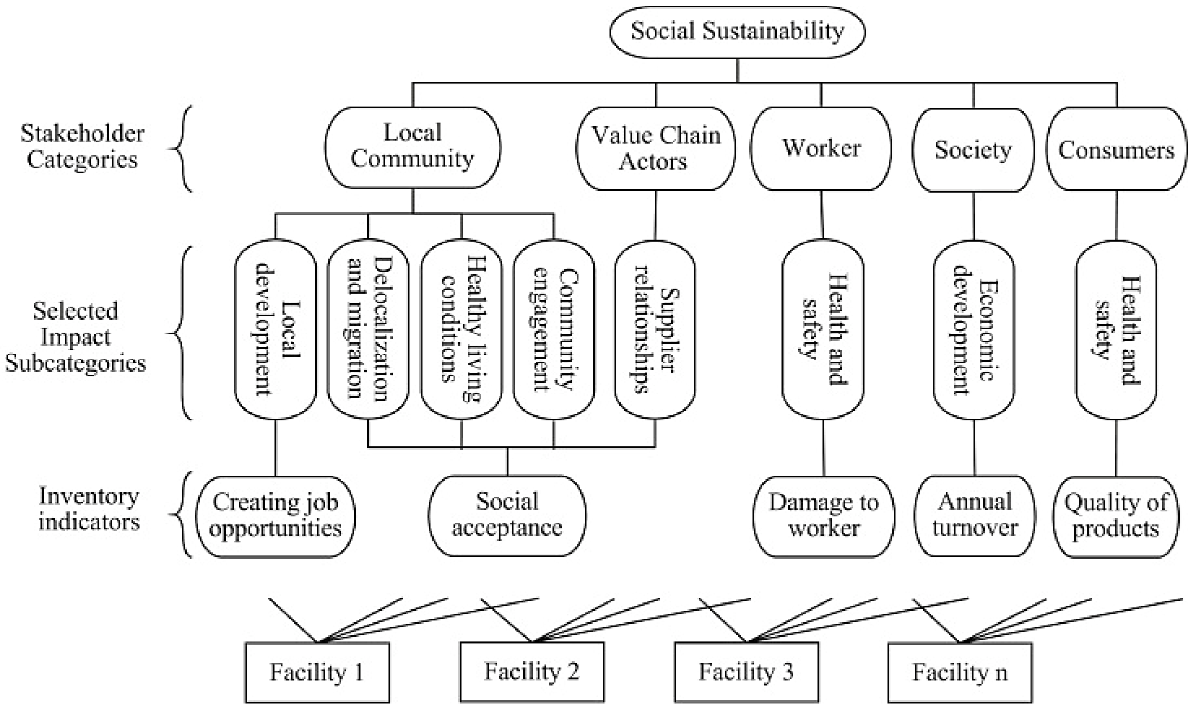


Figure 3.2:The selected impact subcategories and the developed inventory indicators by Mirdar (2017)

Andrews (2009) introduced four steps of goal and scope definition, life cycle inventory analysis, life cycle impact assessment, and life cycle interpretation to combine social issues and Life cycle assessment (LCA) and introduced Social LCA(S-LCA). Several researchers have used S-LCA to assess the social impact of different activities and decisions. For example, material selection in buildings, using special kinds of fuel, or even changes in socioeconomic parameters of societies (Beygi *et al.*, 2021; De Feo *et al.*, 2021; Hosseinijou *et al.*, 2013; Martín-Gamboa *et al.*, 2021; Pizarro-Loaiza *et al.*, 2021; Vavra *et al.*, 2021). There have been several attempts in the MSWM literature to identify the most important criteria impacting the IMSWM system under different conditions.

To develop a social objective function representing the social aspects of decisions, the different parameters related to social criteria should be identified, and their weights compared to each other should be identified. Multi-criteria decision-making (MCDM) techniques have been used widely in the literature to gain this goal.

Tsai *et al.* (2020) used the exploratory factor analysis (EFA) to select valid and reliable selection from the attributes from the literature. Tsai *et al.* (2020) identified several significant parameters in different aspects of IMSWM. In the aspect of social acceptability, the following parameters were selected as significant parameters:

- Community concerns
- Legislation and policies
- Stakeholders' involvement
- The institutional and organizational administration framework
- Occupational safety and health

Based on the literature on IMSWM, Phonphoton & Pharino (2019) identified other parameters as significant parameters in social aspects of IMSWM:

- The living condition of the local community (Garfì et al., 2009).
- The health of the community (Aragonés-Beltrán et al., 2010; Contreras et al., 2008; Garfì et al., 2009; Hanan et al., 2013; Hung et al., 2007; Josimović et al., 2015).
- Flexibility with population growth (Garfì et al., 2009).
- Social acceptability (Hanan et al., 2013; Hung et al., 2007).
- Landscape impact, visual impact (Aragonés-Beltrán et al., 2010; Feo & De Gisi, 2014; Garfì et al., 2009; Josimović et al., 2015; Moeinaddini et al., 2010)

Masoud Rabbani *et al.* (2021) also identified the most significant social indicators for assessing treatment facilities. Then they used the pairwise comparisons in super decision software to identify the weights of the social indicators. Table 3.3 indicates the weights of the social indicators calculated by Masoud Rabbani *et al.* (2021)

Table 3.3: social indicators weights

Indicator	Weight

Social acceptance	0.107
Job opportunities	0.076
Public health	0.304
Land occupation	0.057
Occupational health	0.238
Quality of products	0.218

Based on the literature review, 11 social indicators are selected to assess the social acceptance of the model. These indicators are from each of the groups indicated in Table 3.3 and indicated in Table 3.4, along with their calculated weights.

Table 3.4:Weights of attributes obtained from super decision software by Rabbani (2021)

	Indicator group	Indicator	References	weights
1	Social acceptance	Proximity to population hubs	(Asefi et al., 2019)	0.046568
2		Visual pollution	(Habibi *et al.*, 2017)	0.046568
3		Proximity to major roads	(Asefi et al., 2019; Galante *et al.*, 2010; Minciardi *et al.*, 2008)	0.046568
4		Odor pollution	(Gabriel *et al.*, 2017; Lyeme *et al.*, 2016; Toutouh *et al.*, 2019)	0.046568
5	Job opportunitie s	Job creation opportunity	(Bahrani *et al.*, 2016; Heidari *et al.*, 2019; Mamashli & Javadian, 2021; Olapiriyakul *et al.*, 2019)	0.095818
6	Public health	Proximity to groundwater resources	(Cheng *et al.*, 2003; Singh, 2019; Su *et al.*, 2008; Yousefloo & Babazadeh, 2020; Zhang *et al.*, 2010)	0.171818

7		Soil contamination from facilities	(Ahluwalia & Nema, 2007; Habibi *et al.*, 2017; Mamashli & Javadian, 2021; Singh, 2019; Yousefloo & Babazadeh, 2020)	0.171818
8	Land occupation	Land use	(Olapiriyakul *et al.*, 2019; Ooi *et al.*, 2021; Pourreza Movahed *et al.*, 2020; Rizwan *et al.*, 2020)	0.048318
9		Land cost	(Ding *et al.*, 2018; Gbanie *et al.*, 2013; Ishimura & Takeuchi, 2019; Ooi *et al.*, 2021)	0.048318
10	Occupational health	Noise pollution	(Ahani *et al.*, 2019; Galante *et al.*, 2010; Yu & Solvang, 2017)	0.138818
11		Worker's health	(Ahluwalia & Nema, 2007; Gautam & Kumar, 2005; Guerrero *et al.*, 2013; Mamashli & Javadian, 2021; Tsai *et al.*, 2020)	0.138818

3.1.4.3.1 Proximity to population

Not in my backyard (NIMBY) refers to a group of opposition against proposed developments in specific residential areas. These residents are against the development because the changes are close to their houses. Solid waste activities have a high potential of being opposed by the people who do not want these facilities near their houses. Also, because of several health hazards of some solid waste management activities, there have been some regulations on the distance of some of these facilities from residential areas. For example, EPA (2002) dictates a landfill facility should be at least 250 meters away from any sensitive area.

To identify the proximity of the number of residential buildings in a radius of any facility, the facility is ranked based on the number of households in its neighborhood. Based on the health hazards and the NIBMY syndrome, the lower number of households in the neighborhood is a more suitable solution for the system.

3.1.4.3.2 Visual pollution

Because of the several pollution including odor, noise, and air pollution, waste management facilities are not considered pleasant locations. Being exposed to these facilities damages the people's ability to enjoy the scenery and is considered a negative point for the facility. To calculate this indicator, different activities in the system are ranked based on people's opinions to identify the facilities with the most visual pollution. Then for this indicator, the affected population is also calculated to identify the ranking of facilities based on this indicator.

3.1.4.3.3 Proximity to major roads

Asefi *et al.* (2019) indicated that closeness to major roads can reduce the total cost of waste management systems, but placing the waste management facilities too close to the roads might create additional traffic and interfere with the flow of normal traffic. Asefi *et al.* (2019) propose a 100-meter buffer zone from each side of the road and score the suitability of the location by ranking the location based on proximity to major roads. The geographical information of the roads in the case study is extracted from shapefiles provided by ACT Government GeoHub. For each candidate location, the proximity of the location to the nearest main road is calculated, and the locations are ranked based on the proximity. Based on the open street map data for the street network of the case study, the roads and junctions with the “Primary “ attribute are considered main roads.

3.1.4.3.4 Odor pollution

Different waste management facilities have different odor pollution specific to them. Some facilities like the incinerator and landfills have more power pollution than others. To calculate this indicator, the facility types are ranked based on their odor pollution. Then the affected population for each facility is calculated using the number of households in a radius. The total odor effect of any facility is then calculated using these numbers. Antonopoulos *et al.* (2014) researched odor from different waste treatment activities and estimated the total odor from different waste facilities. The amounts of odor from waste management facilities are demonstrated in Table 3.5.

Table 3.5: odor from facilities

Facility	Odor (U/yr.)
Transfer stations	80
Material recovery	45
Digestion	217
Anerobic digestion	217
Landfill	185
Incineration	4.41

3.1.4.3.5 Job creation

Vernon *et al.* (2001) indicated that the requirement of governments to create more sustainable societies had driven them to consider the environmental and social impacts of their proposed activities to balance them with their economic effects on employment and inflation. Vernon *et al.* (2001) also demonstrate that because of the potential of some waste management strategies, there has been a considerable debate on the effect of different waste management strategies on employment.

The department of the environment, water, heritage and arts of Australia in the report of Economics for the Department of the Environment & Arts (2009), aimed to determine the net amount of direct and indirect employment as a result of different waste management policies like recycling, recovery, reduction, etc. Recycling waste includes more activities compared to other sectors in the waste management system. These activities include sorting, transferring, and transforming new materials that, according to Economics for the Department of the Environment & Arts (2009), most of them are labor-intensive, meaning that they need manpower for the activities. This report indicates that when 90% of waste is recycled, every 4200 tons of waste can create one full-time job. However, if 75% and more of waste is directed to landfills, every 10000 tons of waste can create a job opportunity. Based on access economics (2009), recycling creates 9.2 direct jobs per 10000 tons of waste. While landfilling creates 2.8 direct jobs for the same amount of waste. Table 3.6 shows the number of direct jobs created per 10000 tons of waste in each type of facility in the waste management system.

Table 3.6:job creation opportunity for waste facilities

Facility	Direct job opportunity per 10000 tons of waste	References
Transfer station	6.8	(Economics for the Department of the Environment & Arts, 2009)
Recycle facility	9.2	
Treatment facility	8.8	
landfill	2.8	
market	4.2	

3.1.4.3.6 Proximity to groundwater resources

Solid waste management activities, especially landfilling, can have potential hazards for groundwater resources. The leach from landfills can contaminate the soil and eventually the underground water reservoir. Therefore EPA (2002) has ranked areas with groundwater vulnerability, and based on this ranking, a landfill cannot be built in areas with high and very high vulnerability.

Based on The ACT Government Groundwater Monitoring Bores, groundwater depth is calculated. This indicator is calculated for the facility using the depth of groundwater and the amount of processed waste in the facility.

3.1.4.3.7 Soil contamination

Shankar *et al.* (2017)indicated that soil contamination in solid waste facilities occurs mostly in landfill facilities. In landfill facilities, due to the production of leaches based on the level of control over leaches, it can contaminate soil under and around the landfill facilities. Based on soil contamination hazards for the facilities, the ranking of the facilities is indicated in Table 3.7

Table 3.7:soil contamination by facilities

Facility	Rank
Transfer station	3
Recycle facilities	2
treatment facilities	4
Landfills	5
Markets	1

3.1.4.3.8 Land use

The usage of the land is an important decision factor when the land is being selected for solid waste activities. The usage of the surrounding lands of a waste facility is also important for decision-making. Different kinds of facilities require different safety distances from specific land uses. Based on Olapiriyakul *et al.* (2019), incinerators and landfills require more safety distance from some land uses. Table 3.8 shows their proposed safety distances from waste facilities.

Table 3.8: Safety distance from waste facilities by Olapiriyakul *et al.* (2019).

Land use	**Transfer station(km)**	**Incinerator (km)**	**Landfill (km)**
Residential	1	2	1
Archaeological heritage site	1	1	1
River	1	1	1

Pond	-	0.3	0.3
Main road	-	0.3	0.3

The land use information of the case study (ACT) has been extracted from shapefiles extracted from ACT government GeoHub. Then the distance of center points of closest land use for each type of land use is calculated from any waste facility, and there are ranked and based on the safety distance from land-use centroids.

3.1.4.3.9 Land cost

Land price is an essential factor in location selection for waste facilities. Land price affects the overall cost of the solid waste management system. This parameter has been considered in the economic objective function as the fixed cost of facilities. However, based on the suitability of waste management facilities, they have a different effect on the price of land around them. Gbanie *et al.* (2013) suggested that the price of land in cities directly depends on the number of people living in that area and the distance from major roads. The land cost indicator is calculated Using the least distance from main roads.

3.1.4.3.10 Noise pollution

Solid waste management activities usually involve the usage of heavy machinery and several workers that can cause noise pollution. Transportation of solid waste also creates noise pollution on all the collection routes. Ahani *et al.* (2019) indicated that the amount of noise can directly relate to both the amount of waste that is being dealt with and the number of affected people. To calculate this indicator, the total affected people is calculated using the household number in the radius and then multiplied by the noise pollution of each activity in the system and the amount of processed waste. Usually, noise pollution is considered in the worker health indicators because of the distance of waste management facilities from residential areas.

However, based on the different collection vehicles, the noise pollution from the vehicles is different, and the model is trying to identify the solution with the least noise pollution. Table 3.9 shows the measured noise levels by OMS (2020) from the Melbourne landfill.

Table 3.9: Noise levels of Melbourne landfill

Location	Direction	Day	Evening	Night
Riding Boundary Rd, Truganina	East	44	47	42
Western Highway, Ravenhall	north	58	51	49

Sheahan Rd, Rockbank	North-west	47	51	51
Middle Rd, Truganina	South-west	42	62	43

Similar assessments have been done for other waste management facilities. Considering the average noise pollution throughout the 24 hours and in all directions that data are available based on the references, the noise pollution of waste management facilities is shown in Table 3.10.

Table 3.10: Noise level of waste management facilities

Facility	Noise pollution	References
Transfer station	50.09	(County Solid Waste Division, 2012)
Recycle facility	51.33	Wetherill Park NSW
Treatment facility	31.5	(Mcleod & Bunker, 2016)
landfill	48.91	(OMS, 2020)

Worker's health

Tsai *et al.* (2020) studied the occupational hazard in waste management facilities based on the classification of important factors in selecting waste management facilities provided by Turcott Cervantes *et al.* (2018). Based on this ranking, the facility groups are ranked from 1 to 5, with 1 being the safest and 5 having the most occupational hazard. The ranking for each type of facility is indicated in Table 3.11.

Table 3.11: Workers' health in waste management facilities

Facility	Rank
Transfer station	2
Recycle facilities	3
treatment facilities	4
Landfills	5
Markets	1

3.1.4.4 Social indicator parameters

Based on the classification of social indicators for the problem and using the weights introduced by Rabbani *et al.* (2021), the data from the case study for different system facilities are gathered for each indicator. As the different indicators in the model have different units and measures, the vector normalization method is used to normalize the parameters. Then these values are multiplied by their weights introduced in Social sustainability objectives. The sum of normalized weighted indicators is calculated to create the social acceptance objective function for each facility. These values are indicated in Table 3.12

Table 3.12: Social acceptance of facilities

name	*population*	*visual*	*roads*	*odor*	*job*	*Groundwater*	*soil*	*Land use*	*Land cost*	*noise*	*Worker health*	*Social acceptance*
TS1	2966	4	1220	80	0.00068	13364	3	6491	922.0008	50.09	2	0.17499
TS2	4640	4	724	80	0.00068	11439	3	27945	2440.001	50.09	2	0.19919
TS3	2288	4	1507	80	0.00068	250	3	16708	447.0007	50.09	2	0.15401
GR	3491	3	44	45	0.00092	13244	2	9231	1292.023	51.33	3	0.17148
MR	3491	3	44	45	0.00092	13244	2	9231	1292.023	51.33	3	0.17148
PAR	3491	3	44	45	0.00092	13244	2	9231	1292.023	51.33	3	0.17148
PLR	3491	3	44	45	0.00092	13244	2	9231	1292.023	51.33	3	0.17148
AR	3491	3	44	45	0.00092	13244	2	9231	1292.023	51.33	3	0.17148
HR	3491	3	44	45	0.00092	13244	2	9231	1292.023	51.33	3	0.17148
MR	3491	3	44	45	0.00092	13244	2	9231	1292.023	51.33	3	0.17148
TR	3491	3	44	45	0.00092	13244	2	9231	1292.023	51.33	3	0.17148
OR	3491	3	44	45	0.00092	13244	2	9231	1292.023	51.33	3	0.17148
OT	3491	3	44	45	0.00092	13244	2	9231	1292.023	51.33	3	0.17148
CO	5854	4	68	217	0.00088	3656	4	20547	2649.015	31.5	4	0.22516
AD	5854	4	68	217	0.00088	3656	4	20547	2649.015	31.5	4	0.22516
LA	0	5	200	185	0.00028	17924	5	34007	0.005	48.91	5	0.23717
IN	0	5	200	185	0.00028	17924	5	34007	0.005	48.91	5	0.23717
GM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
MM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899

PAM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
PLM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
AM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
HM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
MM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
TM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
OM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
OTM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
COM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
ADM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
LAM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899
INM	189	2	2250	1	0.00042	22245	1	9062	0.000444	40.03	1	0.11899

TS1, TS2, TS3: transfer station 1,2,3; GR: glass recycle; MR: Metal recycle; PAR: paper recycle; PLR: plastic recycle; AR: ash recycle; HR: hazardous recycle; MAR: masonry recycle; TR: textile recycle; OR: other recycle; OT: organic treatment; CO: composting; AD: anaerobic digestion; LA: Landfilling; IN: incineration; GM: glass market; MM: Metal market; PAM: paper market; PLM: plastic market; AM: ash market; HM: hazardous market; MAM: masonry market; TM: textile market; OM: other markets; OTM: organic treatment market; COM: composting market; ADM: anaerobic digestion market; LAM: landfill market; Incineration market

For each facility, the amount of waste processed at each facility is calculated and multiplied by the social acceptance measure of that facility. Using this function, a suitability indicator is calculated for each facility in the system using the social acceptance Indicators and TOPSIS method. The acceptance measure indicates the suitability of each facility compared to other facilities. The aim is to maximize the social acceptance of the whole system.

$$
\begin{aligned}
maximize\ \ f3(x) \quad & \quad (3) \\
= +\Bigg\{ & \left(\sum_{i\in G}\sum_{j\in K} d1_{i,j} + \sum_{i\in G}\sum_{j\in K} r1_{i,j}\right) SAM_j \\
& + \left(\sum_{i\in G}\sum_{j\in R} r2_{i,j} + \sum_{i\in K}\sum_{j\in R} r3_{i,j}\right) SAM_j + \left(\sum_{i\in K}\sum_{j\in T} t1_{i,j}\right) SAM_j \\
& + \left(\sum_{i\in G}\sum_{j\in L} d2_{i,j} + \sum_{i\in K}\sum_{j\in L} d3_{i,j} + \sum_{i\in R}\sum_{j\in L} d4_{i,j} + \sum_{i\in T}\sum_{j\in L} d5_{i,j}\right) SAM_j \\
& + \left(\sum_{i\in R}\sum_{j\in M} p1_{i,j} + \sum_{i\in T}\sum_{j\in M} p2_{i,j} + \sum_{i\in L}\sum_{j\in M} p3_{i,j}\right) SAM_j \Bigg\}
\end{aligned}
$$

3.1.5 Model Constraints

The model is subject to several inequality and equality constraints that are introduced in this section.

Waste generation constraint

$$mixed_{waste_i} = \sum_{j \in K} d1_{i,j} + \sum_{j \in L} d2_{i,j} \qquad \forall i \in G \qquad (4)$$

$$recyclable_{waste_i} = \sum_{j \in K} r1_{i,j} + \sum_{j \in R} r2_{i,j} \qquad \forall i \in G \qquad (5)$$

Constraints (4) and (5) ensure that all the mixed/recyclable waste generated at the generation point at node i is collected and transferred to either a transfer station or landfill/recycling facility.

Mass balance constraints

$$\sum_{i \in G} d1_{i,j} + \sum_{i \in G} r1_{i,j} = \sum_{i \in R} r3_{j,i} + \sum_{i \in T} t1_{j,i} + \sum_{i \in L} d3_{j,i} \qquad \forall J \in K \qquad (6)$$

$$\sum_{i \in G} r2_{i,j} + \sum_{i \in K} r3_{i,j} = \sum_{i \in L} d4_{j,i} + \sum_{i \in M} p1_{j,i} \qquad \forall J \in R \qquad (7)$$

$$\sum_{i \in K} t1_{i,j} = \sum_{i \in L} d5_{j,i} + \sum_{i \in M} p2_{j,i} \qquad \forall j \in T \qquad (8)$$

$$\sum_{i \in G} d2_{i,j} + \sum_{i \in K} d3_{i,j} + \sum_{i \in R} d4_{i,j} + \sum_{i \in T} d5_{i,j} = \sum d6_j + \sum_{i \in M} p3_{j,i} \qquad \forall j \in L \qquad (9)$$

Constraints (6) to (9) ensure that the total amount of input waste that enters the transfer stations/facilities/market at node j is processed and transferred to the appropriate facilities, and no waste remains at the station/facilities.

Capacity constraints

$$\sum_{i \in G} d1_{i,j} + \sum_{i \in G} r1_{i,j} \leq transfer_{c_j} transfer_{e_j} \qquad \forall j \in K \qquad (10)$$

$$\sum_{i \in K} r2_{i,j} + \sum_{i \in G} r3_{i,j} \leq recycle_{c_j} recycle_{e_j} \qquad \forall j \in R \qquad (11)$$

$$\sum_{i \in G} t1_{i,j} \leq treatment_{c_j} treatment_{e_j} \qquad \forall j \in T \qquad (12)$$

$$\sum_{i \in G} d2_{i,j} + \sum_{i \in K} d3_{i,j} + \sum_{i \in R} d4_{i,j} + \sum_{i \in T} d5_{i,j} \leq landfill_{c_j} landfill_{e_j} \qquad \forall j \in L \qquad (13)$$

$$\sum_{i \in K} p1_{i,j} + \sum_{i \in R} p2_{i,j} + \sum_{i \in t} p3_{i,j} \leq market_{c_j} market_{e_j} \quad \forall j \in M \quad (14)$$

Constraints (10) to (14) limit the maximum total amount of disposal and recyclable waste that enters the transfer station/facilities/market at node j from generation points to their capacity of them.

Minimum amounts

$$\sum_{i \in G} d1_{i,j} + \sum_{i \in G} r1_{i,j} \geq transfer_{m_j} transfer_{e_j} \quad \forall j \in K \quad (15)$$

$$\sum_{i \in K} r2_{i,j} + \sum_{i \in G} r3_{i,j} \geq recycle_{m_j} recycle_{e_j} \quad \forall j \in R \quad (16)$$

$$\sum_{i \in G} t1_{i,j} \geq treatment_{m_j} treatment_{e_j} \quad \forall j \in T \quad (17)$$

$$\sum_{i \in G} d2_{i,j} + \sum_{i \in K} d3_{i,j} + \sum_{i \in R} d4_{i,j} + \sum_{i \in T} d5_{i,j} \geq landfill_{m_j} landfill_{e_j} \quad \forall j \in L \quad (18)$$

$$\sum_{i \in K} p1_{i,j} + \sum_{i \in R} p2_{i,j} + \sum_{i \in t} p3_{i,j} \geq market_{m_j} market_{e_j} \quad \forall j \in M \quad (19)$$

Constraints (15) to (19) limit the minimum total amount of disposal and recyclable waste that enters the transfer station/facilities/market at node j from generation points to the minimum establishment limit of them.

Waste -Technology compatibility constraints

$$r2_{i,j} \leq recyclable_{waste_i} compatability_{i,j} \quad \forall i \in G \quad \forall j \in R \quad (20)$$

$$p1_{j,l} \leq \left(\sum_{i \in K} r2_{i,j} + \sum_{i \in G} r3_{i,j} \right) compatability_{j,l} \quad \forall j \in R \quad \forall l \in M \quad (21)$$

$$p2_{j,k} \leq \left(\sum_{i \in G} t1_{i,j} \right) compatability_{j,k} \quad \forall j \in T \quad \forall k \in M \quad (22)$$

$$p3_{j,n} \leq \left(\sum_{i \in G} d2_{i,j} + \sum_{i \in K} d3_{i,j} + \sum_{i \in R} d4_{i,j} + \sum_{i \in T} d5_{i,j}\right) compatability_{j,n} \qquad \begin{array}{c} \forall j \in L \\ \forall n \in M \end{array} \qquad (23)$$

Constraint (20) ensures that a recycling facility is only established when a certain minimum percentage of a specific material is in waste proportion.

Constraint (21) to (23) ensures that the recycled product in the recycling/treatment/disposal facility is transferred to a compatible waste product market.

Non-negativity

$$\left(d1_{i,j}, d2_{i,j}, d3_{i,j}, d4_{i,j}, d5_{i,j}, r1_{i,j}, r2_{i,j}, r3_{i,j} t1_{i,j}, p1_{i,j}, p2_{i,j}, p3_{i,j}\right) \in \{\mathbb{R}^9\}^+ \qquad (24)$$

Binary variables

$$\left(transfer_{e_i}, recycle_{e_i}, treatment_{e_i}, landfill_{e_i}, market_{e_i},\right) \in \{0,1\}^5 \qquad (25)$$

3.2 Solution Methods

The model is formulated as a mixed-integer linear programming (MILP) problem. In addition, two well-known algorithms, namely non-dominated sorting genetic algorithms versions 2 and 3 (NSGA II and III), are adopted for developing suitable heuristic algorithms.

3.2.1 The MILP Epsilon Constraint Method

As Mavrotas (2009) indicates, in a single objective mathematical programming problem, the output is the optimal solution. However, in problems with more than one objective function usually a solution that optimizes all the objective functions at the same time does not exist. In multi-objective problems, the aim is to find the most preferred solution rather than the best solution. Therefore, in these problems, Pareto optimality replaces the optimality.

Hwang & Masud (1979), based on the stage where the decision-makers preference is applied to the problem, classified the solution methods for multi-objective mathematical programing problems into 3 groups:

- Priori methods
- Interactive methods
- Posteriorly methods

To deal with hard multiple objective problems, Becerra & Coello (2006) proposed the epsilon constraint method which is used to change the problem to a single objective by considering one objective function as the main and transforming the rest of the objective functions into constraints. This method has several advantages compared to Pareto-generating methods, such as the weighted sum method (Mahmoudsoltani *et al.*, 2018). However, in more extensive and more complex problems, MILP solvers cannot find results in a reasonable time. The model is solved three times, and in each solution, one of the objective functions is considered the main objective, and the other two are transformed into constraints.

3.2.2 The Evolutionary Approaches

The elitist NSGA developed by Deb *et al.* (2002) is one of the most popular evolutionary algorithms in multi-objective optimization.

Pseudocode of NSGA-II Algorithm	Pseudocode of NSGA-III Algorithm
Input: g: generations to solve	Input: g: generations to solve
Initialization (creating random population)	Initialization (creating random population)
Objective and constraint evaluation	Objective and constraint evaluation
Ranking Population	Ranking Population
Crossover (creating child population)	Crossover (creating child population)
Mutation	Mutation
For i = 1 to g:	For i = 1 to g:
For each child and parent in the population:	For each child and parent in the population:
Rank population	Rank population
Identify non-dominated solutions	Identify non-dominated solutions
Calculating crowding distance	Calculating crowding distance
Selecting the best solutions based on ranks	Selecting the best solutions based on ranks
End	End
Generate population for next generation	Normalize solutions using min and intercepts of objectives
	Associate each solution with a reference point
	Select best solutions using niche-preserving operator
	Generate population for next generation
	Normalize solutions using min and intercepts of objectives

Deb and Jain (2014) modified the NSGA-II algorithms by using the reference directions concept. In their method, called NSGA-III, the survival and non-dominated sorting are done like NSGA-II. The difference is that in the selection process, the solutions are selected based on their distances to some reference points, as shown in the pseudocodes.

3.2.2.1 Solution repair

Evolutionary algorithms (EA) are designed to deal with unconstrained optimization problems. For example, the waste generation constraint assures that all the generated waste in any generation node is completely removed from the generation site for a certain generation point. Mass-balance constraints in facilities also ensure that any facility's input and output amounts of waste should be equal. The existence of these equality constraints reduces the feasible space dramatically. Especially for evolutionary optimization, it is nearly impossible to find the true solution that satisfies all the equality constraints as the feasible region is very small and sometimes just a small node. Therefore, a repair function is created to modify the solution to make them feasible to deal with these equality constraints. Furthermore, the waste type compatibility with the recycling facilities and the compatibility of the recycled products with the markets should be considered in the repair function to avoid creating infeasible solutions.

A sample generation node N is used to demonstrate the used repair function. Let's assume that total mixed waste generation at node N equals D. Based on the network topology, the generated mixed waste at this node has overall four options to be collected (variables), namely $\mathrm{d1}_{11}$, $\mathrm{d1}_{12}$, $\mathrm{d1}_{13}$ and $\mathrm{d2}_{11}$.The waste collection equality constraint for this node is indicated in equation (26):

$$d1_{11} + d1_{12} + d1_{13} + d2_{11} = D \tag{26}$$

To have a feasible solution, this constraint should always be valid. To find the right value of variables that can satisfy this constraint, four random numbers (r1, r2, r3, r4) are generated that satisfies the equation (27):

$$\frac{r1}{r1+r2+r3+r4} + \frac{r2}{r1+r2+r3+r4} + \frac{r3}{r1+r2+r3+r4} + \frac{r4}{r1+r2+r3+r4} = 1 \tag{27}$$

So, we replace the values of the variables with values indicated in equations (28) to make sure the equality constraint is satisfied:

$$d1_{11} = \frac{r1}{r1+r2+r3+r4} * D; \quad d1_{12} = \frac{r2}{r1+r2+r3+r4} * D; \quad d2_{11} = \frac{r3}{r1+r2+r3+r4} * D; \; d1_{11} = \frac{r4}{r1+r2+r3+r4} * D \tag{28}$$

The repair function is constructed using all the equality constraints following this logic. The constructed repair function takes the current population of solutions as an input. Before evaluation, the repair function is applied to all the population. This repair assures that the equality constraint is satisfied for all the repaired solutions.

The random numbers r1 to r4 can take any value between 0 and 1. However, analyzing the solutions from exact methods shows that in most feasible solutions, only one of them is 1, and the rest are zero. This means at any node if the waste has multiple paths to choose from, in the optimal solutions, usually just one path is chosen instead of distributing waste between all possible paths. This analysis is indicated in, where only nodes with w=1 are selected. The color map shows the ratio of such nodes in each solution for the solutions obtained from the MILP method, reflecting that in all the feasible solutions, at least 80% of the nodes have w =1.

As our proposed repair function is completely stochastic, the chance of selecting 0 and 1 for the value of random coefficients is meager. To help the EA converge better toward the Pareto front, the repair function is modified with a clipping mechanism, in which in a percent of the function's executions for repair function, in the list of generated random numbers, the largest random number in the list is replaced by 1, and all the other members of the list are replaced by 0. In this function, a chance value is defined to identify the number of random sets produced with the new function (0,1 sets), and the rest of the random sets are generated randomly. A summary of the algorithms used in the repair function is shown in the pseudo-code below.

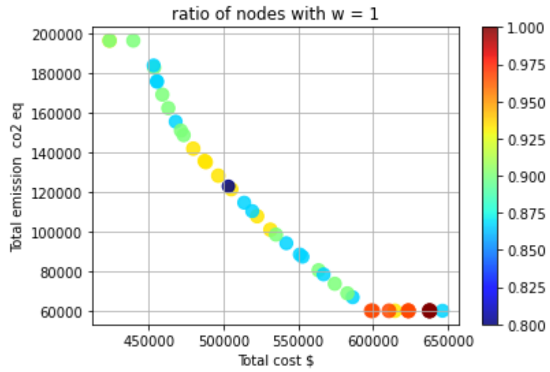


Figure 3.3: Solution nodes with only one output waste stream

Algorithm1: Create random numbers

Input: the length of the needed random numbers list.

Chance: the desired chance of creating a list of 0 and 1 numbers instead of random numbers.

Function randmaker (num, chance)

```
    Random_list = a list of a random number between 0 and 1 with the length of num
    If random_n >= chance then
        return Random_list
    Else
        random_list[max] ←1: change the value of a maximum number in the list to 1
        any other member of random list←0
    Return random_list
```

Algorithm2: Repair function

Input: population of variable values in each iteration of EV

Function MyRepair(population , chance)

```
    For every p in the population
        For every equality constraint as a+b+c = d:
```

```
3:      If the equality constraint is violated, then :
4:          Length ← number of participants in the constraint
5:          Random_list ← randmaker(length, chance)
6:          Sum_randoms← sum of generated random numbers
7:          For any i in random_list:
8:              Pop[i]←(i / sum_randoms) * d
9:              if pop[i] existes:
10:                 Go to 13
11:             Else:
12:             Replace i=1 with a compatible stream

13:  Return modified pop
```

3.3 Case Study

3.3.1 Model Data

Canberra is the capital city of Australia. With a population of 467194, Canberra is the ninth-largest city in Australia. Canberra is a planned city that was built to ensure its neutrality between states as the capital city. Figure 3.4 shows a demographic map of the Australian capital territory and its districts.

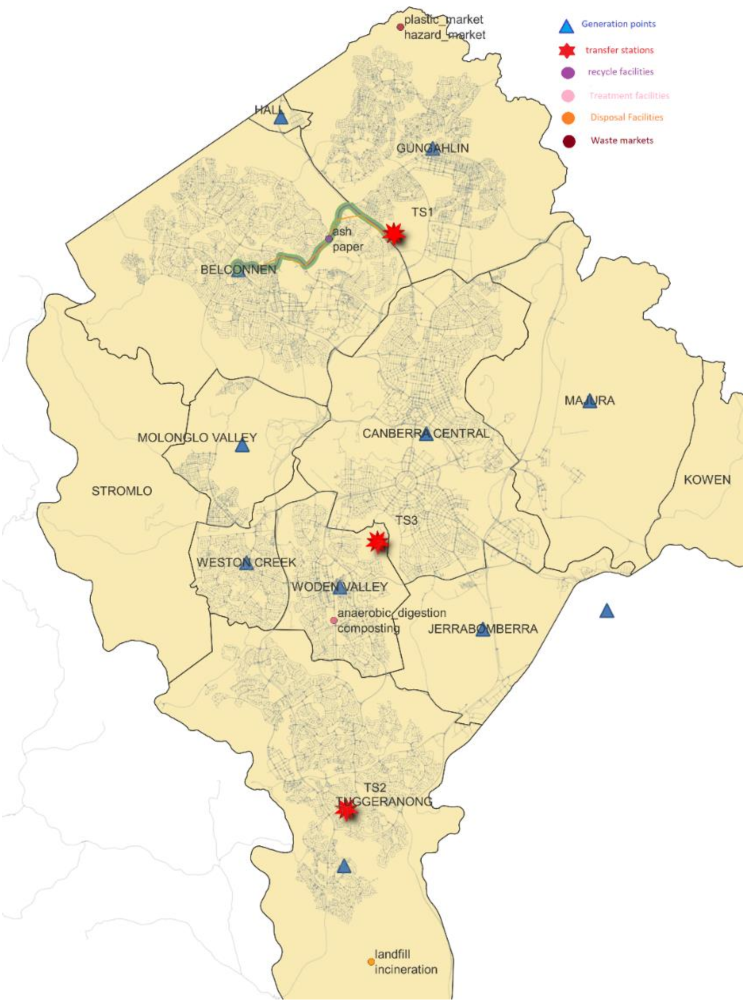


Figure 3.4: ACT suburbs map

The location and properties of the facilities of the model are presented in Table 3.13-Table 3.18

name	Waste type	xcoord	ycoord	Fixed cost ($/ton)	Variable cost	Sell price ($/ton)	Capacity (ton)	Min amount (ton)	GHG (CO2eq)
Glass market	glass	149.1171	-35.1322	8000	100	155	1800	20	0.05
Metal market	metal	149.1171	-35.1322	8000	100	179	1800	20	0.05
Paper market	paper	149.1171	-35.1322	8000	100	232	1800	20	0.05

Plastic market	plastic	149.1171	-35.1322	8000	100	195	1800	20	0.05
Ash market	ash	149.1171	-35.1322	8000	100	227	1800	20	0.05
Hazard market	hazard	149.1171	-35.1322	8000	100	197	1800	20	0.05
Masonry market	masonry	149.1171	-35.1322	8000	100	221	1800	20	0.05
Textile market	textile	149.1171	-35.1322	8000	100	242	1800	20	0.05
Other markets	other	149.1171	-35.1322	8000	100	233	1800	20	0.05
Organic market	organic	149.1171	-35.1322	8000	100	183	1800	20	0.05
Composting market	composting	149.1171	-35.1322	8000	100	156	1800	20	0.05
Anaerobic digestion market	Anaerobic digestion	149.1171	-35.1322	8000	100	186	1800	20	0.05
Landfill market	landfill	149.1171	-35.1322	8000	100	245	1800	20	0.05
Incineration market	incineration	149.1171	-35.1322	8000	100	193	1800	20	0.05

In all the tables the amounts are presented in tons. The GHG emissions of facilities are presented as a kilogram of CO2 equivalent per ton of waste.

Table 3.13 indicates the coordinates of waste generation points along with their number of covered household units. According to Pickin et al. (2020), the average household waste generation in the ACT is 9.54 kg of mixed waste and 4.65 kg of recyclable waste every week. Waste generation in each suburb is calculated using the number of households in each suburb multiplied by the average household weekly waste generation.

Table 3.13: Generation points

name	*xcoord*	*ycoord*	*household number*	*mixed waste (TONNE)*	*recycle waste (TONNE)*
BELCONNEN	149.0431404	-35.2274455	4208	208.93	101.84
CANBERRA_CENTRAL	149.1333365	-35.28930061	4208	208.93	101.84

GUNGAHLIN	149.1334711	-35.17891595	2501	124.18	60.53
HALL	149.0616655	-35.16794295	8	0.39	0.19
JERRABOMBERRA	149.1620851	-35.36444086	71	3.55	1.73
MAJURA	149.2101637	-35.27518018	48	2.37	1.15
TUGGERANONG	149.0989083	-35.45722489	2477	123	59.95
WESTON_CREEK	149.0497842	-35.34072415	707	35.09	17.10
WODEN_VALLEY	149.094117	-35.34937041	1255	62.29	30.36
MOLONGLO_VALLEY	149.046641	-35.29506683	397	19.71	9.61
QUEANBEYAN	149.220431	-35.35618	1556	77.27	37.66

The location of proposed transfer stations along with the properties of each station is demonstrated in Table 3.14.

Table 3.14: Transfer stations

name	xcoord	ycoord	Fixed cost ($/ton)	Variable cost ($/ton)	Capacity (ton)	Min amount (ton)	GHG (co2eq)
TS1	149.116	-35.2123	11000	100	900	20	0.032
TS2	149.0993	-35.4354	12000	100	900	20	0.032
TS3	149.1114	-35.3317	11000	100	900	20	0.032

Fixed cost is the cost of operation in every facility regardless of the amount of waste, that is applied when the facility is established and processing waste. Variable cost is the cost of processing each unit of waste at the facility. The minimum amount is the minimum amount of waste that is needed to establish a waste transfer station. The proportion column shows the minimum ratio of waste that is classified as disposal waste and will be transferred directly to landfills. Table 3.15

name	Waste type	xcoord	ycoord	Fixed cost ($/ton)	Variable cost ($/ton)	Sell price	Capacity (ton)	Min amount (ton)	GHG (CO2eq)
Glass market	glass	149.1171	-35.1322	8000	100	155	1800	20	0.05
Metal market	metal	149.1171	-35.1322	8000	100	179	1800	20	0.05
Paper market	paper	149.1171	-35.1322	8000	100	232	1800	20	0.05

Plastic market	plastic	149.1171	-35.1322	8000	100	195	1800	20	0.05
Ash market	ash	149.1171	-35.1322	8000	100	227	1800	20	0.05
Hazard market	hazard	149.1171	-35.1322	8000	100	197	1800	20	0.05
Masonry market	masonry	149.1171	-35.1322	8000	100	221	1800	20	0.05
Textile market	textile	149.1171	-35.1322	8000	100	242	1800	20	0.05
Other markets	other	149.1171	-35.1322	8000	100	233	1800	20	0.05
Organic market	organic	149.1171	-35.1322	8000	100	183	1800	20	0.05
Composting market	composting	149.1171	-35.1322	8000	100	156	1800	20	0.05
Anaerobic digestion market	Anaerobic digestion	149.1171	-35.1322	8000	100	186	1800	20	0.05
Landfill market	landfill	149.1171	-35.1322	8000	100	245	1800	20	0.05
Incineration market	incineration	149.1171	-35.1322	8000	100	193	1800	20	0.05

indicate the information and location of proposed waste management facilities in the model.

Table 3.15: Recycling facilities

name	xcoord	ycoord	Fixed cost ($/ton)	Variable cost ($/ton)	Capacity (ton)	Min amount (ton)	GHG (CO2eq)	Sell price ($/ton)
glass	149.0855	-35.2148	18000	359.21	1500	20	0.05	200
metal	149.0855	-35.2148	18000	359.21	1500	20	0.05	250
paper	149.0855	-35.2148	18000	359.21	1500	20	0.05	220
plastic	149.0855	-35.2148	18000	359.21	1500	20	0.05	230
ash	149.0855	-35.2148	18000	359.21	1500	20	0.05	190

hazard	149.0855	-35.2148	18000	359.21	1500	20	0.05	100
masonry	149.0855	-35.2148	18000	359.21	1500	20	0.05	200
textile	149.0855	-35.2148	18000	359.21	1500	20	0.05	180
other	149.0855	-35.2148	18000	359.21	1500	20	0.05	160
organic	149.0855	-35.2148	18000	359.21	1500	20	0.05	110

Table 3.16: Treatment facilities

name	xcoord	ycoord	Fixed cost ($/ton)	Variable cost ($/ton)	Capacity (ton)	Min amount (ton)	GHG (CO2eq)	Sell price ($/ton)
composting	149.0916	-35.3624	12000	150	1500	20	125	200
anaerobic digestion	149.0916	-35.3624	12000	150	1500	20	125	50

Table 3.17: Disposal facilities

name	xcoord	ycoord	Fixed cost ($/ton)	Variable cost ($/ton)	Sell price ($/ton)	Capacity (ton)	Min amount (ton)	GHG (CO2eq)
landfill	149.1127	-35.4941	30000	717.11	100	20000	20	300
incineration	149.1127	-35.4941	30000	717.11	120	20000	20	300

Table 3.18: Markets

name	Waste type	xcoord	ycoord	Fixed cost ($/ton)	Variable cost	Sell price ($/ton)	Capacity (ton)	Min amount (ton)	GHG (CO2eq)
Glass market	glass	149.1171	-35.1322	8000	100	155	1800	20	0.05

Metal market	metal	149.1171	-35.1322	8000	100	179	1800	20	0.05
Paper market	paper	149.1171	-35.1322	8000	100	232	1800	20	0.05
Plastic market	plastic	149.1171	-35.1322	8000	100	195	1800	20	0.05
Ash market	ash	149.1171	-35.1322	8000	100	227	1800	20	0.05
Hazard market	hazard	149.1171	-35.1322	8000	100	197	1800	20	0.05
Masonry market	masonry	149.1171	-35.1322	8000	100	221	1800	20	0.05
Textile market	textile	149.1171	-35.1322	8000	100	242	1800	20	0.05
Other markets	other	149.1171	-35.1322	8000	100	233	1800	20	0.05
Organic market	organic	149.1171	-35.1322	8000	100	183	1800	20	0.05
Composting market	composting	149.1171	-35.1322	8000	100	156	1800	20	0.05
Anaerobic digestion market	Anaerobic digestion	149.1171	-35.1322	8000	100	186	1800	20	0.05
Landfill market	landfill	149.1171	-35.1322	8000	100	245	1800	20	0.05
Incineration market	incineration	149.1171	-35.1322	8000	100	193	1800	20	0.05

The sell price column in the market table indicates the sale price of each unit of waste products at each market. The number is negative as it reduces the system's total cost in the objective function.

The distances between generation points and different facilities are calculated using the real street network of the case study. The shortest path between any two nodes in the network is found through the street network provided by (*OpenStreetMap*). The transportation cost per ton for paths is calculated using the spreadsheet provided by Litman (2011).

Table 3.19: Transportation cost per ton per kilometer between system facilities

Origin	**Destination**	**Cost $ per ton per km**
Generation points	Transfer stations	2.2
Generation points	Landfill	2.5
Generation points	Recycle facilities	2.2
Transfer stations	Recycle facilities	2.6
Transfer stations	Treatment facilities	2.2
Transfer stations	Landfill	2.2
Recycle facilities	market	2.8
Recycle facilities	Landfill	2.2
Treatment facilities	market	2
Treatment facilities	Landfill	2
Landfill	Market	2.2

3.3.2 Waste Streams

Each generation point generates two kinds of waste.

- Mixed waste
- Recycle waste.

There are two options for the collection of mixed waste.

1- Direct transport of mixed waste to landfill facility
2- Transfer the collected mixed waste to transfer stations.

For recyclable waste also, two options are available

1- Direct transfer to recycling facilities
2- Transfer to transfer stations

In transfer stations, the waste is sorted and sent to recycling, and treatment facilities, and the residual disposal waste is sent to landfill facilities.

In recycling facilities, the recycled materials are sent to compatible markets for selling, and the residue disposal waste is sent to landfill facilities.

In treatment facilities, the treated useful materials are sent to compatible markets for selling, and the residue disposal waste is sent to landfill facilities.

In landfill facilities, the disposal waste is buried, and the products from landfills are sent to compatible markets for selling.

3.4 MILP Solution of the System

The deterministic single objective model of the proposed system is modeled as a mixed-integer linear problem (MILP).

Table 3.20 indicates the properties of the developed MILP problem.

Table 3.20: Properties of MILP model

Number of objectives	3
Number of variables	492
Number of continuous variables	462
Number of integer variables	31
Number of constraints	551

The commercial “Gurobi solver” is selected to solve the problem because it provides a free academic license. And also, the inclusion of the python module helped to model the problem easier with the gurobi solver. In the first step, the model is solved only considering the economic objective function to minimize the system's total cost.

Solving the model with only the cost objective function results in a minimum total cost of \$423814 as the minimum possible cost of the system. The value of other objective functions for this solution is shown in Table 3.21: MILP objectives considering economic objectives only.

Table 3.21: MILP objectives considering economic objectives only

Objective	Value	Unit
Economic objective	372799.66	\$
Environmental objective	196057.77	CO_2 eq
Social objective	610.57	Social acceptance measure

In the next step, the model is solved only by considering the environmental objective function, to minimize the total GHG emissions of the system. Solving the model with only the Environmental objective function results in a minimum total GHG emission of 60349.74 tons of CO2 equivalent. The value of other objective functions for this solution is shown in Table 3.22.

Table 3.22: MILP objective values considering Environmental objectives only

Objective	Value	Unit
Economic objective	547086.56	$
Environmental objective	60130.07	Tone CO_2 eq
Social objective	526.36	Social acceptance measure

In the last step, the model is solved only considering the social objective function to maximize the total social acceptance of the system. Solving the model with only the social objective function results in a maximum social acceptance of 1803.42. The value of other objective functions for this solution is shown in Table 3.23.

Table 3.23: MILP objective values considering the only social objective function

Objective	Value	Unit
Economic objective	1417998.46	$
Environmental objective	386470.58	Tone CO_2 eq
Social objective	910.1	Social acceptance measure

The maximum and minimum values between these separate solutions are identified and used as lower and upper bounds of objective functions for implementing the multi-objective problem. We can use these numbers as boundaries for objective functions and use the epsilon constraint method to solve the multi-objective problem. In this method, only one objective is active, and the rest of the objective functions are converted to constraints. These values for all three objective functions are indicated in Table 3.24.

Table 3.24: Upper and lower bounds of objective functions

Objective	Upper bound	Lower bound	Unit
Economic objective	1417998.46	372799.66	$
Environmental objective	386470.57	60130.06	Tone CO_2 eq
Social objective	910.10	526.35	Social acceptance measure

Epsilon constraint method is an algorithm transformation method to model multi-objective problems in mathematical programming methods. In this method, a primary objective function is selected as the main objective, and the rest of the objective functions are transformed into constraints. Therefore, the problem of n, objectives, and c, constraints transform into a single objective problem with c+(n-1) constraints.

Using the upper and lower bounds, in the first step, considering the economic objective function as the main objective, the environmental and social objective functions are transformed into constraints. The value of the epsilon is calculated using intervals between upper and lower bounds. These epsilon values are then used as the right-hand side value for constraints transformed from objective functions. The problem is solved using different epsilon values (100 values to obtain a smoother Pareto front line) to identify the Pareto front solutions. Figure … shows the Pareto front solutions for the epsilon method with economic objective as the main objective function. The same method is used for each objective function as the main objective. Pareto front solutions for these solutions are indicated in Figure 3.5.

Pareto front solutions-cost objective

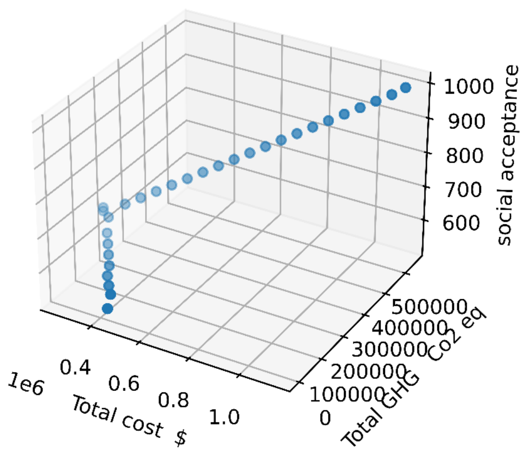


Figure 3.5: Pareto front solution of epsilon method with the economic objective

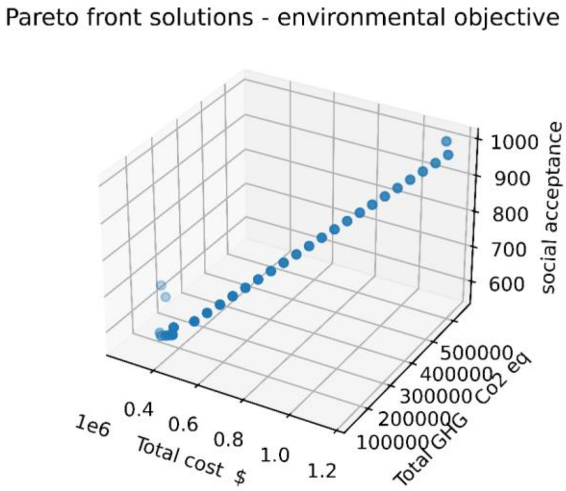


Figure 3.6: Pareto-front solutions for epsilon method with environmental objectives

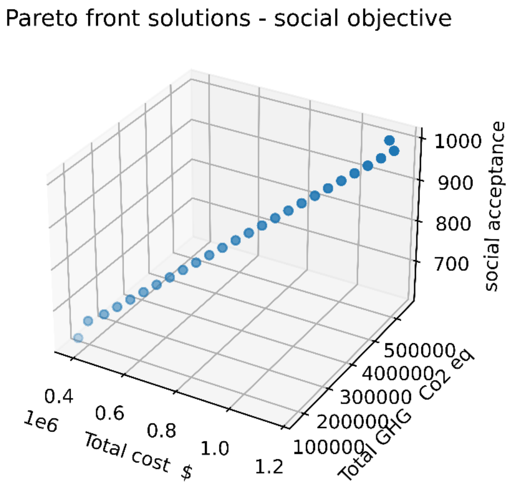


Figure 3.7: Pareto-front solutions for the epsilon method with the social objective

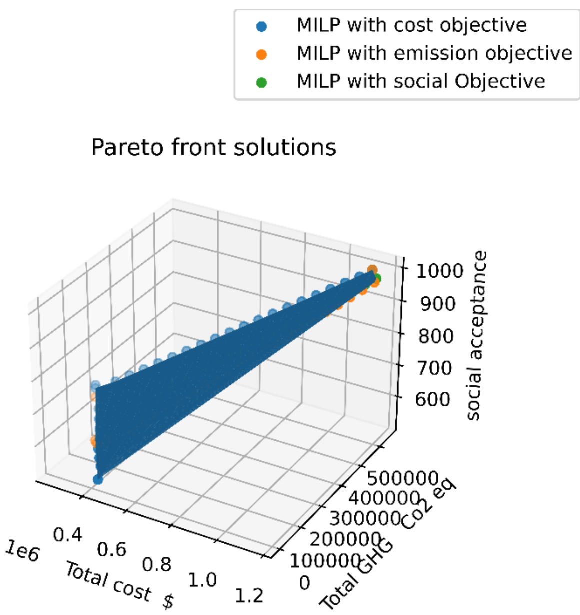


Figure 3.8: Pareto-front solutions of MILP with three objectives

Combining the solutions from different epsilon methods can result in real Pareto front solutions to the multi-objective problem. As the problem has three objective functions, a Pareto front is a three-dimensional plane. This surface is indicated in Figure 3.8.

Chapter 4 :Solution of the System Using the Evolutionary Optimization Algorithms

The deterministic single objective model of the proposed system is modeled as a mixed-integer linear problem (MILP). Table 4.1 indicates the properties of the developed MILP problem.

Table 4.1: Properties of MILP model

Number of objectives	3
Number of variables	492
Number of continuous variables	462
Number of integer variables	31
Number of constraints	551

4.1.1 Parameter Tuning

Several parameters affect the performance of evolutionary algorithms. One Population is the number of solutions evaluated in each generation, and it can affect the algorithm's convergence rate. Other than that, the crossover and mutation operators in the algorithms use a probability percentage that identifies how many of the situations the operator should be executed. ETA is also an important parameter that specifies the distance of child solutions from the parents. Identifying the best set of these parameters to be used with our model requires several runs with changing one parameter and keeping the others fixed to identify the exact effect of each parameter. Taguchi *et al.* (1986) introduced a methodology for applying designed experiments. In this method, the number of experiments reduces significantly. Based on the Taguchi method, a special design of orthogonal arrays is generated for parameter tuning.

Table 4.2: Combination of parameter values

Parameters	Parameter Level		
	1	2	3
Population Size	50	100	200
Crossover probability (%)	50	70	90
Mutation probability (%)	5	10	15
ETA	0.1	0.5	0.9

Taguchi design summary:

Taguchi Array	L9(3^4)
Factors:	4
Runs:	9

Columns of L9(3^4) array: 1 2 3 4

$Average\ IGD(A, \rho^*)$ is used as the response variable (below Equation), where ρ^* consist of the non-dominated solutions among all experimental runs (treatments) for the parameter tuning. The solution (x_f, y_f) obtained for fth run and the Euclidean distance between point x_f and point y_f is represented by $d(x_f, y_f)$. The orthogonal array and the corresponding $IGD(A, \rho^*)$ values are shown in the below Table.

$$Average\ IGD(A, \rho^*) = \sum_{f=1}^{10} (\frac{1}{|\rho^*|} \sum_{x \in \rho^*} \min_{y \in T} d(x_f, y_f)) \qquad (29)$$

Table 4.3: Orthogonal table and IGD values

scenario	Population Size	Crossover Probability (%)	Mutation Probability (%)	ETA	Average IGD values for NSGA-II (after 5 runs)	Average IGD values for NSGA-III (after 5 runs)
1	50	50	5	0.1	0.0711	0.2382
2	50	70	10	0.5	0.0822	0.3285
3	50	90	15	0.9	0.1079	0.1840
4	100	50	20	0.9	0.2887	0.1458
5	100	70	15	0.1	0.1307	0.3584
6	100	90	5	0.5	0.0788	0.4487
7	200	50	15	0.5	0.1708	0.1600
8	200	70	5	0.9	0.0737	0.4329
9	200	90	10	0.1	0.1052	0.3238

4.1.1.1 NSGA-II

Design Summary

Taguchi Array L9(3^4)

Factors: 4

Runs: 9

Table 4.4:Response Table for Means

Level	Population Size	Crossover Probability (%)	Mutation Probability (%)	ETA
1	0.08707	0.17687	0.07453	0.10233
2	0.16607	0.09553	0.15870	0.11060
3	0.11657	0.09730	0.13647	0.15677
Delta	0.07900	0.08133	0.08417	0.05443
Rank	3	2	1	4

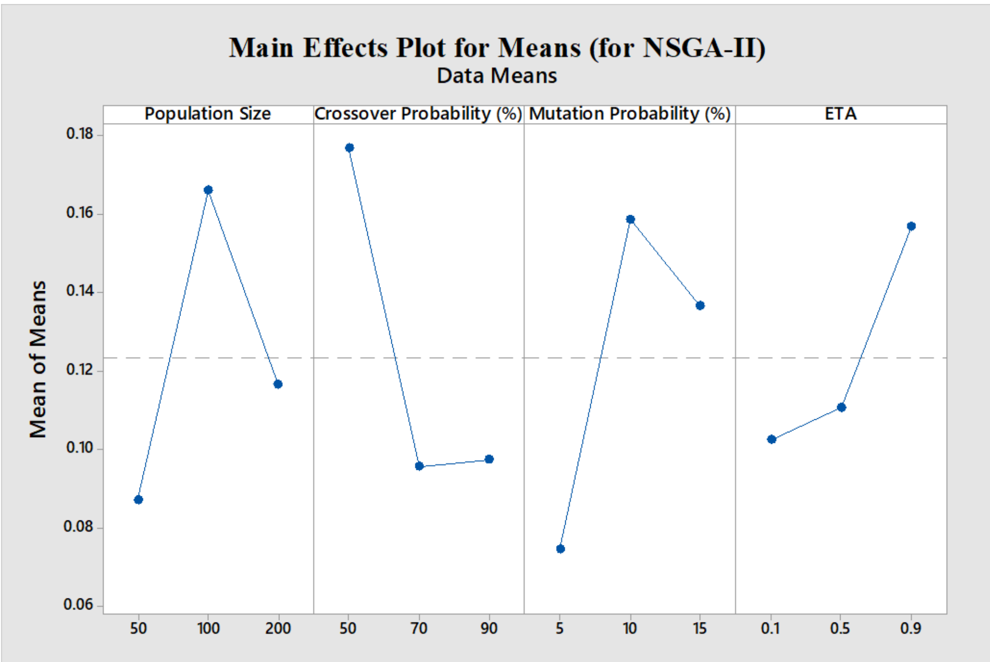


Figure 4.1: mass effect plot for means (for NSGA-II)

Optimal combination is Population size 50; Crossover probability 70; Mutation probability 5%; ETA 0.1

4.1.1.2 NSGA-III

Table 4.5: Response Table for Means (NSGA-III)

Level	Population Size	Crossover Probability (%)	Mutation Probability (%)	ETA
1	0.2502	0.1813	0.3733	0.3068
2	0.3176	0.3733	0.2660	0.3124
3	0.3056	0.3188	0.2341	0.2542
Delta	0.0674	0.1919	0.1391	0.0582
Rank	3	1	2	4

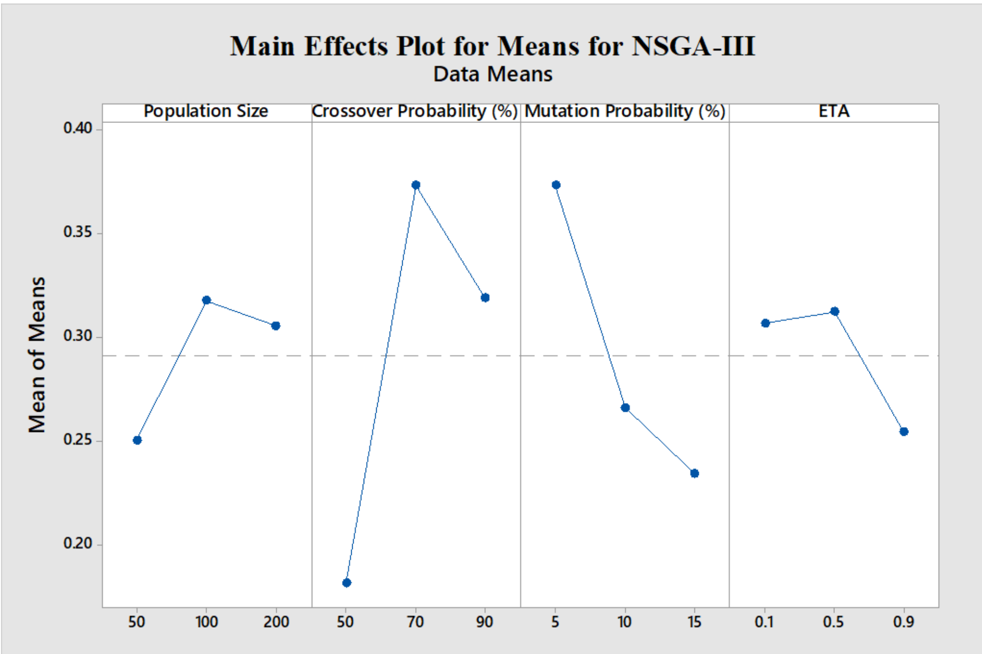


Figure 4.2: Main effects plot for means (for NSGA-III)

Optimal combination is Population size 50; Crossover probability 50; Mutation probability 15%; ETA 0.9

4.1.2 Solution of the Model Using the Evolutionary Optimization Algorithms

Evolutionary algorithms use several operators to create and evaluate a new population of solutions. The best combination of hyperparameters is identified using the Taguchi parameter tuning method. Using the Taguchi method, the best combination of parameters for the NSGA-II algorithm is identified as Population size 50, Crossover probability 70%, Mutation probability

5%, and ETA 0.1, and for the NSGA-III algorithm, the parameters are identified as Population size 50, Crossover probability 50%, Mutation probability 15% and ETA 0.9. The details of the parameter tuning along with IGD values for different runs are indicated in Appendix A4 of the supplementary materials.

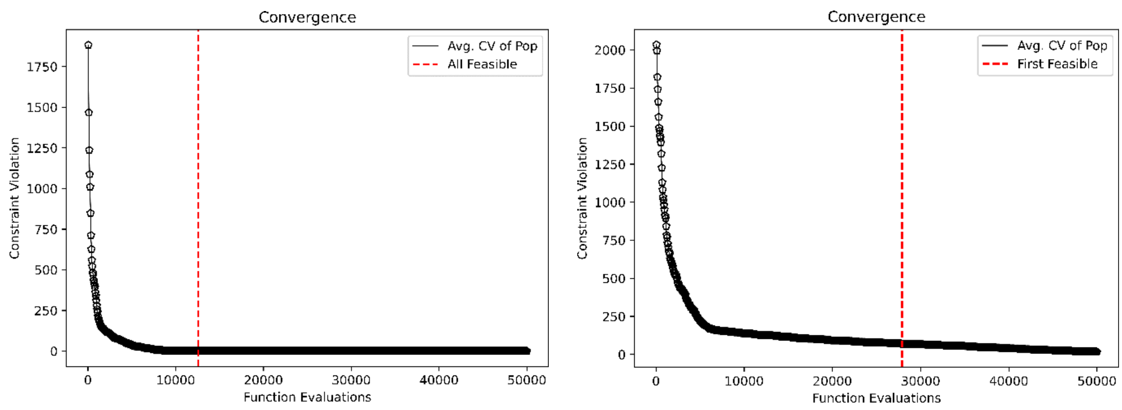
Using the tuned parameters and the developed repair function, the problem is solved using the non-dominated sorting algorithms (i.e., NSGA-II and NSGA-III). The results for 10 runs of the NSGA-II and NSGA-III are indicated in Table 4. For comparability, the limit of 50000 evaluations is set for both algorithms. To consider the random nature of the evolutionary algorithms, each algorithm is executed 10 times with different seed numbers. Then the average results between 10 runs are reported in Table 4.6.

Table *4.6*: Evolutionary algorithm results

	algorithm	**SEED**	**IGD**	**IGD+**	**Time (In seconds)**
1	**NSGA_II**	1233173	0.547503	0.083977	62979.23
2		2658299	0.538237	0.094788	62725.93
3		9756337	0.501592	0.067797	63467.22
4		3961556	0.585613	0.082628	62868.12
5		5451775	0.485442	0.055643	62711.53
6		1277363	0.555952	0.072727	62865.26
7		367403	0.50591	0.067813	62989.82
8		8278618	0.515952	0.09212	62687.01
9		6213578	0.527762	0.082654	63214.49
10		5293192	0.501866	0.059948	62476.49
Average			**0.526583**	**0.07601**	**62898.51**
11	**NSGA_III**	9283463	0.621697	0.215452	62538.6
12		9007353	0.723665	0.110169	62158.35
13		9247660	0.673851	0.194296	62117.52
14		9077299	0.59621	0.230006	62119.46
15		6297550	0.723587	0.10524	62298.63
16		1150907	0.711288	0.104169	62307.12
17		1964176	0.674308	0.111959	62034.52
18		7267221	0.645583	0.25579	62203.67
19		7568642	0.668115	0.272199	62278.91
20		810730	0.676415	0.12297	62149.55

Average	**0.595578**	**0.121826**	**62220.633**

Figure 4.3 shows the convergence rate of both algorithms. In the case of the NSGA-II algorithm (Figure 4.3 (a)), after 11850 evaluations at generation 236, the whole population becomes feasible. However, in the NSGA-III algorithm in most of the cases, the solutions did not reach a whole feasible population before the limit of 50000 evaluations that are set for both algorithms. For the NSGA-III algorithm, the evaluation number of reaching the first feasible solution is indicated in Figure 4.3(b). The solving time for both algorithms are almost identical; however, the NSGA-II algorithm converges faster toward the Pareto front, and the number of non-dominated solutions by NSGA-II is higher than NSGA-III



(a) NSGA-II (b) NSGA-III

Figure 4.3: Convergence plot for NSGA-II and NSGA-III

The establishment of different facilities in the system is an important decision based on the objective functions preference of the decision-maker. Solving the model using the NSGA-II algorithm tuned parameters for 10 different seed numbers led to 129 total non-dominated solutions. The table indicates the ratio of the establishment of each facility between all non-dominated solutions. This table indicates that transfer stations are always established in the system in all optimal solutions. Landfill and incineration facilities are also always present in the optimal solution. However, in the case of recycling facilities, they are established nearly in half of the solutions.

Table 4.7: Percentage of the establishment of different facilities in non-dominated solutions

WM main component	Facility /Technology	Establishment percentage (percent)		Facility /Technology	Establishment percentage (Percent)
Transfer station	TS1	100	Disposal facilities	landfill	100
	TS2	100		incineration	100
	TS3	100	Market facilities	Glass market	16
Material recovery technology	Glass	58		Metal market	20
	metal	41		Paper market	13
	paper	44		Plastic market	19
	plastic	38		Ash market	23
	ash	56		Hazard market	26
	hazard	60		Masonry market	75
	masonry	100		Textile market	8
	textile	47		Other markets	6
	other	34		Organic market	8
	organic	28		Composting market	0
Waste treatment technology	composting	0		Anaerobic digestion market	2.5
	Anaerobic digestion	2.5		Landfill market	100
				Incineration market	100

4.2 Chapter Summary

In this Chapter, an optimization model is developed for the IMSWM system. The model is solved using the exact methods and also Evolutionary algorithms. However, developing a realistic model for the IMSWM system requires consideration of several uncertainties in the system that would affect all the objective functions. Considering uncertainties in the model is an essential extension to the developed model in this Chapter, which is the main motivation for the research work in the next Chapter. Integrated Solid Waste Management System: Modeling and Solving the Problem Under Uncertainty.

Chapter 5 :Integrated solid waste management system: modelling and solving the problem under uncertainty

5.1 Introduction

Although the deterministic model and solution approaches are explained in Chapter 3, to develop a more realistic management system the uncertainties in the system should be considered in the model. Based on Hannan *et al.* (2020), a great amount of research in waste management has been considering several parameters of the model to be deterministic. The values of all the model parameters are considered known, and the problem is solved based on these known values. However, there are several parameters in the waste management system in the real world that are subject to uncertainties, i.e., all the information about a parameter is not known, and the parameter's value is subject to changes. In optimization problems, decisions are made based on the present value of parameters. The consequences of these decisions are not known until a later stage after the decision when the value of uncertain parameters changes.

Although uncertainty can affect many parameters in a waste management system, M. A. A. Hannan *et al.* (2020) indicated the amount of generated waste, transportation cost, and waste transformation and processing coefficients as the most important ones. Masoud Rabbani *et al.* (2021) developed a waste management system considering the distance and travel time between facilities as stochastic parameters. The social aspect of the problem was considered a constraint in the model having an upper bound threshold for the social acceptance of each facility. The model was applied to a case study of Tehran, Iran, and solved using the Lexicographic and AUGMECON2 to deal with the identified uncertainties using fuzzy programming approach. Markov *et al.* (2020) also considered container fill level as the uncertain parameter in their model and solved it using a developed Adaptive Large Neighborhood Search (ALS) algorithm considering only economic objectives and a forecast model for the fill level of containers.

The stochasticity in the problem is dealt with using a two-stage probabilistic method. For example, Tirkolaee *et al.* (2021) developed a model to assess the sustainability of solid waste management under the COVID-19 pandemic situation focusing on infectious medical waste. As with most of the literature in this field, the demand parameter was considered uncertain. Unlike the other research, they used total traveling time, total violation from time windows, and disposal site risks as the main objective functions. Their model was applied to a case study in Sari, Iran And to address the uncertainty in demand, they utilized a fuzzy chance-constraint programming technique. Tirkolaee *et al.* (2020) developed a multi-trip capacitated arc routing problem for urban solid waste management and considered waste generation an uncertain parameter. The demand is considered uncertain and modeled by a fuzzy method and based on that a chance constraint programming algorithm is used to address the uncertainties.

Asefi et al. (2019) indicated that, despite the number of different studies that have considered uncertainty in their work, there is still a research gap in considering the effect of uncertainty on all the system components. Few studies have considered more than one parameter in their model as uncertain (Ameknassi *et al.*, 2017; Temur & Yanık, 2017; Ziaei & Jabbarzadeh, 2021). The multiple uncertain parameters were usually from the same category in those studies like cost, pollution, or risk. However, different, uncertain parameters from different categories should be considered simultaneously to obtain more realistic results.

Considering uncertainties in different management system levels like generation, transportation, waste processing, and final market of products can help assess the combined effect of these parameters. Therefore, besides the need for a holistic waste management system, the uncertain nature of model parameters should be considered to obtain more realistic results. Also, as one of the main sustainable development objectives, the social objective is highly sensitive to any changes in model parameters. Therefore, the uncertainty in parameters can affect the level of social acceptance of the model. Assessing this effect is an important task in creating a sustainable waste management system that is absent from the literature. Social acceptance is affected by several social suitability indicators discussed in sections 3.2.4 of this thesis.

Based on the literature, the following research gaps are identified:

- The majority of the studies have considered single uncertain parameters in their model, and in a few models that consider multiple uncertainties the parameters are usually focused on one component of the system. Considering uncertainty in several levels of a waste management system from generation to waste markets is an important aspect of the problem that needs to be addressed.
- Uncertainty in parameters highly affects the social acceptance of the system, and therefore, a comprehensive formulation is needed for the social objective function that considers all the social suitability indicators to assess the true effect of uncertainties on the social acceptance of the model.

Therefore, in this Chapter, the main objective is to consider the holistic IMSWM model developed in Chapter 3 and assess the effect of uncertainty in parameters in that model. A robust multi-objective municipal solid waste management is developed to consider several uncertainties in the parameters. The model is developed to minimize the cost and GHG emissions of the system and maximize the social suitability of the system.

5.2 Material and Methods

Based on the literature, four main sources of uncertainty are considered: waste generation, facility capacity, transportation cost, and final selling price of products. The probability distributions of these parameters are identified by using real data extracted from the national waste report. Later, 20 uncertainty scenarios were generated based on this distribution. Then the developed model in section 3.1 was updated using these uncertainty sets to identify the effect of uncertain parameters on objective function values and recommended policies.

5.2.1 Model Formulation

In this section, the developed model is considered as a base for the robust model. The uncertain parameters are defined with ~ character.

Nomenclature for the model

Model Sets

$g \in G$ waste generation nodes

$k \in K$ potential transfer station nodes

r∈R potential recycling nodes

$t \in T$ potential treatment nodes

l∈L potential landfill nodes

m∈M potential waste market nodes

Variable Sets

Waste amount variables cannot be negative numbers. Therefore, each defined variable is a continuous variable with a lower bound of 0. The facility establishment variables are defined as binary variables 1 when the facility is established and 0 otherwise.

Disposal waste variables:

$d1_{i,j}$: disposal waste amount from generation point i to transfer stations j, $i \in G, j \in K$

$d2_{i,j}$: disposal waste amount from generation point i directly to landfill j, $i \in G, j \in L$

$d3_{i,j}$: disposal waste amount from transfer station i to landfill j , $i \in k, j \in L$

$d4_{i,j}$: disposal waste amount from recycling facility i to landfill j , $i \in R, j \in L$

$d5_{i,j}$: disposal waste amount from treatment facility i to landfill j , $i \in T, j \in L$

d6i: disposal waste amount that has been disposed of in landfill i, i ∈L

Recyclable waste variables:

$r1_{i,j}$: recyclable waste amount from generation point i to transfer station j, $i \in G, j \in$K

$r2_{i,j}$: recyclable waste amount from generation point i directly to recycle facility j, $i \in G, j \in$R

$r3_{i,j}$: recyclable waste amount from transfer station i to recycle facility j, $i \in$k, $j \in$R

Treatable waste variables:

$t1_{i,j}$: treatable waste amount from transfer station i to treatment facility j , $i \in$k, $j \in$T

Product variables:

$p1_{i,j}$: recycled product amount from recycling facility i to market j , $i \in$R, $j \in$M

$p2_{i,j}$: treated products amount from treatment facility i to market j, $i \in$T, $j \in$M

$p3_{i,j}$: products amount from landfill i to market j, $i \in$L, $j \in$M

Facility establishment variables

transfer_e_i: is 1 when the transfer facility is established at node i and 0 otherwise, $i \in$K

recycle_e_i: is 1 when recycle facility is established at node i and 0 otherwise, $i \in$R

treatment_e_i: is 1 when treatment facility is established at node i and 0 otherwise, $i \in$T

landfill_e_i: is 1 when the transfer facility is established at node i and 0 otherwise, $i \in$L

market_e_i: is 1 when the market is established at node i and 0 otherwise, $i \in$M

Model Parameters

Waste amounts:

node: G

$\widetilde{mixed\_waste_i}$: is the uncertain amount of mixed waste generated at generation node $i \in G$

$\widetilde{recycle\_waste_i}$: is the uncertain amount of recyclable waste generated at generation node $i \in G$

Transportation cost:

node: G

$\widetilde{c_{i,j}}$: is the uncertain cost of transferring one unit of mixed waste on the link $(i,j) \in A, i \in G$,K,R,T,L, $j \in K$, R,T,L,M

Infrastructure cost

transfer_f_i is the fixed cost of opening a transfer station at node $i \in K$

recycle_f_i is the fixed cost of opening a recycling facility at node $i \in$R

treatment_f_i is the fixed cost of opening a treatment facility at node $i \in T$

landfill_f_i is the fixed cost of opening a landfill center at node $i \in$L

market_f_i is the fixed cost of selling at one unit of waste at the market at node $i \in$M

Variable processing cost

transfer_v_i is the variable cost of processing one unit of waste at the transfer station at node $i \in K$

recycle_v_i is the variable cost of processing one unit of waste at a recycling facility at node $i \in$R

treatment_v_i is the variable cost of processing one unit of waste at the treatment facility at node $i \in T$

$landfill\_v_i$ is the variable cost of processing one unit of waste at the landfill center at node $i \in L$

$market\_v_i$ is the variable cost of processing one unit of waste at the market at node $i \in M$

Facility capacities

$\widetilde{transfer\_c}_i$ is the uncertain capacity of the transfer station at node $i \in k$

$\widetilde{treatment\_c}_i$ is the uncertain capacity of the treatment technology $q \in Q$ at node $i \in T$

$\widetilde{recycle\_c}_i$ is the uncertain capacity of the recycling technology $l \in L$ at node $i \in R$

$\widetilde{landfill\_c}_i$ is the uncertain capacity of the landfill facility at node $i \in L$

$\widetilde{market\_c}_i$ is the uncertain capacity of the market facility at node $i \in M$

Minimum amounts for opening new facilities.

$transfer\_m_i$: is the minimum amount of mixed waste required to establish a transfer station at node $i \in K$

$recycle\_m_i$: is the minimum amount of recyclable waste required to establish a recycling facility at node $i \in R$

$treatment\_m_i$: is the minimum amount of treatable waste required to establish a treatment facility at node $i \in T$

$landfill\_m_i$: is the minimum amount of disposal waste required to establish a landfill facility at node $i \in L$

$market\_m_i$: is the minimum amount of product required to establish a market facility at node $i \in M$

Final price of waste

$\widetilde{sell\_price}_i$: is the uncertain price of one unit of product at node $i \in R,T,L$

GHG emissions

GHG_mixed_{ij}: is the total GHG emissions produced in the process of collection and transportation of mixed waste from node i to node j

$GHG\_recycle_{ij}$: is the total GHG emissions produced in the process of collection and transportation of processed waste from node i to node j

$GHG\_transfer_i$: is the total GHG emission from processing one ton of waste in the transfer station i

GHG_recyle_i: is the total GHG emission from recycling one ton of waste in the recycling station i

$GHG\_treatment_i$: is the total GHG emission from the treatment of one ton of waste in the treatment facility i

$GHG\_landfill_i$: is the total GHG emission from the disposal of one ton of waste in the landfill facility i

Compatibility of waste types

Compatibility i,j: is 1 when the waste type from the facility I is compatible to be transferred to facility j and is 0 otherwise

Objective functions

The first objective function is to minimize the total cost of the system which includes four parts: i) the total cost of collection and transportation of waste from generation points to system facilities, ii) the fixed establishment cost of the system facilities, iii) the process cost of the system based on the amount of waste that is being processed at each facility, and iv) the system's total revenue by selling waste products in the compatible markets. The calculation of objective one is shown in Equation (30).

$$
\begin{aligned}
\mathit{Minimize}\ f1 &\left\{\sum_{i\in G}\sum_{j\in K}\widetilde{C_{i,j}}d1_{i,j}+\sum_{i\in G}\sum_{j\in L}\widetilde{C_{i,j}}d2_{i,j}+\sum_{i\in K}\sum_{j\in L}\widetilde{C_{i,j}}d3_{i,j}+\sum_{i\in R}\sum_{j\in L}\widetilde{C_{i,j}}d4_{i,j}+\sum_{i\in T}\sum_{j\in L}\widetilde{C_{i,j}}d5_{i,j}\right.\\
&+\sum_{i\in G}\sum_{j\in K}\widetilde{C_{i,j}}r1_{i,j}+\sum_{i\in G}\sum_{j\in R}\widetilde{C_{i,j}}r2_{i,j}+\sum_{i\in K}\sum_{j\in R}\widetilde{C_{i,j}}r3_{i,j}+\sum_{i\in K}\sum_{j\in T}\widetilde{C_{i,j}}t1_{i,j}+\sum_{i\in R}\sum_{j\in M}\widetilde{C_{i,j}}p1_{i,j}\\
&\left.+\sum_{i\in T}\sum_{j\in M}\widetilde{C_{i,j}}p2_{i,j}+\sum_{i\in l}\sum_{j\in M}\widetilde{C_{i,j}}p3_{i,j}\right\}\\
&+\left\{\sum_{i\in K}transfer_{f_i}transfer_{e_i}+\sum_{i\in R}recycle_{f_i}recycle_{e_i}+\sum_{i\in T}treatment_{f_i}treatment_{e_i}\right.\\
&\left.+\sum_{i\in L}landfill_{f_i}landfill_{e_i}+\sum_{i\in M}market_{f_i}market_{e_i}\right\}\\
&+\left\{\left(\sum_{i\in G}\sum_{j\in K}d1_{i,j}+\sum_{i\in G}\sum_{j\in K}r1_{i,j}\right)transfer_{v_j}+\left(\sum_{i\in G}\sum_{j\in R}r2_{i,j}+\sum_{i\in K}\sum_{j\in R}r3_{i,j}\right)recycle_{v_j}\right.\\
&+\left(\sum_{i\in K}\sum_{j\in T}t1_{i,j}\right)treatment_{v_j}\\
&+\left(\sum_{i\in G}\sum_{j\in L}d2_{i,j}+\sum_{i\in K}\sum_{j\in L}d3_{i,j}+\sum_{i\in R}\sum_{j\in L}d4_{i,j}+\sum_{i\in T}\sum_{j\in L}d5_{i,j}\right)landfill_{v_l}\\
&\left.+\left(\sum_{i\in R}\sum_{j\in M}p1_{i,j}+\sum_{i\in T}\sum_{j\in M}p2_{i,j}+\sum_{i\in L}\sum_{j\in M}p3_{i,j}\right)market_{v_m}\right\}\\
&+\left\{\sum_{i\in R}\sum_{j\in M}p1_{i,j}\,\widetilde{sell\_price}_i+\sum_{i\in T}\sum_{j\in M}p2_{i,j}\,\widetilde{sell\_price}_i+\sum_{i\in L}\sum_{j\in M}p3_{i,j}\,\widetilde{sell\_price}_i\right\}
\end{aligned}
\qquad (30)
$$

The second objective is related to environmental effects of the system quantified by the GHG emission that comprises two main parts: i) the total GHG emission of transporting waste and products between facilities, and ii) the total GHG emission of processing waste inside each facility. Equation (31) shows the calculation for the second objective function to minimize the total GHG emissions of the system.

$$Minimize\ f2 = \Bigg\{\sum_{i\in G}\sum_{j\in K} d1_{i,j}GHGmixed_{i,j} + \sum_{i\in G}\sum_{j\in L} d2_{i,j}GHGmixed_{i,j} + \sum_{i\in G}\sum_{j\in K} r1_{i,j}GHGrecycle_{i,j}$$
$$+\sum_{i\in G}\sum_{j\in R} r2_{i,j}GHGrecycle_{i,j} + \sum_{i\in K}\sum_{j\in R} r3_{i,j}GHGrecycle_{i,j} + \sum_{i\in K}\sum_{j\in T} t1_{i,j}GHGrecycle_{i,j}$$
$$+\sum_{i\in K}\sum_{j\in L} d3_{i,j}GHGrecycle_{i,j} + \sum_{i\in R}\sum_{j\in L} d4_{i,j}GHGrecycle_{i,j} + \sum_{i\in R}\sum_{j\in M} p1_{i,j}\,GHGrecycle_{i,j}$$
$$+\sum_{i\in T}\sum_{j\in L} d5_{i,j}GHGrecycle_{i,j} + \sum_{i\in T}\sum_{j\in M} p2_{i,j}\,GHGrecycle_{i,j} + \sum_{i\in l}\sum_{j\in M} p3_{i,j}\,GHGrecycle_{i,j}\Bigg\} \qquad (31)$$
$$+\Bigg\{\left(\sum_{i\in G}\sum_{j\in K} d1_{i,j} + \sum_{i\in G}\sum_{j\in K} r1_{i,j}\right)GHGtransfer_j$$
$$+\left(\sum_{i\in G}\sum_{j\in R} r2_{i,j} + \sum_{i\in K}\sum_{j\in R} r3_{i,j}\right)GHGrecycle_j + \left(\sum_{i\in K}\sum_{j\in T} t1_{i,j}\right)GHGtreatment_j$$
$$+\left(\sum_{i\in G}\sum_{j\in L} d2_{i,j} + \sum_{i\in K}\sum_{j\in L} d3_{i,j} + \sum_{i\in R}\sum_{j\in L} d4_{i,j} + \sum_{i\in T}\sum_{j\in L} d5_{i,j}\right)GHGlandfill_j\Bigg\}$$

Equation (32) aims to maximize the social acceptance of the whole system as the third objective function of the model.

$$maximize\ \ f3(x) = +\Bigg\{\left(\sum_{i\in G}\sum_{j\in K} d1_{i,j} + \sum_{i\in G}\sum_{j\in K} r1_{i,j}\right)SAM_j \quad + \left(\sum_{i\in G}\sum_{j\in R} r2_{i,j} + \sum_{i\in K}\sum_{j\in R} r3_{i,j}\right)SAM_j$$
$$+\left(\sum_{i\in K}\sum_{j\in T} t1_{i,j}\right)SAM_j + \left(\sum_{i\in G}\sum_{j\in L} d2_{i,j} + \sum_{i\in K}\sum_{j\in L} d3_{i,j} + \sum_{i\in R}\sum_{j\in L} d4_{i,j} + \sum_{i\in T}\sum_{j\in L} d5_{i,j}\right)SAM_j \qquad (32)$$
$$+\left(\sum_{i\in R}\sum_{j\in M} p1_{i,j} + \sum_{i\in T}\sum_{j\in M} p2_{i,j} + \sum_{i\in L}\sum_{j\in M} p3_{i,j}\right)SAM_j\Bigg\}$$

Model Constraints

Waste generation constraint

$$\widetilde{mixed\_waste_i} = \sum_{j\in K} d1_{i,j} + \sum_{j\in L} d2_{i,j} \qquad \forall i \in G \qquad (33)$$

$$\widetilde{recycle\_waste_i} = \sum_{j\in K} r1_{i,j} + \sum_{j\in R} r2_{i,j} \qquad \forall i \in G \qquad (34)$$

Constraint (33) and (34) ensure that all the uncertain amounts of mixed/recyclable wastes generated at the generation point at node i is collected and transferred to either a transfer station or landfill/recycling facility.

Mass balance constraints

$$\sum_{i\in G} d1_{i,j} + \sum_{i\in G} r1_{i,j} = \sum_{i\in R} r3_{j,i} + \sum_{i\in T} t1_{j,i} + \sum_{i\in L} d3_{j,i} \qquad \forall J \in K \qquad (35)$$

$$\sum_{i\in G} r2_{i,j} + \sum_{i\in K} r3_{i,j} = \sum_{i\in L} d4_{j,i} + \sum_{i\in M} p1_{j,i} \qquad \forall J \in R \qquad (36)$$

$$\sum_{i\in K} t1_{i,j} = \sum_{i\in L} d5_{j,i} + \sum_{i\in M} p2_{j,i} \qquad \forall j \in T \qquad (37)$$

$$\sum_{i\in G} d2_{i,j} + \sum_{i\in K} d3_{i,j} + \sum_{i\in R} d4_{i,j} + \sum_{i\in T} d5_{i,j} = \sum d6_j + \sum_{i\in M} p3_{j,i} \qquad \forall j \in L \qquad (38)$$

Constraints (35 - 38) ensure that the total amount of input wastes that enters the transfer stations/facilities/market at node j is processed and transferred to the appropriate facilities, and no waste remains at the station/facilities.

Capacity constraints

$$\sum_{i\in G} d1_{i,j} + \sum_{i\in G} r1_{i,j} \le \widetilde{\text{transfer}}\text{\_c}\ {}_i transfer_{e_j} \qquad \forall j \in K \qquad (39)$$

$$\sum_{i\in K} r2_{i,j} + \sum_{i\in G} r3_{i,j} \le \widetilde{\text{recycle}}\text{\_c}\ {}_i recycle_{e_j} \qquad \forall j \in R \qquad (40)$$

$$\sum_{i\in G} t1_{i,j} \le \widetilde{\text{treatment}}\text{\_c}\ {}_i treatment_{e_j} \qquad \forall j \in T \qquad (41)$$

$$\sum_{i\in G} d2_{i,j} + \sum_{i\in K} d3_{i,j} + \sum_{i\in R} d4_{i,j} + \sum_{i\in T} d5_{i,j} \le \widetilde{\text{landfill}}\text{\_c}\ {}_i landfill_{e_j} \qquad \forall j \in L \qquad (42)$$

$$\sum_{i\in K} p1_{i,j} + \sum_{i\in R} p2_{i,j} + \sum_{i\in t} p3_{i,j} \le \widetilde{\text{market}}\text{\_c}\ {}_i market_{e_j} \qquad \forall j \in M \qquad (43)$$

Constraints (39 – 43) limit the maximum total amount of disposal and recyclable waste that enters the transfer station/facilities/market at node j from generation points to their capacity of them.

Minimum amounts

$$\sum_{i \in G} d1_{i,j} + \sum_{i \in G} r1_{i,j} \geq transfer_{m_j} transfer_{e_j} \qquad \forall j \in K \qquad (44)$$

$$\sum_{i \in K} r2_{i,j} + \sum_{i \in G} r3_{i,j} \geq recycle_{m_j} recycle_{e_j} \qquad \forall j \in R \qquad (45)$$

$$\sum_{i \in G} t1_{i,j} \geq treatment_{m_j} treatment_{e_j} \qquad \forall j \in T \qquad (46)$$

$$\sum_{i \in G} d2_{i,j} + \sum_{i \in K} d3_{i,j} + \sum_{i \in R} d4_{i,j} + \sum_{i \in T} d5_{i,j} \geq landfill_{m_j} landfill_{e_j} \qquad \forall j \in L \qquad (47)$$

$$\sum_{i \in K} p1_{i,j} + \sum_{i \in R} p2_{i,j} + \sum_{i \in t} p3_{i,j} \geq market_{m_j} market_{e_j} \qquad \forall j \in M \qquad (48)$$

Constraints (44 – 48) limit the minimum total amount of disposal and recyclable waste that enters the transfer station/facilities/market at node j from generation points to the minimum establishment limit of them.

Waste -Technology compatibility constraints

$$r2_{i,j} \leq \widetilde{recycle\_waste}_i compatability_{i,j} \qquad \forall i \in G \quad \forall j \in R \qquad (49)$$

$$p1_{j,l} \leq \left(\sum_{i \in K} r2_{i,j} + \sum_{i \in G} r3_{i,j} \right) compatability_{j,l} \qquad \forall j \in R \quad \forall l \in M \qquad (50)$$

$$p2_{j,k} \leq \left(\sum_{i \in G} t1_{i,j} \right) compatability_{j,k} \qquad \forall j \in T \quad \forall k \in M \qquad (51)$$

$$p3_{j,n} \leq \left(\sum_{i \in G} d2_{i,j} + \sum_{i \in K} d3_{i,j} + \sum_{i \in R} d4_{i,j} + \sum_{i \in T} d5_{i,j} \right) compatability_{j,n} \qquad \forall j \in L \quad \forall n \in M \qquad (52)$$

Constraint (49) ensures that a recycling facility is only established when a certain minimum percentage of a specific material exists in waste proportion.

Constraint (50 – 52) ensures that the recycled product in the recycling/treatment/disposal facility is transferred to a compatible waste product market

Non-negativity

$$\left(d1_{i,j}, d2_{i,j}, d3_{i,j}, d4_{i,j}, d5_{i,j}, r1_{i,j}, r2_{i,j}, r3_{i,j} t1_{i,j}, p1_{i,j}, p2_{i,j}, p3_{i,j}\right) \in \{\mathbb{R}^9\}^+ \qquad (53)$$

Binary variables

$$\left(transfer_{e_i}, recycle_{e_i}, treatment_{e_i}, landfill_{e_i}, market_{e_i},\right) \in \{0,1\}^5 \qquad (54)$$

5.2.2 Parameters with Uncertainty

Based on the literature review, it is observed that some of the sources of uncertainty have been used more frequently than others. Based on the literature (see Table 2.2), the waste generation, transportation cost, capacity of facilities, and selling price of products from waste are selected as the most important parameters subject to uncertainty. Here, the proposed model is applied to ACT, Australia as a case study of, that was introduced in Chapter 3.4. The uncertainty data of the selected parameters are gathered from National Waste Report (2020). The data indicated the changes in values of different uncertain parameters through the past years. This data is used to identify the probability distribution of parameters, and based on this distribution, uncertain scenarios are generated.

5.2.2.1 Waste Generation

Waste generation in cities depends on several socio-economic parameters. This means that the amount of generated waste is never known. Thus, in the literature, waste generation is one of the parameters subject to uncertainty. To identify the uncertainty amount in the waste generation for the case study, the data on waste generation are gathered from 2010 to 2019. The historical data of waste generation for mixed and recyclable waste in the ACT are indicated in Table 5.1.

Table 5.1: Municipal solid waste generation in ACT

year	location	stream	management	fate	Tons	Total
2018-2019	ACT	MSW	Landfill	Disposal	78,975	
2018-2019	ACT	MSW	Landfill	Energy recovery	25,407	297,914
2018-2019	ACT	MSW	Recycling	Recycling	193,532	
2017-2018	ACT	MSW	Landfill	Disposal	76,866	
2017-2018	ACT	MSW	Landfill	Energy recovery	26,626	249,031
2017-2018	ACT	MSW	Recycling	Recycling	145,539	
2016-2017	ACT	MSW	Landfill	Disposal	83,326	
2016-2017	ACT	MSW	Landfill	Energy recovery	20,303	220,030
2016-2017	ACT	MSW	Recycling	Recycling	116,401	
2015-2016	ACT	MSW	Landfill	Disposal	80,281	
2015-2016	ACT	MSW	Landfill	Energy recovery	21,335	215,683
2015-2016	ACT	MSW	Recycling	Recycling	114,067	
2014-2015	ACT	MSW	Landfill	Disposal	66,799	
2014-2015	ACT	MSW	Landfill	Energy recovery	18,957	193,091
2014-2015	ACT	MSW	Recycling	Recycling	107,335	
2013-2014	ACT	MSW	Landfill	Disposal	63,453	
2013-2014	ACT	MSW	Landfill	Energy recovery	18,563	213,709
2013-2014	ACT	MSW	Recycling	Recycling	131,693	

2010-2011	ACT	MSW	Landfill	Disposal	63,339	
2010-2011	ACT	MSW	Landfill	Energy recovery	12,721	196,314
2010-2011	ACT	MSW	Recycling	Recycling	120,254	
2009-2010	ACT	MSW	Landfill	Disposal	40,681	
2009-2010	ACT	MSW	Landfill	Energy recovery	12,607	151,500
2009-2010	ACT	MSW	Recycling	Recycling	98,212	
2008-2009	ACT	MSW	Landfill	Disposal	61,828	
2008-2009	ACT	MSW	Landfill	Energy recovery	16,747	182,162
2008-2009	ACT	MSW	Recycling	Recycling	103,587	
2006-2007	ACT	MSW	Landfill	Disposal	75,486	
2006-2007	ACT	MSW	Landfill	Energy recovery	24,161	207,549
2006-2007	ACT	MSW	Recycling	Recycling	107,902	

5.2.2.2 Waste selling price

The selling price of waste products is one of the parameters that are subject to uncertainty, as it depends on both seller and buyer's policies, the global financial situation, and many other parameters. To identify the amount of uncertainty, the selling price of some recycled materials is extracted from the Australian Bureau of Statistics (2020) waste data.

Table 5.2: Changes in the selling price of waste products

	Glass	Hazardous (excl. tires)	Metals	Other	Paper and cardboard	Plastics	Tires
2017-18	**$54**	**$5,582**	**$782**	**$714**	**$188**	**$276**	**$203**
Jul	$50	$6,178	$843	$848	$192	$265	$278
Aug	$43	$8,018	$650	$784	$199	$294	$198
Sep	$37	$5,045	$788	$481	$206	$321	$172
Oct	$42	$6,442	$710	$560	$195	$235	$253
Nov	$28	$4,044	$779	$748	$188	$271	$294
Dec	$62	$1,996	$744	$527	$186	$258	$258
Jan	$59	$17,025	$588	$748	$179	$237	$177
Feb	$42	$6,516	$998	$907	$181	$256	$170
Mar	$36	$2,184	$759	$560	$183	$245	$170
Apr	$92	$5,101	$913	$1,008	$167	$312	$180
May	$94	$5,772	$813	$1,333	$173	$313	$205
Jun	$122	$4,191	$878	$1,230	$199	$293	$178
2018-19	**$44**	**$5,984**	**$820**	**$828**	**$211**	**$231**	**$193**

Jul	$44	$5,740	$896	$625	$219	$284	$380
Aug	$46	$2,207	$885	$1,052	$219	$298	$309
Sep	$30	$12,538	$782	$728	$224	$247	$202
Oct	$53	$5,111	$874	$1,277	$254	$265	$218
Nov	$104	$2,224	$775	$1,186	$247	$217	$220
Dec		$15,469	$848	$650	$223	$198	$197
Jan	$96	$2,274	$836	$1,055	$210	$201	$211
Feb	$352	$9,873	$797	$974	$198	$160	$149
Mar		$6,010	$906	$928	$195	$213	$160
Apr	$40	$4,215	$806	$1,162	$178	$225	$145
May	$24	$6,191	$817	$1,034	$180	$252	$133
Jun	$38	$3,153	$679	$435	$178	$259	$140
2019-20	**$53**	**$7,959**	**$765**	**$775**	**$162**	**$277**	**$209**
Jul	$46	$6,629	$773	$858	$165	$274	$134
Aug	$46	$6,215	$782	$1,312	$169	$362	$164
Sep	$37	$7,724	$926	$579	$168	$273	$121
Oct	$58	$1,830	$806	$675	$165	$273	$155
Nov	$26	$14,107	$737	$957	$131	$274	$220
Dec	$19	$8,459	$653	$884	$120	$287	$213
Jan	$63	$22,054	$878	$1,308	$142	$235	$266
Feb	$63	$9,275	$849	$613	$149	$269	$198
Mar	$60	$9,818	$857	$1,235	$198	$283	$266
Apr	$57	$8,148	$653	$554	$178	$279	$475
May	$105	$5,966	$707	$591	$176	$323	$312
Jun	$1,050	$8,753	$656	$750	$186	$231	$314
Grand Total	**$51**	**$6,513**	**$790**	**$770**	**$187**	**$258**	**$201**

5.2.2.3 Transportation cost

The most important key factor in waste transportation cost that is subject to uncertainty is fuel price. As in the waste management collection system, the primary fuel type is diesel, the data for the price of diesel in Australia in past years is acquired from the *AIP Annual Retail Price Data | Australian Institute of Petroleum* database and is indicated in Table 5.3.

Table 5.3: Fuel prices in Australia (cents)

	NSW	VIC	QLD	SA	WA	NT	TAS	National
2007	134.7	129.8	124.7	133.1	135.9	139.1	135.4	131.3
2008	164.3	160.3	154.9	163.1	166.7	171.1	168.1	161.6
2009	123.3	119.8	119.4	122.1	127.3	132.2	128.4	122.5
2010	130.3	126.5	129.6	129.1	133.3	139.3	134.1	130.1
2011	148.9	145.1	148.3	148.2	150.8	159.0	152.6	148.5
2012	147.9	146.2	149.3	149.5	150.5	158.6	155.1	150.6
2013	154.1	151.2	154.4	154.4	156.3	168.4	159.6	154.3
2014	156.8	153.1	156.6	155.9	159.7	172.6	164.2	156.8
2015	130.1	125.9	131.1	128.2	134.9	138.2	137.8	130.4
2016	117.8	116.2	118.9	116.4	121.6	123.3	122.8	118.5
2017	128.5	128.3	129.5	127.1	132.3	135.1	136.4	129.6
2018	148.9	148.8	148.7	147.6	152.8	164.8	156.9	149.8
2019	147.9	146.0	147.1	147.9	148.9	161.4	158.8	148.0
2020	126.3	126.2	125.7	125.7	127.3	142.1	139.0	126.9
2021	142.9	142.6	142.5	142.2	142.1	157.2	149.2	143.0

5.2.2.4 Capacity of facilities

An IMSWM system involves several facilities to meet the total demand for waste management activities. Determining the capacity of waste management facilities is usually a costly operation and needs careful observation to identify the best capacity for any facility in the system. Waste management facilities sometimes can expand capacity after the first establishment. In this research, to identify the effect of changes in the capacity of facilities, the effect of the expansion of capacity in all the facilities is modeled as different scenarios. These scenarios are constructed using a uniform distribution between the original capacity and the state that the capacity is double the original capacity.

5.2.3 Solution Approach

The probability distribution of the identified uncertain parameters is determined using actual data. A set of 20 scenarios is generated for each uncertain parameter based on the identified probability distribution. The model is then solved using each scenario data, and the solutions are compared to each other to examine the robustness of the model against changes in the uncertain parameters.

In Chapter 3, the NSGA-II and NSGA-III algorithms are used to solve the deterministic problem, and the results indicated that the NSGA-II significantly outperforms the NSGA-III algorithm. To solve the problem with uncertain parameters, after creating the uncertain parameters scenarios, the data for uncertain parameters are replaced by data from one scenario, and the model is solved as a deterministic problem. As the mathematical model in this setting is almost similar to the deterministic model in Chapter 3, based on the supremacy of NSGA-II, this Chapter only considers the NSGA-II algorithm with previously tuned parameters.

Pseudocode of NSGA-II Algorithm for uncertain parameters

Input: g: generations to solve

Input: s: scenario number

Replace Generation, transport cost, capacity, and selling price values with uncertain set s

Initialization (creating random population)

Objective and constraint **evaluation**

Ranking Population

Crossover (creating child population)

Mutation

For i = 1 to g:

For each child and parent in the population:

Rank population

Identify non-dominated solutions

Calculating crowding distance

Selecting the best solutions based on ranks

End

Generate population for next generation

end

5.3 Results and Discussion

Using the identified parameters that are subject to uncertainty, several scenarios are generated to represent the uncertainty IMSWM model. The model is solved for each scenario using the NSGA-II algorithm and the developed solution repair function developed in Chapter 3 for the deterministic model. The results are then compared to each other to identify the effect of uncertainty on the solutions of the model.

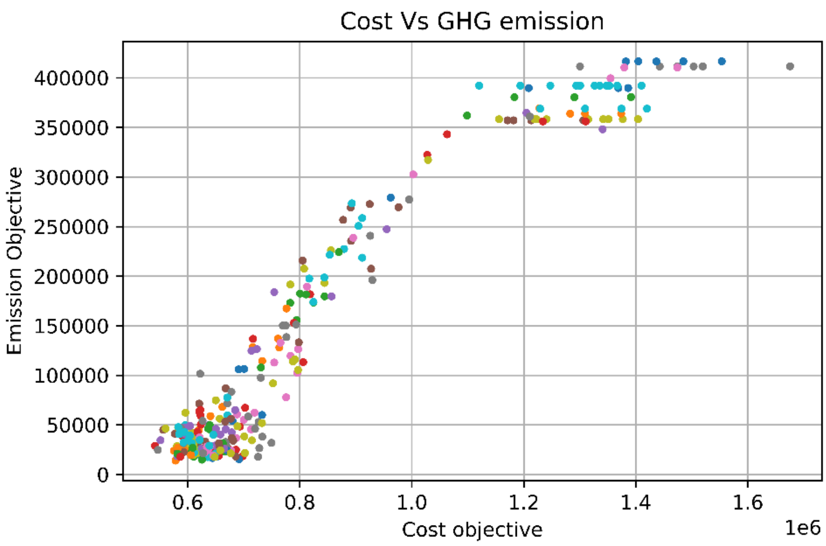
The values of uncertain parameters for each scenario and each parameter which are used in this thesis are indicated in Table A.1 to Table A.5 in the appendix.

5.3.1 Uncertainty in Mixed and Recyclable Waste Generation

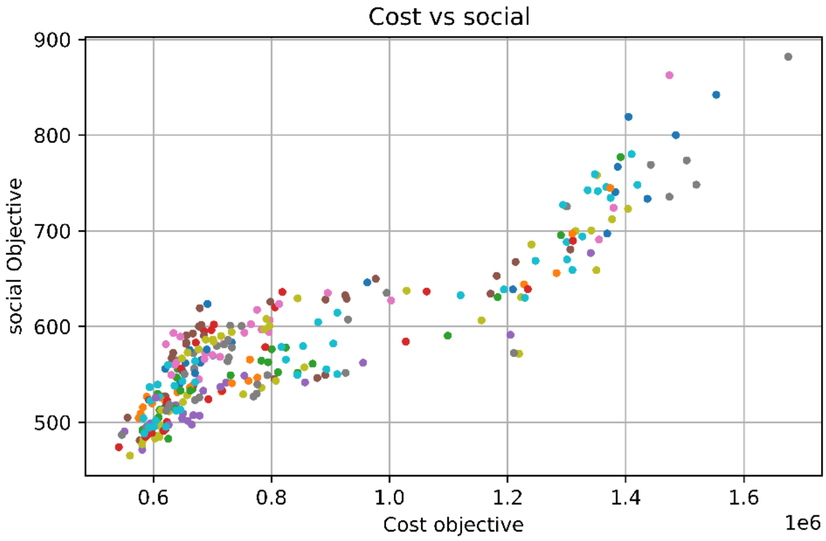
The uncertainty set for mixed and recyclable waste generation in generation points is calculated using the probability distribution of the data, based on the population of each generation point. The values of mixed waste generation for each scenario are indicated in Table A.1.

Using the same method, the values of recyclable waste generation at each generation point are generated and indicated in Table A.2.

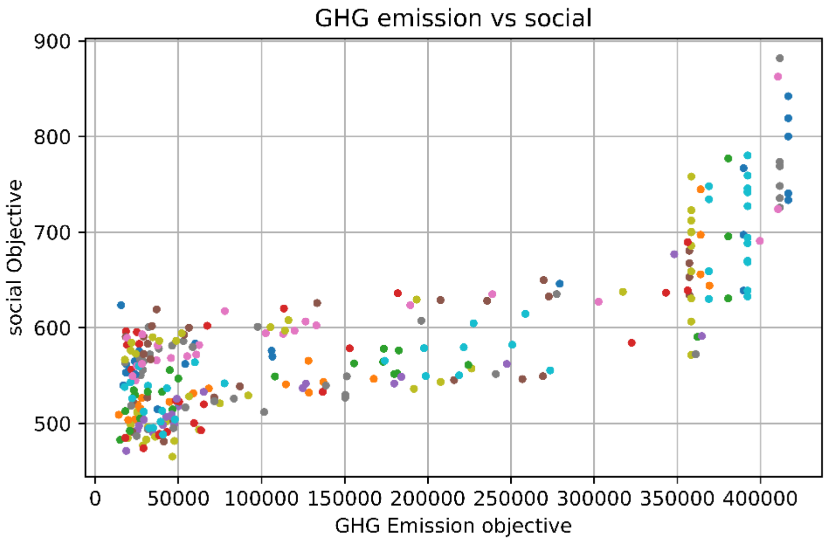
The model is solved for each scenario, and the non-dominated solutions are acquired for each scenario. The solutions of the model with uncertain mixed and recyclable waste generation are visualized for the three sets of two objective functions in Figure 5.1,(a),(b), and (c). Figure 5.2 shows the objective function values for the non-dominated solutions for all three objective functions.



(a)



(b)



(c)

Figure 5.1: Solutions of the model with uncertain waste generation

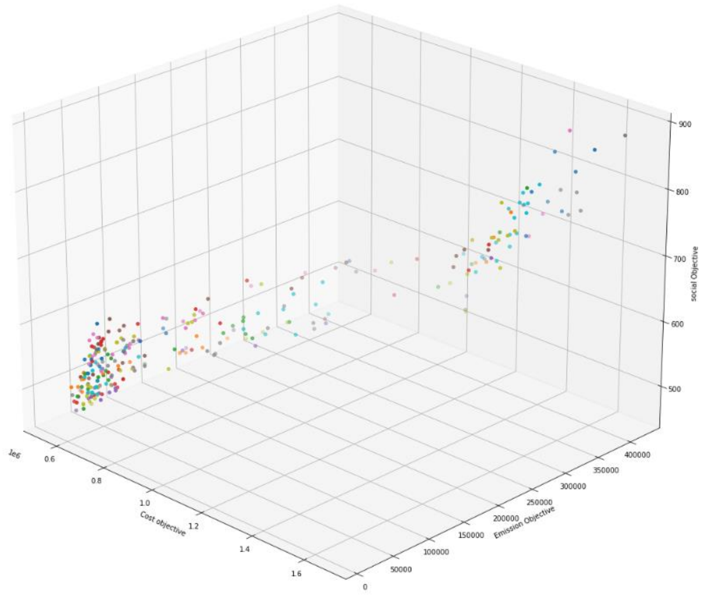
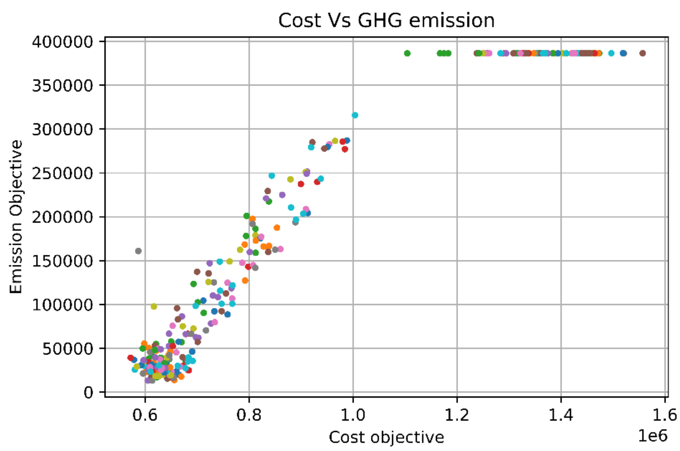


Figure 5.2: Values of three objectives in solutions of the model with uncertain waste generation

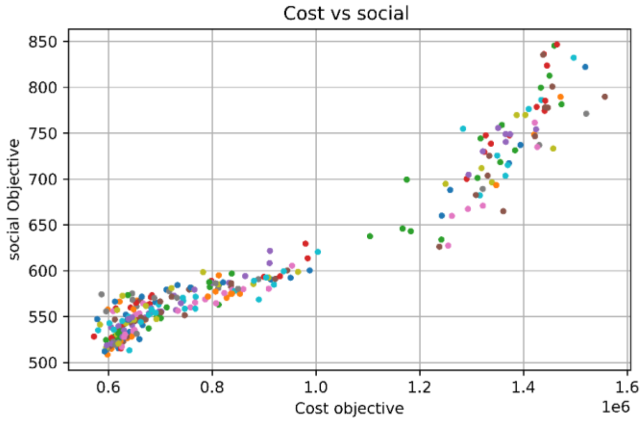
5.3.2 Uncertainty in Transport Costs Between Facilities

The changes in fuel price affect the transportation cost between facilities. Transportation cost also depends on the type of vehicle and labor needed for each kind of mixed and recycled material. Based on the changes in fuel price, the transportation cost between facilities is identified, and 20 scenarios are generated. The transportation cost for every link in the system for each scenario for recycled and mixed waste is indicated in Table A.3.

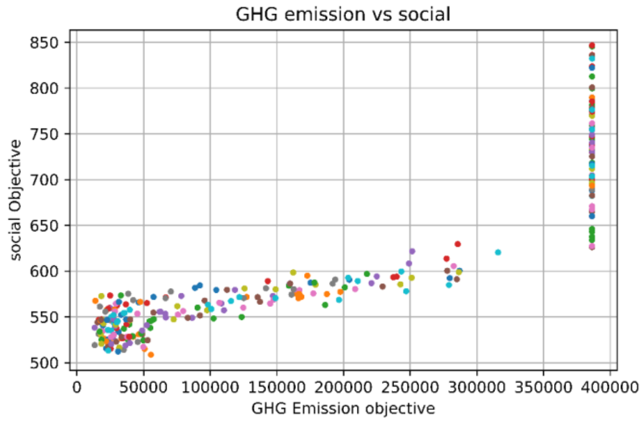
The solutions for each scenario with a different transportation cost are then obtained from the model and are indicated in Figure 5.3, for each set of two objective functions. As the model is a three-objective model, the 3-dimensional visualization of the results for the model with uncertain transportation costs is also indicated in Figure 5.4.



(a)



(b)



©

Figure 5.3: Solutions of the model under uncertain transportation cost

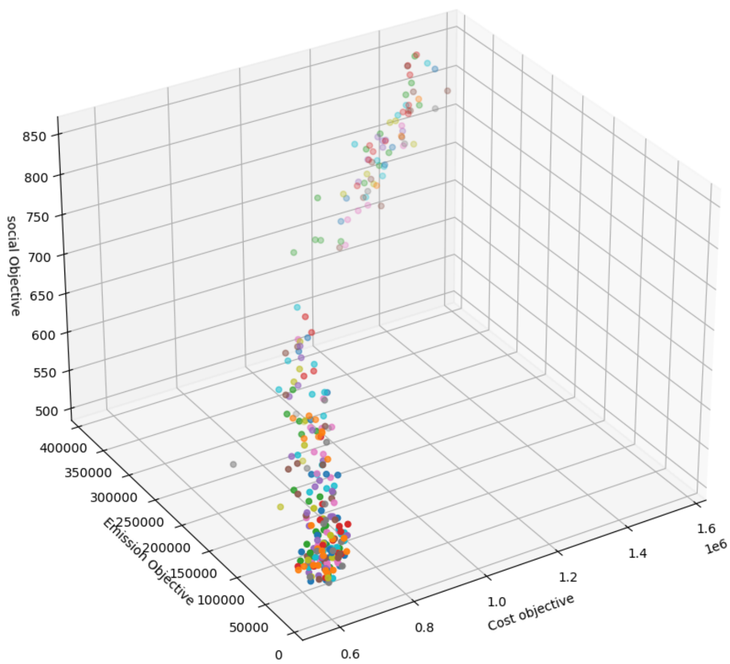
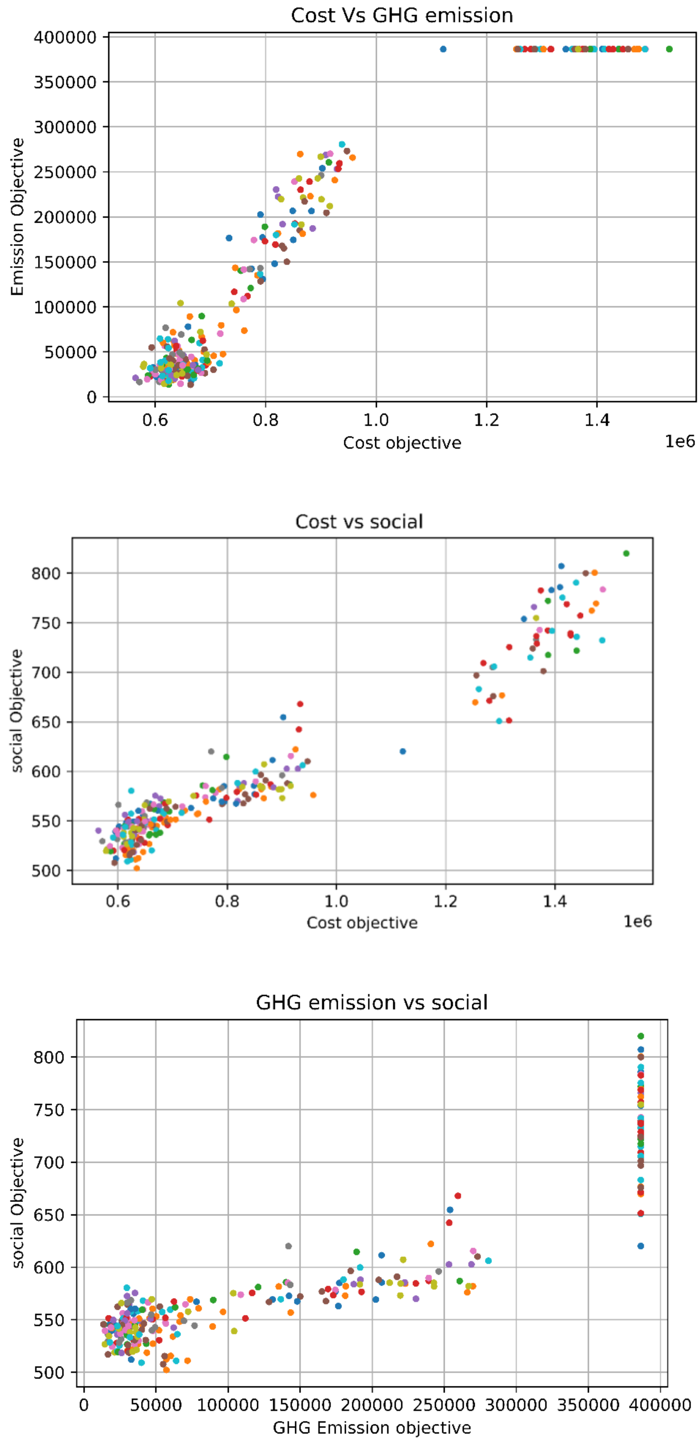


Figure 5.4: Solutions of the model with uncertain transportation costs for all three objectives

5.3.3 Uncertainty in Selling Price of Recycled Materials

Based on the fluctuation in the selling price of recycled materials, 20 scenarios are generated using the probability distribution of prices in real data. The values for the price of each material in each scenario are indicated in Table A.4.



(a)

(b)

(c)

Figure 5.5: Solutions of the model under uncertain selling price

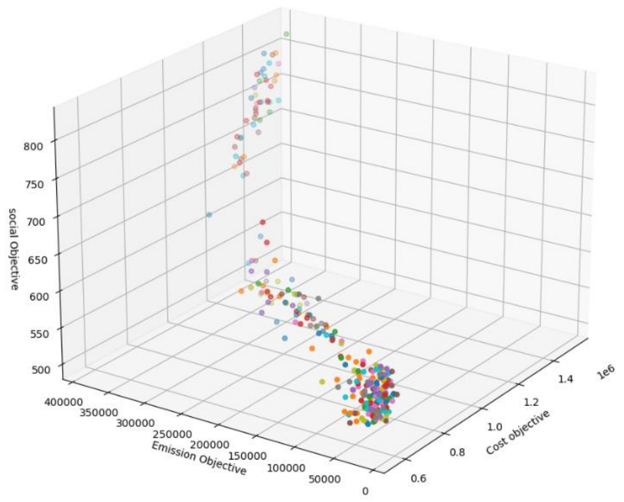
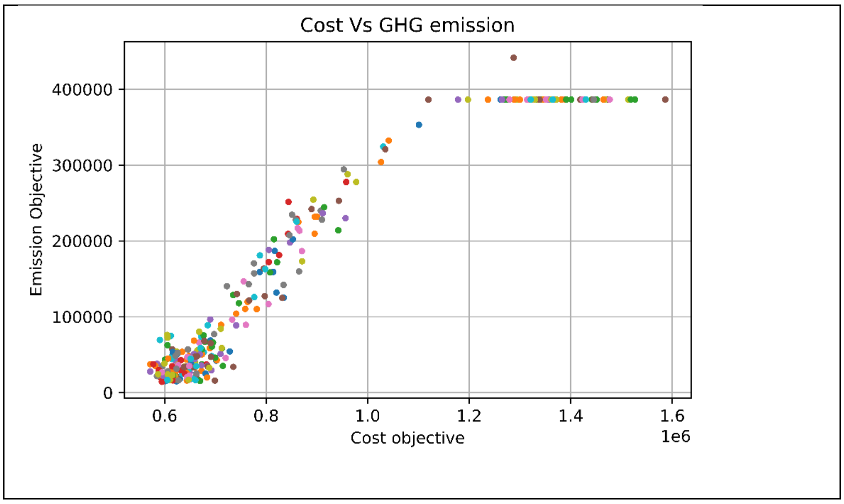


Figure 5.6: Model solution with NSGA-II for each scenario with the uncertain selling price

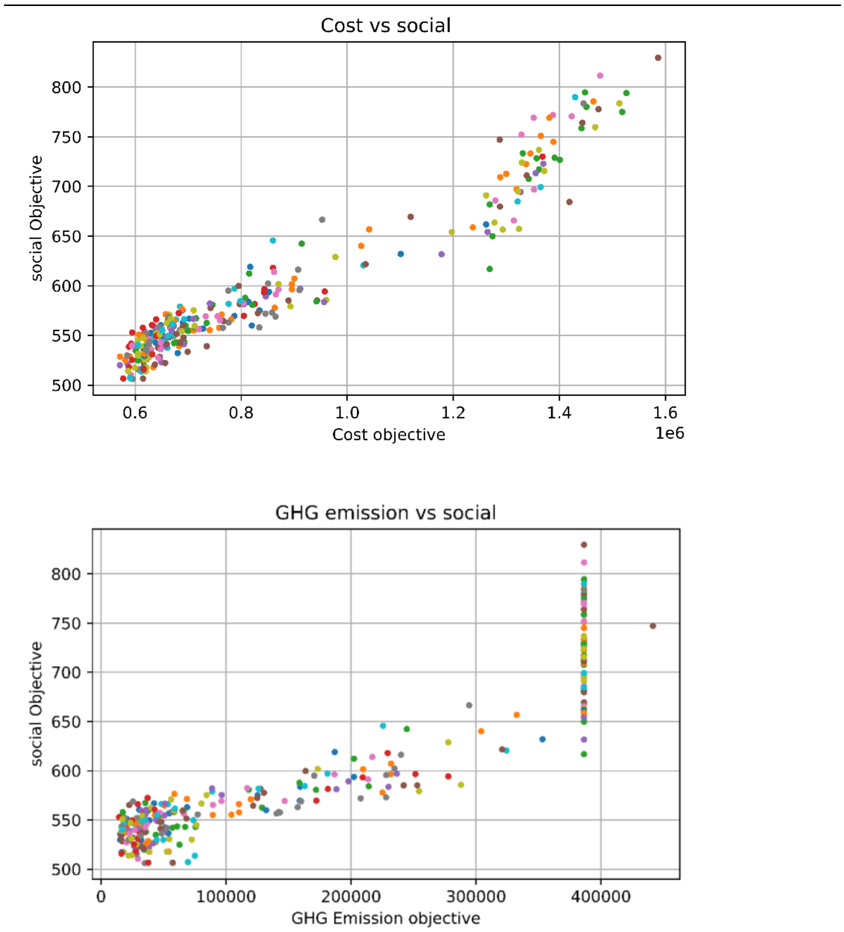
5.3.4 Uncertainty in Capacity of Facilities

Considering the changes in the capacity of any facility in the system affect the overall performance and cost of the system. Identifying the suitable capacity of each facility is one of the most important tasks in designing any waste management system. To identify the effect of changes in the capacity of facilities, 20 scenarios are considered with different capacity values. These capacities are selected using a uniform distribution.

Table A.5, shows the capacity value for different facilities in the system for each scenario.



(a)



(b)

(c)

Figure 5.7: Solutions of the model with uncertain capacity

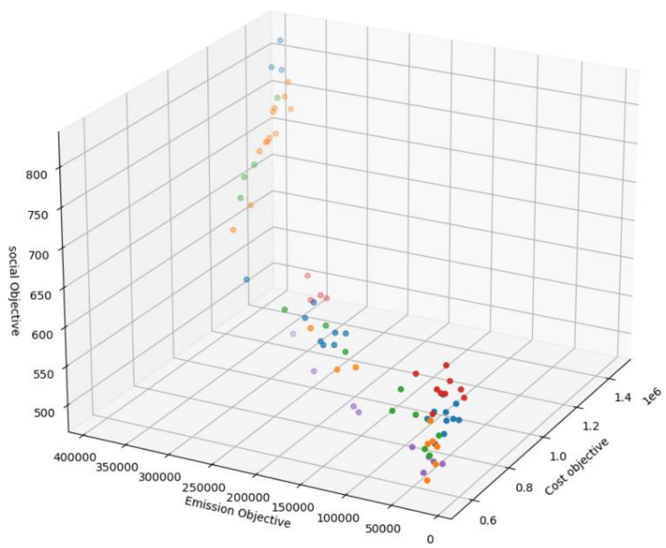
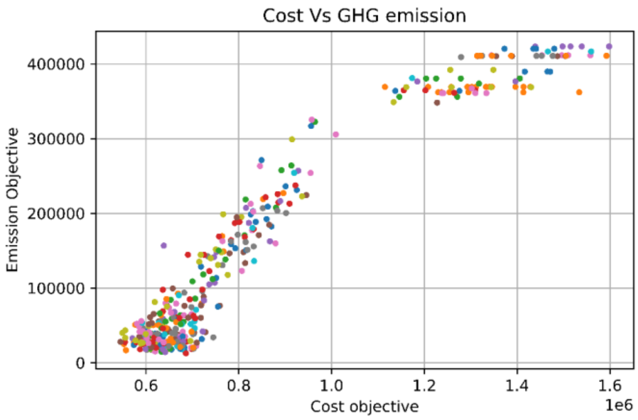


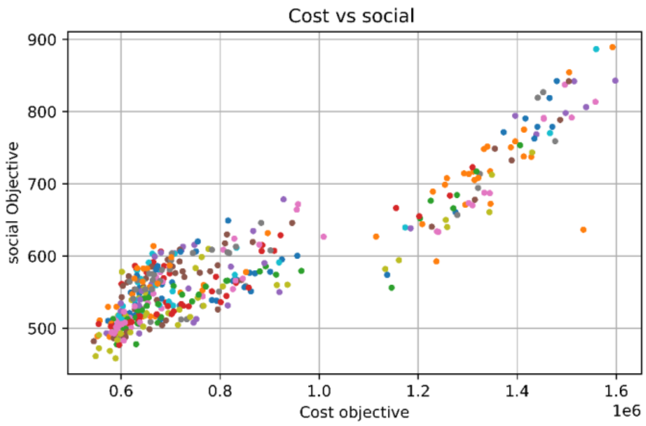
Figure 5.8: The result of the model with scenarios with uncertain capacity using NSGA-II

5.3.5 Uncertainty in All Four Parameters

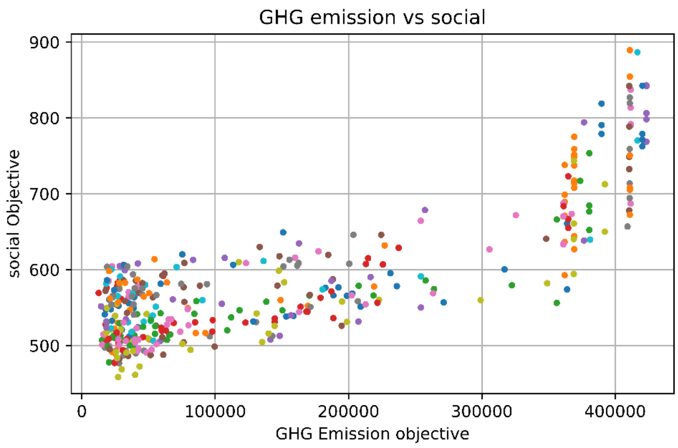
In real-world situations, uncertainty in model parameters usually occurs together. To assess the effect of having multiple uncertain parameters in the model, the values of uncertain parameters introduced for each parameter separately are used together to generate 20 scenarios. In each scenario, the value of each uncertain parameter is selected from the corresponding scenario for each parameter. The solutions of the model considering all four uncertain parameters for each scenario using the NSGA-II algorithm with previously tuned hyperparameters are indicated in Figure 5.9 for each set of 2 objective functions. Figure 5.10 indicates all three objective functions with all four uncertain parameters.



(a)



(b)



(c)

Figure 5.9: Solutions of the model with all four uncertain parameters

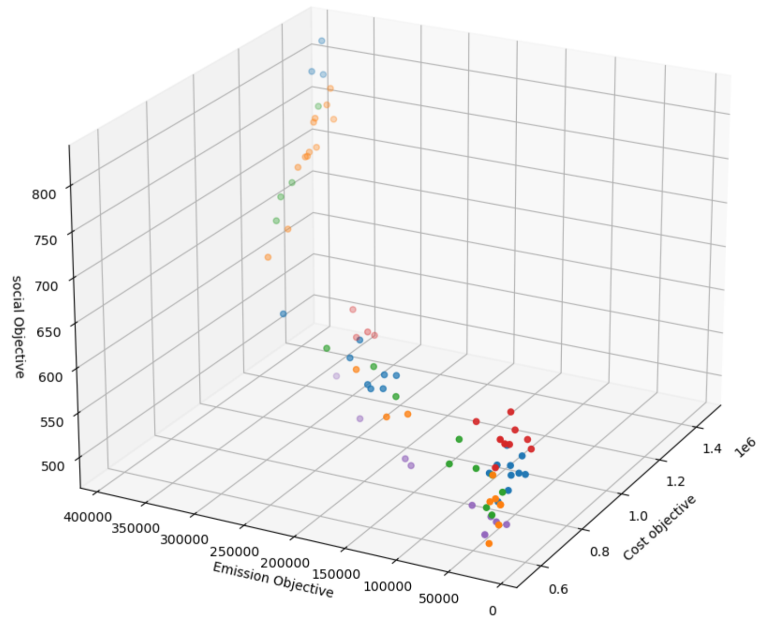


Figure 5.10: Solutions of the model with multiple uncertainties using the NSGA-II algorithm

5.4 Discussion

To identify the effect of changes in uncertain parameters on each objective function, the non-dominated solutions of all scenarios are compared to each other using all uncertain parameters.

Cost objective

Figure 5.11 demonstrates the spread of values for the cost objective function for the model with each uncertain parameter against each other and the model with multiple uncertainties. As indicated in this figure, the cost objective function is more sensitive to changes in transportation costs between facilities parameters. In comparison, uncertainty in final waste product price has the least effect on cost objective between all four selected uncertain parameters. The model with an uncertain selling price also has the lowest median cost objective function value of around 670000 dollars. Based on the results in the model with uncertain selling price, 75% of the solutions have a total system cost between \$620,000 and \$870,000. While for the model with uncertain transportation costs, 75% of the solutions are spread between \$630,000 and \$1,180,000. As indicated in the results, when considering all four uncertain parameters together, the median of cost objectives values is around \$710,000, slightly larger than the median of models with separate uncertain parameters except for the model with uncertain transportation costs that has a higher median. Considering all uncertain parameters together, in 75% of the solutions, the cost objective value is spread between \$620,000 and \$930,000. Based on the results, it is indicated that by controlling the uncertainties in transportation cost parameters using different policies, the decision-maker can make more confident decisions regarding the system's total cost.

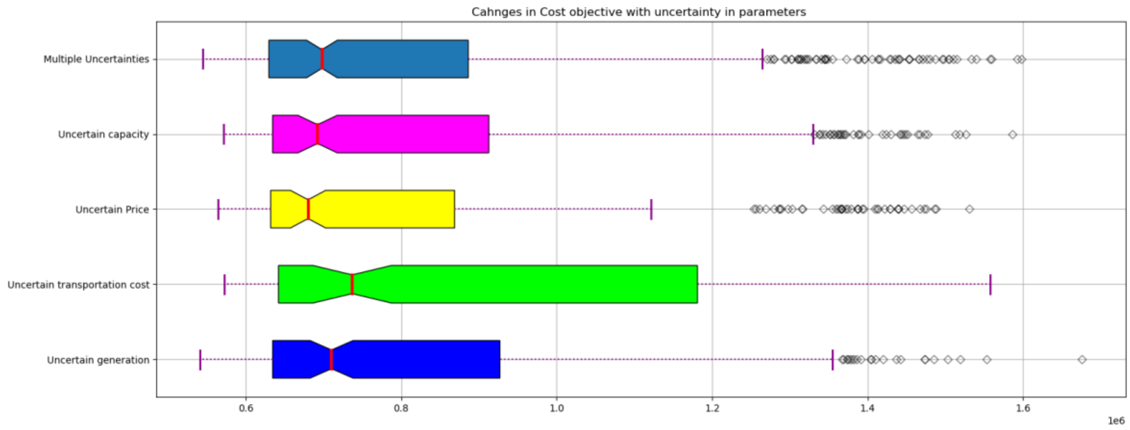


Figure 5.11: Spread of cost objective function in solutions with uncertain parameters

Environmental objective

The spread of GHG emission between solutions of uncertain models is compared in Figure 5.12. Uncertainty in transportation cost also has the largest effect on the Environmental objective function between all four uncertain parameters. Also, the model with uncertain transportation costs has the lowest maximum value among the uncertain models. In 75%of solutions in this model, the GHG emissions value spread between 35000 and 380000 co2eq. While in the model with uncertain generation only, 75% of the solutions have GHG emissions between 30000 and 260000 co2eq. This spared is between 30000 – 220000 and 35000 – 240000 for models with uncertain prices and uncertain capacities respectfully. GHG emission objective function like cost objective is less sense considering all four uncertain parameters together. The main reason for this effect is that some effect of uncertainty in waste generation is neutralized by uncertainties in facility capacities. In the uncertainty in capacities, the expansion of facilities is considered rather than shrinkage. Similar to the Cost objective function, controlling the transportation costs would lead to a more confident decision in the model.

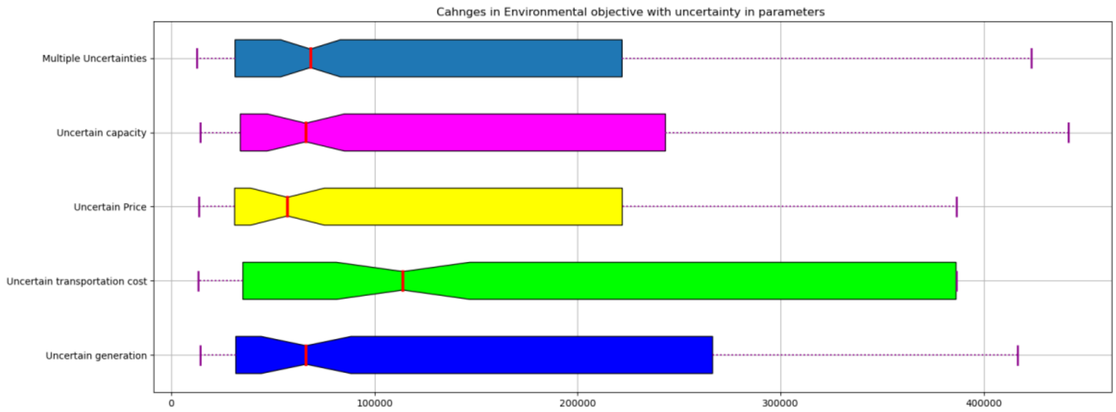


Figure 5.12: Spread of GHG emission in the uncertain models

Social objective

As indicated in Figure 5.13, the social acceptance objective is affected less than other objectives by changes in uncertain parameters. Again, in this objective function, the uncertainty in transportation cost has a slightly larger effect on the value of the social acceptance measure. In 75% of the non-dominated solutions gained by the model with uncertain transportation costs, the social acceptance measure fluctuates between 550 and 640. However, as the optimization aims to maximize social acceptance, the model with uncertainty has a slightly better median value (around 570) for this objective function. Considering all four uncertain parameters in the model led to results with 75% of the solution having social acceptance between 525 and 610. However, as indicated in the figure regarding the social acceptance, the transportation cost and waste generation as uncertain parameters have a more similar effect on the models. With uncertain generation, the social acceptance is generally lower than the model's results with uncertain transportation costs.

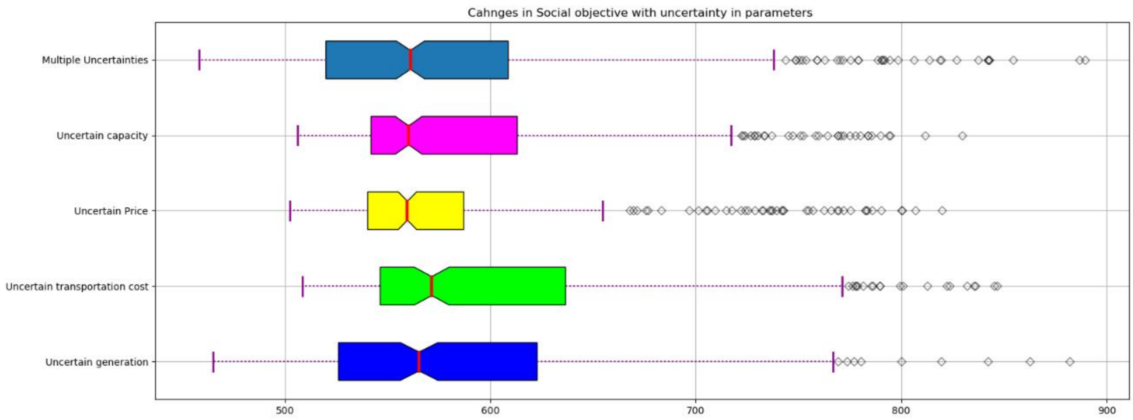


Figure 5.13: Spread of social acceptance objective in uncertain models

5.5 Managerial Implications

Between the uncertain parameters, the uncertainty in transportation cost has the largest effect on all three objectives. For economic and environmental objectives, the average value of the two objectives is higher than the models with other uncertain parameters. This means considering transportation cost uncertainty leads to more cost and GHG emissions. However, the model with uncertain transportation costs has the best social acceptance among all the parameters. This improvement is smaller than the disadvantage of having more costs and emissions in the system. Therefore, the total system cost and emission can be lowered by controlling transportation costs. Applying proper policies like depositing fuel and scheduled maintenance of the collection and transportation fleet can lead to more constant transportation costs and lower the total system cost and emissions.

5.6 Chapter Summary

In this Chapter, the deterministic model which was developed in Chapter 3 is further extended to consider several uncertainties that would affect the parameters of the model. The model is solved using the evolutionary algorithm using the developed repair function and tuned parameters.

Chapter 6 : Conclusions and Future Research Directions

6.1 Summary of Research

In this research, an integrated municipal solid waste management system (IMSWM) is developed using a mathematical programming approach. The major components of an IMSWM system, namely waste transfer stations, material recovery facilities, waste treatment facilities, waste disposal facilities, and waste markets are considered to create a holistic system. The waste composition is an important factor in selecting appropriate and compatible technologies for waste processing. The model is a three-objective problem that considers three main sustainable development objectives: economic, environmental, and social objectives. The economic objective function determines the total system cost of collection, transportation, processing, and disposal of waste along with the cost revenue of the system from waste markets. The environmental objective function calculates the overall GHG emission generated from both transportation and processing activities in the system. The most important indicators that affect the social acceptance of the IMSWM system are identified in the literature. Using the TOPSIS method, a social suitability measure is defined for each facility in the system. This measure is then used in the social objective function to determine the overall social acceptance of the model.

The model is subject to several constraints classified into two major groups equality and inequality constraints. The equality constraints include collecting mixed and recyclable waste from generation points and mass balance in waste management facilities. Inequality constraints include facilities along with their capacity and minimum allowable waste for each facility. The compatibility of each waste type with each facility is also determined using an inequality constraint. For each facility, a binary variable is assigned for the establishment of that facility that identifies if any facility is established in the system or not. The model is then applied to a case study of the Australian Capital Territory.

The model is developed as a mixed-integer mathematical programming problem and solved using the epsilon constraint method to obtain the true Pareto front of the solutions. Gurobi commercial solver is selected as the solver. A meta-heuristic algorithm is developed based on modified NSGA algorithms to increase the model's applicability in larger problems. The model is solved using two instances of NSGA-II and NSGA-III algorithms and the results indicated that the NSGA-II algorithm significantly outperforms the NSGA-III.

Meanwhile, to deal with several uncertainties that exist in the parameters of the model, key parameters that would be subject to uncertainty are identified. Based on the real data extracted from waste reports, the probability distribution of the uncertain parameters is identified. For each parameter, a set of 20 scenarios is generated representing the uncertainty in the parameter. The model is solved for each parameter separately and the effect of fluctuations in that parameter on the objective functions are compared to each other. Finally, a more realistic scenario is considered where all four parameters are uncertain and solved for 20 scenarios.

6.2 Value and Significance

Advanced waste recycling and treatment technologies can help reduce the amount of waste buried underground and turn it into valuable products or energy. Selecting the proper set of these technologies for any environment is a delicate task that should consider all aspects of sustainable development, namely economic, environmental, and social. In this study, a multi-objective MILP model was developed as a decision support system for optimizing integrated municipal solid waste management (IMSWM). The model aims to minimize the total system cost, minimize the total GHG emissions, and maximize the social acceptance of the whole system. An optimum solution of the model contains the location of transfer stations, waste recycling facilities with different technologies, waste treatment facilities, waste disposal facilities, and market facilities. The solution also specifies the allocation of waste to each facility. Social acceptance of the system is determined by adding the social acceptance measure of each activity in the system based on social indicators selected from the literature and expert's opinions. Australian Capital Territory is selected as a case study for testing the applicability of the proposed model, because of the availability of the data and good potential for future development of WM systems.

This study contributes to the WM literature by developing a model with three separate objective functions to select the best WM technologies based on waste composition. The obtained results can help policymakers assess an existing system's performance or design a new system. The results can help the decision-makers decide on what type of technologies are needed, the location of any facility in the system, and the capacity and size of each facility. Sensitivity analysis shows that the model is sensitive to changes in the waste generation, the capacity of facilities, the waste transport cost, and the final selling price of products.

Between the proposed waste markets, the markets for energy from landfills and incineration facilities are established in most of the solutions because of the system's high profitability and cost revenue. Identifying and applying the new methods to generate energy from waste in these facilities is highly recommended for the case study.

6.3 Discussion and Managerial implications

Based on the model's optimum solutions, some suggestions can be made for the IMSWM system. Waste transfer stations are considered a very suitable management method in the case study. The results indicate that in 100% of the feasible, non-dominated solutions, gained by the NSGA-II algorithm transfer stations are established and being used in the solution. Analysis of the results also shows that in only 9% of the feasible solution, the recyclable waste is first transported to the transfer station and sent to appropriate facilities after processing. Therefore, a separate collection of mixed and recyclable waste is recommended for the case study. However, in the case of the mixed waste collection, in 39% of the non-dominated solution, the waste is transported to the transfer station, and the rest is transported directly to disposal facilities. Therefore, to reduce the total costs of the system, a reduction in transfer station capacity would be recommended while preserving the feasibility of the model.

To answer the first research question of this study, the selection of special material recovery technology for different types of materials in the waste composition depends highly on the selling price of waste and the social aspects of material recovery facilities. Based on the results, In the case study, Masonry is a type of waste with a high potential for material recovery, and a higher after-process value is established at 100% of the feasible solutions. Hazardous waste recovery is also highly recommended as it has the second-highest establishment ratio among non-dominated solutions. On the other hand, the Environmental and health hazard of hazardous waste types is the factors that have not been discussed in this research, making hazardous material recovery a profitable option for the system. This proposal is also backed up by the fact that waste treatment technologies as alternative options for processing hazardous waste are only established in 1% of the non-dominated solutions. Material recovery is a better option for this type of waste. Glass, metal, paper, plastic, and ash are the materials that have been selected for recovery in nearly 50% of the solutions. Based on the results, establishing material recovery facilities that accept multiple types of these materials would reduce the system's total cost.

Another question that this study intended to answer was how transfer stations can affect the waste management system compared to a mixed collection system without transfer stations. The results indicate that in 100% of the Best non-dominated solution obtained using the evolutionary algorithms, transfer stations are established and used in the optimum model solution. Therefore we can conclude with a high confidence level that using transfer stations in the case study would lead to a more optimum system.

To answer the third research question, in this study, the main social acceptance indicators are identified. Using these indicators, the social acceptance measure of system activities is calculated using TOPSIS methods. This social acceptance measure is used as a social objective function, and in all scenarios, the model is solved to maximize the social acceptance of the system.

Using incineration beside sanitary landfills is highly suggested due to less soil contamination and lower cost. With the advances in technologies, the GHG emissions of the incineration plants are also more controllable, making them a more suitable option for waste disposal. Sanitary landfills remain the main option for waste disposal because of the lower cost of establishment and operation. However, with the increasing requirement of land for landfills and Environmental pollution from incineration plants, identifying and using better disposal technologies are also recommended.

The availability of the waste markets is highly dependent on government policy and the current state of the waste buyers. Changes in waste export regulations affect the availability of markets for special waste types. Therefore, with the available options identified, using a special waste market depends on processed waste and the type of waste product available.

To answer the 4th question of the research, the main parameters with uncertainty are identified, and using the real data the uncertain scenarios for each parameter are generated. The model is solved for all scenarios and combines multiple uncertain parameters. The results have indicated that the uncertainty in transportation cost has a large effect on objective functions followed by other parameters.

6.4 Future Research Directions

In this thesis, a holistic IMSWM model is developed considering all three sustainable development objectives: economic, environmental, and social. The parameters with uncertainty are identified, and several uncertain scenarios are generated. The problem is solved using the developed NSGA-II algorithm, and the fluctuations in objective functions are observed and discussed. However, several newer methods have been developed in the field of stochastic optimization. Considering those algorithms and comparing the results against those methods can be a future research topic. Also, the Evolutionary algorithm developed in this thesis based on NSGA-II can be further enhanced to deal with several equality constraints in the system.

Considering the effect of natural disasters and pandemics on the system is also an interesting topic to further develop this model. In this study, the generation points are considered in the center of residential districts. However, in the real world, the collection usually takes place from the curbside and in front of houses. Adding the Vehicle routing problem as an addition to the current optimization problem to minimize the transportation cost can be an interesting topic to extend this research. Size and type of collection fleets considering traffic data and peak hours is also an interesting idea to follow up with this optimization model.

Considering different kinds of waste including industrial, construction and demolition, food waste, medical waste, and electronic waste can be an important addition to this model. Consideration of different waste types requires considering new facilities and technologies related to these types of waste.

Adding land development studies to identify the best location options for different facilities is also an important step that can help reduce the number of calculations by ignoring the unsuitable locations for specific facilities.

All the calculations in this model are done using the latest historic waste generation data. However, development in societies and changes in the lifestyle of people might differ the amount and type of generated waste in the future. Recent advances in artificial intelligence and machine learning can help estimating a more realistic waste generation for the future and model a more realistic and optimized model.

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Appendix A

In this section, the values of the uncertain parameters in each scenario are indicated. Each table indicated one uncertain parameter and the value of that specific parameter in each scenario. In total 20 scenarios are created using the probability distributions.

Table A.1: Values of mixed waste generation in each uncertain scenario(tons)

scenario	BELCONNEN	CANBERRA_CENTRAL	GUNGAHLIN	HALL	JERRABOMBERRA	MAJURA	TUGGERANONG	WESTON_CREEK	WODEN_VALLEY	MOLONGLO_VALLEY	QUEANBEYAN
0	210.74	210.74	125.26	0.39	3.58	2.39	124.07	35.39	62.83	19.88	77.94
1	199.67	199.67	118.68	0.37	3.39	2.26	117.55	33.53	59.53	18.84	73.84
2	205.78	205.78	122.31	0.38	3.50	2.33	121.14	34.56	61.35	19.41	76.10
3	223.34	223.34	132.74	0.42	3.79	2.53	131.48	37.51	66.59	21.07	82.60
4	188.23	188.23	111.88	0.35	3.20	2.14	110.82	31.61	56.12	17.76	69.62
5	193.12	193.12	114.78	0.36	3.28	2.19	113.69	32.43	57.58	18.22	71.42
6	216.06	216.06	128.42	0.40	3.67	2.45	127.20	36.29	64.42	20.38	79.91
7	222.55	222.55	132.27	0.42	3.78	2.52	131.02	37.38	66.35	20.99	82.31
8	193.75	193.75	115.16	0.36	3.29	2.20	114.06	32.54	57.76	18.28	71.66
9	212.07	212.07	126.05	0.40	3.60	2.41	124.85	35.62	63.23	20.01	78.43
10	225.28	225.28	133.90	0.42	3.83	2.56	132.63	37.84	67.17	21.25	83.32
11	196.78	196.78	116.96	0.37	3.34	2.23	115.85	33.05	58.67	18.56	72.78
12	195.78	195.78	116.36	0.37	3.33	2.22	115.26	32.88	58.37	18.47	72.41
13	192.57	192.57	114.45	0.36	3.27	2.18	113.37	32.34	57.41	18.17	71.22
14	197.22	197.22	117.22	0.37	3.35	2.24	116.10	33.12	58.80	18.61	72.94
15	228.93	228.93	136.07	0.43	3.89	2.60	134.77	38.45	68.25	21.60	84.67
16	221.95	221.95	131.92	0.41	3.77	2.52	130.67	37.28	66.17	20.94	82.09
17	195.22	195.22	116.03	0.36	3.32	2.21	114.93	32.79	58.20	18.42	72.20
18	222.14	222.14	132.03	0.41	3.77	2.52	130.78	37.31	66.23	20.96	82.16
19	199.49	199.49	118.57	0.37	3.39	2.26	117.44	33.50	59.48	18.82	73.78

Table A.2: Values of recyclable waste generation in each scenario

	BELCONNEN	CANBERRA_CENTRAL	GUNGAHLIN	HALL	JERRABOMBERRA	MAJURA	TUGGERANONG	WESTON_CREEK	WODEN_VALLEY	MOLONGLO_VALLEY	QUEANBEYAN
0	102.72	102.72	61.05	0.19	1.74	1.16	60.47	17.25	30.62	9.69	37.99
1	97.32	97.32	57.84	0.18	1.65	1.10	57.29	16.34	29.01	9.18	35.99
2	100.30	100.30	59.61	0.19	1.70	1.14	59.05	16.84	29.90	9.46	37.09
3	108.86	108.86	64.70	0.21	1.85	1.23	64.08	18.28	32.45	10.27	40.26
4	91.75	91.75	54.53	0.17	1.56	1.04	54.01	15.41	27.35	8.66	33.93
5	94.13	94.13	55.95	0.18	1.60	1.07	55.41	15.81	28.06	8.88	34.81
6	105.32	105.32	62.59	0.20	1.79	1.19	62.00	17.69	31.40	9.94	38.95
7	108.48	108.48	64.47	0.20	1.84	1.23	63.86	18.22	32.34	10.23	40.12
8	94.44	94.44	56.13	0.18	1.60	1.07	55.59	15.86	28.15	8.91	34.92
9	103.37	103.37	61.44	0.20	1.76	1.17	60.85	17.36	30.82	9.75	38.23
10	109.81	109.81	65.26	0.21	1.86	1.24	64.64	18.44	32.74	10.36	40.61
11	95.92	95.92	57.01	0.18	1.63	1.09	56.46	16.11	28.59	9.05	35.47
12	95.43	95.43	56.72	0.18	1.62	1.08	56.18	16.02	28.45	9.00	35.29
13	93.86	93.86	55.79	0.18	1.59	1.06	55.25	15.76	27.98	8.85	34.71
14	96.13	96.13	57.13	0.18	1.63	1.09	56.59	16.14	28.66	9.07	35.55
15	111.59	111.59	66.32	0.21	1.89	1.26	65.69	18.74	33.27	10.53	41.27
16	108.19	108.19	64.30	0.20	1.84	1.22	63.69	18.17	32.25	10.21	40.01
17	95.16	95.16	56.56	0.18	1.62	1.08	56.02	15.98	28.37	8.98	35.19
18	108.28	108.28	64.35	0.20	1.84	1.23	63.74	18.18	32.28	10.22	40.04
19	97.24	97.24	57.79	0.18	1.65	1.10	57.24	16.33	28.99	9.17	35.96

Table A.3: Values of mixed waste transportation cost between facilities in each scenario(Dollar per ton)

	generation to transfer	generation to recycle	generation to landfill	transfer to recycle	transfer to treatment	transfer to landfill	recycle to landfill	recycle to market	treatment to landfill	treatment to market	landfill to market
0	2.69	1.84	2.41	1.81	1.78	2.29	2.38	1.87	2.32	2.67	2.47
1	2.66	2.04	2.41	2.23	2.01	1.69	1.93	2.13	1.63	1.87	2.23
2	2.12	1.92	1.73	2.07	2.43	2.27	2.38	2.02	2.58	2.43	1.80
3	1.95	1.95	2.47	1.84	2.07	1.99	2.07	1.91	2.07	1.84	2.27
4	2.26	2.23	2.43	2.09	2.82	2.16	2.23	2.23	1.82	2.25	2.56
5	2.48	2.35	2.33	1.82	2.10	2.80	2.59	2.02	2.39	1.94	2.06
6	2.42	1.94	2.23	2.68	2.02	2.36	2.62	2.54	2.11	2.24	1.86
7	2.61	2.57	2.21	2.41	2.43	2.20	1.68	2.48	2.08	1.91	2.27
8	2.10	2.18	2.03	1.61	2.26	2.08	2.29	1.52	2.04	1.64	2.31
9	2.22	1.93	1.84	2.16	2.10	1.79	2.10	2.10	2.45	2.25	2.16
10	2.27	1.94	1.69	1.74	2.89	2.05	2.36	2.15	2.21	2.04	2.04
11	1.77	2.21	2.31	2.81	2.15	2.14	2.09	2.56	2.66	2.18	2.02
12	1.97	2.27	2.76	1.78	2.34	2.33	2.34	2.01	2.31	3.15	1.92
13	2.44	2.20	2.09	1.87	2.28	1.87	1.77	2.12	2.06	3.20	2.32
14	2.43	1.71	2.75	2.13	2.10	2.57	2.32	2.54	2.51	2.68	1.79
15	2.06	1.89	2.20	1.77	1.86	2.13	1.95	2.55	2.53	2.50	1.69
16	2.56	2.38	2.18	2.48	2.71	1.99	2.33	2.41	1.56	2.75	2.25
17	1.69	2.42	2.20	2.19	1.98	2.02	2.15	1.81	2.43	2.10	2.84
18	1.79	2.51	2.14	2.47	2.53	2.42	2.57	2.66	2.11	2.35	3.02
19	1.83	1.77	1.45	2.43	2.13	2.33	2.70	2.15	2.34	1.88	1.61

Table A - 6.1:Values of recyclable waste transportation costs between facilities in each scenario

	generation to transfer	generation to recycle	generation to landfill	transfer to recycle	transfer to treatment	transfer to landfill	recycle to landfill	recycle to market	treatment to landfill	treatment to market	landfill to market
0	1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.68
1	2.30	2.30	2.30	2.30	2.30	2.30	2.30	2.30	2.30	2.30	2.30
2	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55
3	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12
4	2.49	2.49	2.49	2.49	2.49	2.49	2.49	2.49	2.49	2.49	2.49
5	2.35	2.35	2.35	2.35	2.35	2.35	2.35	2.35	2.35	2.35	2.35

6	2.27	2.27	2.27	2.27	2.27	2.27	2.27	2.27	2.27	2.27	2.27
7	1.88	1.88	1.88	1.88	1.88	1.88	1.88	1.88	1.88	1.88	1.88
8	2.14	2.14	2.14	2.14	2.14	2.14	2.14	2.14	2.14	2.14	2.14
9	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28
10	2.06	2.06	2.06	2.06	2.06	2.06	2.06	2.06	2.06	2.06	2.06
11	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33
12	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02
13	2.45	2.45	2.45	2.45	2.45	2.45	2.45	2.45	2.45	2.45	2.45
14	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40
15	2.17	2.17	2.17	2.17	2.17	2.17	2.17	2.17	2.17	2.17	2.17
16	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04
17	2.51	2.51	2.51	2.51	2.51	2.51	2.51	2.51	2.51	2.51	2.51
18	2.07	2.07	2.07	2.07	2.07	2.07	2.07	2.07	2.07	2.07	2.07
19	1.86	1.86	1.86	1.86	1.86	1.86	1.86	1.86	1.86	1.86	1.86

Table A.4: The values of the selling price in each scenario for each material

scenario	Glass	Hazardous	Metals	Other	Paper and cardboard	Plastics	Tires
0	32.0092	755.758	634.0552	393.2712	136.9589	193.5443	85.78626
1	84.31518	8668.23	827.2176	957.9166	196.4016	277.0675	243.4614
2	129.3649	12317.92	902.0249	1176.59	219.4224	309.4141	304.5253
3	51.23114	5987.936	772.2799	797.3247	179.4954	253.3125	198.6167
4	119.8188	11544.55	886.1732	1130.253	214.5443	302.5598	291.5858
5	93.85144	9440.807	843.053	1004.206	201.2747	283.9147	256.3876
6	77.56065	8121.013	816.0014	925.1297	192.95	272.2176	234.3058
7	5.778265	2305.584	696.8032	576.6939	156.2686	220.6765	137.0064
8	54.73015	6271.407	778.0902	814.3091	181.2834	255.8249	203.3595
9	79.44089	8273.34	819.1236	934.2564	193.9108	273.5677	236.8544
10	39.80182	5061.993	753.3009	741.8461	173.6549	245.106	183.1245
11	89.45656	9084.757	835.7551	982.8731	199.0289	280.7591	250.4304
12	32.82117	4496.457	741.7092	707.9617	170.0878	240.0938	173.6624
13	110.6753	10803.79	870.9899	1085.87	209.8719	295.9946	279.192
14	102.663	10154.67	857.685	1046.978	205.7775	290.2416	268.3314
15	59.46022	6654.613	785.9447	837.2692	183.7005	259.2212	209.771
16	35.72947	4732.073	746.5386	722.0787	171.5739	242.182	177.6045
17	122.5102	11762.59	890.6423	1143.317	215.9196	304.4923	295.2338
18	40.90763	5151.58	755.1372	747.2138	174.22	245.9	184.6234

19	3.09454	2088.163	692.3467	563.6669	154.8972	218.7495	133.3686

Table A.5: Values of uncertain capacity for each scenario

	TS1	TS2	TS3
0	1307	1307	1307
1	1021	1021	1021
2	1178	1178	1178
3	1632	1632	1632
4	725	725	725
5	851	851	851
6	1444	1444	1444
7	1612	1612	1612
8	868	868	868
9	1341	1341	1341
10	1683	1683	1683
11	946	946	946
12	920	920	920
13	837	837	837
14	957	957	957
15	1777	1777	1777
16	1597	1597	1597
17	906	906	906
18	1602	1602	1602
19	1016	1016	1016

	composting	Anaerobic digestion
0	2178	2178
1	1701	1701
2	1964	1964
3	2721	2721
4	1208	1208
5	1419	1419
6	2407	2407
7	2687	2687
8	1446	1446
9	2235	2235
10	2804	2804
11	1577	1577
12	1534	1534
13	1395	1395
14	1595	1595
15	2962	2962
16	2661	2661
17	1509	1509
18	2669	2669
19	1693	1693

	landfill	incineration
0	29042	29042
1	22681	22681
2	26188	26188
3	36275	36275
4	16113	16113
5	18918	18918
6	32098	32098
7	35820	35820
8	19281	19281
9	29802	29802
10	37392	37392
11	21021	21021
12	20448	20448
13	18601	18601
14	21273	21273
15	39487	39487
16	35480	35480
17	20127	20127
18	35589	35589
19	22578	22578

	glass	metal	paper	plastic	ash	hazard	masonry	textile	other	organic
0	2178	2178	2178	2178	2178	2178	2178	2178	2178	2178
1	1701	1701	1701	1701	1701	1701	1701	1701	1701	1701
2	1964	1964	1964	1964	1964	1964	1964	1964	1964	1964
3	2721	2721	2721	2721	2721	2721	2721	2721	2721	2721
4	1208	1208	1208	1208	1208	1208	1208	1208	1208	1208
5	1419	1419	1419	1419	1419	1419	1419	1419	1419	1419
6	2407	2407	2407	2407	2407	2407	2407	2407	2407	2407
7	2687	2687	2687	2687	2687	2687	2687	2687	2687	2687
8	1446	1446	1446	1446	1446	1446	1446	1446	1446	1446
9	2235	2235	2235	2235	2235	2235	2235	2235	2235	2235
10	2804	2804	2804	2804	2804	2804	2804	2804	2804	2804
11	1577	1577	1577	1577	1577	1577	1577	1577	1577	1577
12	1534	1534	1534	1534	1534	1534	1534	1534	1534	1534
13	1395	1395	1395	1395	1395	1395	1395	1395	1395	1395
14	1595	1595	1595	1595	1595	1595	1595	1595	1595	1595
15	2962	2962	2962	2962	2962	2962	2962	2962	2962	2962
16	2661	2661	2661	2661	2661	2661	2661	2661	2661	2661
17	1509	1509	1509	1509	1509	1509	1509	1509	1509	1509
18	2669	2669	2669	2669	2669	2669	2669	2669	2669	2669
19	1693	1693	1693	1693	1693	1693	1693	1693	1693	1693

	Glass market	Metal market	Paper market	Plastic market	Ash market	Hazard market	Masonry market	Textile market	Other markets	Organic market	Composting market	Anaerobic digestion market	Landfill market	Incineration market
0	2614	2614	2614	2614	2614	2614	2614	2614	2614	2614	2614	2614	2614	2614
1	2041	2041	2041	2041	2041	2041	2041	2041	2041	2041	2041	2041	2041	2041
2	2357	2357	2357	2357	2357	2357	2357	2357	2357	2357	2357	2357	2357	2357
3	3265	3265	3265	3265	3265	3265	3265	3265	3265	3265	3265	3265	3265	3265
4	1450	1450	1450	1450	1450	1450	1450	1450	1450	1450	1450	1450	1450	1450
5	1703	1703	1703	1703	1703	1703	1703	1703	1703	1703	1703	1703	1703	1703
6	2889	2889	2889	2889	2889	2889	2889	2889	2889	2889	2889	2889	2889	2889
7	3224	3224	3224	3224	3224	3224	3224	3224	3224	3224	3224	3224	3224	3224
8	1735	1735	1735	1735	1735	1735	1735	1735	1735	1735	1735	1735	1735	1735
9	2682	2682	2682	2682	2682	2682	2682	2682	2682	2682	2682	2682	2682	2682
10	3365	3365	3365	3365	3365	3365	3365	3365	3365	3365	3365	3365	3365	3365
11	1892	1892	1892	1892	1892	1892	1892	1892	1892	1892	1892	1892	1892	1892
12	1840	1840	1840	1840	1840	1840	1840	1840	1840	1840	1840	1840	1840	1840
13	1674	1674	1674	1674	1674	1674	1674	1674	1674	1674	1674	1674	1674	1674
14	1915	1915	1915	1915	1915	1915	1915	1915	1915	1915	1915	1915	1915	1915
15	3554	3554	3554	3554	3554	3554	3554	3554	3554	3554	3554	3554	3554	3554
16	3193	3193	3193	3193	3193	3193	3193	3193	3193	3193	3193	3193	3193	3193
17	1811	1811	1811	1811	1811	1811	1811	1811	1811	1811	1811	1811	1811	1811
18	3203	3203	3203	3203	3203	3203	3203	3203	3203	3203	3203	3203	3203	3203
19	2032	2032	2032	2032	2032	2032	2032	2032	2032	2032	2032	2032	2032	2032