

# Sustainable Hazardous Waste Management: A Two-Stage Dynamic Multi-Period Decision Framework

by

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## Abstract

This thesis presents a comprehensive two-stage dynamic multi-period decision framework for sustainable hazardous waste management. The first stage involves optimizing the location and allocation of waste treatment facilities with a focus on minimizing both cost and emission. The second stage contains a dynamic multi-period vehicle routing problem (DMPVRP), which allows for real-time adjustments based on variable pickup dates to cope with dynamics, such that cost, risk, and emission are simultaneously minimized. Trade-offs between these objectives are managed by assigning weight to each objective in both stages. A case study of the healthcare waste management network in Shanghai, China, demonstrates the model's applicability and effectiveness. Results indicate that the proposed system significantly improves cost efficiency, reduces environmental impact, and minimizes risk to human health compared to the current system. Sensitivity analyses further validate the robustness of the proposed framework, showing improvements across all aspects. This research provides valuable insights for policymakers and waste management authorities aiming to enhance the sustainability and resilience of hazardous waste management systems.

**Keywords:** Dynamic vehicle routing problem, sustainable hazardous waste management, multi-stage decision-making, multi-period location-routing problem.

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# Contents

<b>Abstract</b>	<b>ii</b>
<b>Acknowledgements</b>	<b>iii</b>
<b>List of Tables</b>	<b>vi</b>
<b>List of Figures</b>	<b>viii</b>
<b>1 Introduction</b>	<b>1</b>
<b>2 Literature Review</b>	<b>6</b>
2.1 Location routing hazardous waste management . . . . .	6
2.2 Location routing for hazardous waste with uncertainties . . . . .	10
2.3 Sustainable hazardous waste management . . . . .	13
2.4 Dynamic vehicle routing problem in waste management . . . . .	14
2.5 Research gaps . . . . .	17
<b>3 Model Development</b>	<b>19</b>
3.1 Problem statement . . . . .	19
3.2 Model development for the decision framework . . . . .	23

3.2.1	Stage 1: Location-allocation . . . . .	23
3.2.2	Stage 2: Dynamic multi-period VRP (DMPVRP) . . . . .	26
<b>4</b>	<b>Numerical Case Study</b>	<b>33</b>
4.1	Relevant data . . . . .	35
4.2	The first stage result (location-allocation) . . . . .	36
4.3	The second stage result (routing decision) . . . . .	40
4.4	Trade-off between objectives . . . . .	43
4.5	A comparison with the current system . . . . .	45
4.6	Sensitivity analyses . . . . .	50
4.6.1	Varying the capacity of vehicles . . . . .	50
4.6.2	Varying first available pickup date . . . . .	53
<b>5</b>	<b>Conclusions and Future Directions</b>	<b>59</b>
5.1	Conclusion . . . . .	59
5.2	Managerial insights . . . . .	60
5.3	Future research . . . . .	62
	<b>Bibliography</b>	<b>64</b>

# List of Tables

3.1	Stage 1 notation . . . . .	24
3.2	Stage 2 notation for the sub-network associated with each built facility	27
4.1	Data for generation nodes. . . . .	37
4.2	Emission data for treatment facilities for each technology. . . . .	38
4.3	Construction costs and capacity data for treatment facilities . . . . .	38
4.4	Optimization results for stage 1 for different $w$ . . . . .	39
4.5	Allocation of generation nodes to selected facilities for $w = 0.4$ . . . . .	40
4.6	Data for vehicles and third-party . . . . .	41
4.7	Result of the second stage problem for $w_1 = 50$ and $w_2 = 50$ . . . . .	42
4.8	Risk and Emission values with different wight $w_1$ assigned to Emission. . . . .	44
4.9	Risk and Cost values with different wight $w_2$ assigned to Cost. . . . .	45
4.10	A comparison with the current system in stage 1. . . . .	47
4.11	A comparison with current system in stage 2 for network with facility F0. . . . .	48
4.12	An overall comparison with current system for both stages. . . . .	50
4.13	Sensitivity analysis for vehicle capacity. . . . .	51
4.14	First available pickup dates distribution for all four scenarios . . . . .	55

4.15 Result of varying first available pickup date . . . . . 56

# List of Figures

3.1	A two-stage decision framework for hazardous waste management. . .	20
3.2	A sample two-tiered network with a planning horizon of 3 days . . . .	22
4.1	The medical waste management network in Shanghai, China. . . . .	34
4.2	Relative changes in Risk, Cost, and Emission as a function of weights $w_1$ and $w_2$ . . . . .	46

# Chapter 1

## Introduction

Hazardous waste remains an unavoidable by-product of industrial operations and manifests in various forms, such as solid, sludge, liquid, packaged, or containerized gases, originating from both large-scale industrial sectors and small businesses (Alumur and Kara, 2007). Furthermore, waste materials are considered hazardous if they exhibit properties such as toxicity, flammability, reactivity, corrosivity, or infectiousness (Samanlioglu, 2013). For example, in a healthcare context, items like contaminated needles, expired pharmaceuticals, and infectious biological waste pose significant risks to human health and the environment if not handled properly. A significant amount of hazardous waste is presently being generated across various industries and service sectors, including but not limited to production and manufacturing, chemical processes, construction, healthcare, and household activities. In Canada, approximately 8 million tonnes of hazardous waste are generated each year. However, only 40% of this waste undergoes treatment. The remaining 60% is either disposed of in landfill sites or discharged into municipal sewers (Dowling,

1985). China's generation of hazardous waste experienced a significant increase from 13.57 million tonnes in 2008 to 69.36 million tonnes in 2017 (Liu and Xu, 2019). Hazardous Waste Haulers Environmental (HWH Environmental) reveals that in the United States, an estimated 35 million tons of hazardous materials are managed annually. Any improper processing of hazardous waste can pose a considerable risk to human health and environmental systems such as water, air, and soil. Consequently, it is crucial to implement hazardous waste management strategies that are both economically feasible and environmentally sustainable (Zhang et al., 2022).

The Resource Conservation and Recovery Act (RCRA) provides the foundation for managing hazardous waste effectively. Under this legislation, the Environmental Protection Agency (EPA) has implemented a thorough regulatory framework. This framework is intended to guarantee the safe handling of hazardous waste throughout its entire lifecycle, often referred to as "cradle to grave." This approach ensures that hazardous waste is carefully managed from its generation, through transportation, treatment, and storage, all the way to its final disposal. The management of hazardous waste encompasses a series of crucial procedures, including collection, transportation, treatment, and disposal (Samanlioglu, 2013). It is imperative to execute these processes with meticulous care to minimize costs. However, there are two other objectives namely risk and emission that need to be considered for both humans and the environment. The whole processes of managing hazardous waste represents a complex decision-making challenge and failure to consider all aspects properly can cause an improper design of the network and consequently risk for the surrounding human population and environment (Alumur and Kara, 2007). Therefore, it is imperative to ensure sustainable collection and transportation, considering

the social, economic, and environmental aspects of sustainable development. This thesis attempts to design a sustainable network for hazardous waste collection where all three aspects of sustainability are jointly considered.

Another issue that is a significant concern in the network design of a hazardous waste management system is the uncertainties, which include factors related to waste generation, collection, and processing, and hence can have significant impacts on the long-term strategic decision making, as well as daily operations. However, the majority of existing mathematical models for hazardous waste management rely on deterministic inputs, overlooking the inherent uncertainty associated with various parameters (Erdem, 2022; Zabihian-Bisheh et al., 2024; Taslimi et al., 2020; Tirkolae et al., 2021). In reality, it is impossible to make decisions with full knowledge of all input parameters in advance (Yu et al., 2020). Examples of unpredictable uncertainties, such as those caused by weather or traffic conditions (Ke, 2022), uncertain travel or service duration, variable costs (Negarandeh and Tajdin, 2022), fluctuating demand or waste quantities (Zhao et al., 2021), and changing risk factors (Ke et al., 2020; Rabbani et al., 2019), underscore the complexity of the situation.

A specific uncertain scenario arises when the first available pickup dates for each node may differ from another, yet this has not been thoroughly examined. Such a situation is notable, particularly when the waste generation rate varies over time. The present work is influenced by research managing hazardous waste logistics with random release dates, where the pickup nodes may vary in different trips (Tasouji Hassanpour et al., 2023b). Unlike conventional approaches, our study addresses a critical gap in the literature by focusing on the dynamic nature of hazardous waste management. Specifically, we confront a scenario where the first available pickup dates for

each generation node varies among nodes and only becomes available on the prior day. This nuanced aspect necessitates the development of a Dynamic Multi-Period Vehicle Routing Problem (DMPVRP) tailored to accommodate such variability. DMPVRP is particularly effective in handling such uncertainties because it adjusts vehicle routes in real time based on updated information. This adaptability ensures that routing plans remain efficient and feasible even as new data about pickup dates is received. Applying DMPVRP in our context allows us to dynamically respond to the uncertainty in pickup dates, ensuring an efficient and robust routing strategy.

Specifically in this study, we develop a two-stage decision framework for sustainably managing hazardous waste containing two optimization models respectively for location and dynamic routing. In more detail, the locations of waste treatment facilities and allocations of generation nodes to facilities are determined in the first stage, and the second stage is a multi-period dynamic vehicle routing problem. The second stage dynamic VRP model includes multiple demand nodes, multiple capacitated vehicles, and multiple periods. At the start of each period, the model updates its input parameters, such as new pickup dates, to dynamically adjust the routing plans. This approach enables the model to respond in real-time to the most current information, allowing for more efficient routing decisions. For instance, while some nodes may be ready for pickup from the first day, the model may choose to service them on a later day if it leads to a more optimal overall routing plan. To the best of our knowledge, this is the first time such a multi-period, two-stage sustainable hazardous waste location-routing problem is developed to enhance the design of hazardous waste collection networks. In summary, contributions of our study are as follows.

- Introducing a two-stage decision framework for hazardous waste location routing problem. The first stage focuses on optimizing facility locations, while the second stage addresses a dynamic multi-period routing plan.
- Three dimensions of sustainability are taken into account: 1) economic (cost), 2) social (population-based hazardous material risk), and 3) environmental (fuel and emission). In detail, the first stage involves considering facility costs and emission, and the second stage aims to minimize risks and emissions related to processing and collection.
- Particularly in the second stage, we address the problem's dynamic nature by formulating a DMPVRP. Instead of optimizing routes for only one day, our approach extends the routing plan for a set of consecutive days, allowing for route optimization over the present and all future days in the planning horizon. This multi-period strategy minimizes total travel time across the entire planning period.
- A case study of Shanghai, China, is conducted, offering practical insights and managerial implications for authorities in managing real-world healthcare waste.

The remainder of this thesis is organized as follows. Chapter 2 provides a review of related literature. Chapter 3 presents the problem statement and model formulation for both stages. Chapter 4 applies the model to a real case study to demonstrate its practical application. Finally, Chapter 5 offers conclusions, future study suggestions, and managerial insights.

# Chapter 2

## Literature Review

The primary research closely related to this study predominantly falls into four categories: (1) location-routing problems in managing hazardous waste, (2) location-routing for hazardous waste with uncertainties, (3) sustainable hazardous waste management, and (4) dynamic vehicle routing problem in waste management. In this section, we review all these four categories and mention relevant studies.

### **2.1 Location routing hazardous waste management**

Determining optimal locations for establishing waste management facilities is a strategically significant yet costly decision, demanding thorough considerations. The routing problem involves identifying the most efficient path for collection vehicles within the waste management network, with the main objective of minimizing adverse impacts on the exposed population and the environment in a cost-effective manner. Location routing problem which integrates both facility location and vehicle routing, resulting in more practical and comprehensive solutions for waste management

(Tasouji Hassanpour et al., 2023b).

Starting with the early contribution of Zografros and Samara (1989), which focused on integrating location and vehicle routing decisions in hazardous waste transportation and disposal, a diverse body of literature has since emerged in this area. Their work presented a multi-objective model aimed at fulfilling various objectives related to travel time, transportation, and disposal risk within a waste management system limited to a single type of waste. ReVelle et al. (1991) proposed a hazardous location-routing problem to minimize transportation costs and the risk of hazardous material. To do this they created a multi-objective optimization model and used sensitivity analysis to examine how risk would affect the network for managing hazardous waste. List and Mirchandani (1991) developed a same problem with multiple types of hazardous waste and treatment technology. They considered three objective functions to minimize total risk, total risk equity, and transportation cost. Current and Ratick (1995) investigated a model with objectives concerning cost, risk, and equity in risk distribution. Their model incorporates a cost function comprising three terms: the first accounts for transportation costs, while the second encompasses the fixed and variable costs associated with system facilities. Nema and Gupta (1999) and Nema and Gupta (2003) addressed the location-routing problem of optimizing hazardous waste management systems considering treatment and disposal facilities. To provide insights for future research directions in this field they proposed two more realistic constraints on waste types properties, including waste-waste and waste-technology compatibility requirements.

To manage multiple types of hazardous waste, Alumur and Kara (2007) tackled a multi-objective location-routing problem. They integrated various constraints that

had been overlooked in the literature into their model in order to develop a successful HWM system. For instance, in their suggested model, the compatibility between waste and treatment technology was addressed as a linear constraint, and the type of technology for each treatment facility was taken into consideration as a decision variable. Samanlioglu (2013) built a multi-objective location-routing model for industrial hazardous waste management. That work focused on decision-making regarding the establishment and routing of treatment, recycling, and disposal centers for hazardous materials. Three criteria were considered: minimizing total cost, transportation risk, and site risk. Boyer et al. (2013) presented a location routing problem for industrial hazardous waste. They investigated a comprehensive waste management system composed of recycling, treatment, and disposal facilities with all possible relationships between system components. Considering fuzzy service level requirements for waste generation centers, Ghezavati and Morakabatchian (2015) constructed a multi-objective location routing model in a real-world scenario involving the Petrochemical Special Economic Zone (PETZONE) in Khuzestan, Iran. With the aid of the model, they chose the best locations for suitable treatment, recycling, and disposal centers as well as the routes for moving various types of industrial waste between these centers. The mathematical model took into account three factors, including minimizing total costs of transportation and establishment of centers as well as total transportation and site risk associated with population exposure along transportation routes and surrounding treatment and disposal facilities.

Zhao et al. (2016) addressed regional hazardous waste management systems and proposed a multi-objective mixed-integer linear programming (MILP) formulation. The objective of the formulation was to minimize total cost and risk in decisions re-

lated to transportation and location. The authors applied an augmented  $\epsilon$ -constraint, an augmented weighted Tchebycheff, and weighted-sum approaches to explore efficient solutions. Asgari et al. (2017) delved into a location-routing problem for obnoxious waste with different types of waste and several treatment technologies in a distribution network containing generation nodes, treatment, and disposal facilities. They developed three objective functions to minimize treatment and disposal facility undesirability, total cost, and risk of the problem. Zhao and Ke (2017) incorporated an inventory risk in a location routing problem for exclusive waste management. They characterized environmental risk as a volume-based risk assessment approach by explosive waste management. The authors put up a bi-objective model that accounts for both inventory risk and the optimization of route and facility location. Additionally, the bi-objective formulation was converted into a single objective model using a TOPSIS-based solution process. Aydemir-Karadag (2018) explored the location-routing problem for hazardous waste by developing a model that maximizes the profit of the hazardous waste management (HWM) system over a long-term planning horizon. The suggested model integrates multiple components of the HWM system, including the ability to handle multiple wastes, waste compatibility with various technologies, and electricity generation from waste. Furthermore, Rabbani et al. (2018) established a location-routing problem to simultaneously minimize the total cost, total transportation risk, and site risk. That model was then solved by a multi-objective evolutionary algorithm. Hu et al. (2019) designed a novel multi-objective optimization method by proposing traffic restrictions on inter-city roads constraint for finding the optimal routes in hazardous material logistics. To make their problem more realistic and practicable, they considered multiple paths between every possible

origin-destination pair. Their multi-objective model addressed the important aspects of risk, cost, and customer satisfaction in hazardous material logistics management.

## **2.2 Location routing for hazardous waste with uncertainties**

In all the previously reviewed studies, the location-routing problem was addressed under a deterministic environment ignoring the dynamic and transformational nature of the practical situations. Therefore, due to the severe effects of such uncertainties on planning decisions, not paying attention to the uncertain nature of the problem may contribute to sub-optimal or even infeasible design solutions. To cope with uncertainty researchers considered uncertainty in some of the parameters of their study. For instance, Zhang and Zhao (2011) investigated a problem focusing on waste generation amount uncertainties. The uncertain nature of this parameter in real-life situations stems from the complexity and fluctuations of the production processes in different industries. Berglund and Kwon (2014) addressed uncertainty in hazardous materials transportation by developing a robust facility location model. They optimized hazmat processing site locations to minimize total cost and exposure risk, considering the uncertainty in hazmat routing decisions. It is obvious that with respect to the random capacity variations and different traffic conditions, transportation time or cost in urban road networks is strongly uncertain. Transportation cost was considered as a source of uncertainty in the work of Ardjmand et al. (2016). Rabbani et al. (2019) formulated a multi-objective stochastic mixed-integer nonlin-

ear programming model for a multi-period hazardous waste location routing problem. They integrated decisions of three levels with locating, vehicle routing, and inventory control for industrial hazardous waste location routing problems. Ghaderi and Burdett (2019) developed a two stage stochastic programming model for location and transporting hazardous materials in a bi-modal transportation network. They considered how best to strategically transport and route hazardous materials through a bi-modal transportation network consisting of road and rail links. Minimization of transportation cost and risk were two objective functions of their study. Yu et al. (2020) developed a stochastic two-echelon multi-objective hazardous waste location routing problem. Finding the best route for the vehicles for collecting hazardous waste to minimize cost and risk was one of the leading purposes of their study. The amount of generated waste and transportation costs were considered uncertain in this study. Delfani et al. (2021) built a robust multi-objective mathematical model for hazardous waste location routing problem. Objective functions minimized the total costs, total risk from hazardous waste, and site risk from the population within a certain radius of the facilities. They applied a basic possibilistic chance-constrained programming approach to deal with the uncertainty of the model's parameters. Zhao et al. (2021) proposed a scenario-based bi-objective robust approach for managing infectious waste during the COVID-19 pandemic. They assumed uncertainties in waste generation and transportation disruptions, focusing on optimizing the location of temporary facilities, collection tours, and transportation routes to minimize costs and risks. Tirkolaei et al. (2021) examined the significant uncertainty arising from the COVID-19 pandemic's impact on waste management systems, particularly concerning infectious medical waste. To effectively manage this uncertainty, the study

employed a novel mixed-integer linear programming model that incorporates the uncertainty surrounding service priorities and time windows for hospitals, which vary based on the level of risk. Utilizing a robust fuzzy optimization approach, Raeisi and Jafarzadeh Ghouschi (2022) investigated the multi-objective location-routing problem (LRP) concerning hazardous wastes. Their study focused on addressing uncertainties in transportation costs and waste generation amounts within the model. Incorporating resiliency and profitability concepts into the model, a sustainable hospital waste management network was designed in the study of Negarandeh and Tajdin (2022). The proposed model dealt with the uncertainty in waste generation using a robust fuzzy programming approach, accounting for variations in waste generation and transportation costs. Tasouji Hassanpour et al. (2023a) tackled the challenge of managing infectious waste during a pandemic by employing a stochastic location-routing problem. That approach enabled the analysis of sudden increases in waste volume and the consequent fluctuations in service times, offering insights into effective waste management strategies amidst unpredictable circumstances. A decision framework for a hazardous waste collection network, accounting for uncertain release dates was developed by Tasouji Hassanpour et al. (2023b). They employed a cost-based clustering approach to locate transfer stations and allocate generation nodes. Results, combined with subjective risk aversion and estimated release dates, formed an initial collection plan, adaptable based on actual release dates.

## 2.3 Sustainable hazardous waste management

Regarding sustainability, only a limited number of studies have delved into the sustainability aspect of hazardous waste management within the existing literature. In the context of sustainability, the three interrelated aspects—economic, environmental, and social—are considered. Integrating these aspects not only enriches the understanding of waste management practices but also fosters the development of more comprehensive and effective waste management systems. Liu et al. (2021) explored the optimization of industrial hazardous waste transportation within the context of green supply chain management. They emphasized the importance of integrating green purchasing, hazardous waste storage, and green disposal to promote sustainability. Tsai et al. (2021) analyzed the industrial hazardous waste trends in Taiwan from 2010 to 2020, emphasizing sustainable resource management. They examined environmental policies and recycling initiatives under the revised Waste Management Act, showcasing successful circular economy models in various industries. Recommendations were provided to policymakers and environmental engineers to enhance sustainability in waste management practices. Erdem (2022) focused on designing a sustainable network for hazardous medical waste collection during the COVID-19 pandemic. They introduced an electric vehicle routing problem to optimize routes, rosters, and charging strategies, aiming to minimize health risks and achieve cost-effective, emission-free waste management. Zabihiyan-Bisheh et al. (2024) addressed the urgent need for sustainable management of hazardous waste generated from manufacturing and healthcare sectors. A multi-objective mixed-integer nonlinear programming model was developed to optimize facility locations, waste transportation routes,

and residue handling. By integrating sustainability considerations, the model aims to minimize costs, hazards, and CO<sub>2</sub> emissions. Li et al. (2024) applied a binary molten salt thermal treatment method for detoxifying spent cathode carbon block waste and recycling carbonaceous materials, promoting sustainability in hazardous waste management.

## **2.4 Dynamic vehicle routing problem in waste management**

DVRP has evolved as an essential extension of the traditional Vehicle Routing Problem (VRP) to address real-time operational uncertainties. Unlike the static VRP, where demand and travel times are predetermined and unchanging, DVRP adapts to dynamic conditions such as incoming customer requests, cancellations, and fluctuating travel times. This concept was initially introduced by researchers like Psaraftis (1980) in the late 1980s, who recognized the need for routing algorithms that could respond dynamically to real-time information. Over the years, DVRP research has advanced significantly, focusing on developing methods that can handle temporal uncertainties and customer variability more effectively. These advancements have improved the ability of DVRP models to maintain efficient and feasible routes in the face of continuously changing data, ensuring better service levels and operational efficiency. For a comprehensive review of DVRP, refer to the survey papers by Pillac et al. (2013) and Rios et al. (2021).

Only a few studies have explored the application of DVRP in waste management,

focusing on optimizing collection routes to improve efficiency and reduce costs. Research in this area has considered various factors such as real-time traffic conditions, dynamic customer demands, and the uncertainty of waste generation. Sreelekshmi and Nair (2017) introduced innovative approaches to address the dynamic nature of routing problems in waste management. By utilizing the Modified Capacitated K-Means algorithm for customer clustering and the Variable Neighbourhood Search algorithm for route optimization, the research aimed to minimize the total expected routing risk in a DVRP. Mohammadi et al. (2023) presented a novel approach to waste management by integrating dynamic routing schemes with multi-compartment vehicles, addressing the challenges of increasing municipal solid waste rates. They proposed a discrete choice model for re-optimization in DVRP, dynamically selecting routes based on waste generation levels and travel costs. Bouleft and Elhilali Alaoui (2023) addressed the Dynamic Multi-Compartmental Vehicle Routing Problem (DM-CVRP) for intelligent waste collection in urban environments. They formulated a linear mathematical programming model to optimize dynamic routes, minimizing total costs including transportation and penalty costs. The study applied a hybridized genetic algorithm (GA) to solve the DM-CVRP and validates its effectiveness through extensive numerical experiments. Marković et al. (2024) explored the challenge of waste management in urban areas by focusing on the DVRP in waste collection. They introduced a smart waste collection container prototype and proposes a methodology based on heuristics to define optimal dynamic routes. The goal was to minimize total costs, particularly transportation costs, by leveraging modern information and communication technologies. The study emphasized the importance of efficient route planning in waste collection systems and highlights the potential of smart technologies

in improving waste management efficiency. Zhao et al. (2024) formulated an energy-efficient multi-trip dynamic vehicle routing model for waste collection, addressing the challenges of unpredictable disturbances during waste collection and the environmental impact of vehicle emissions. The model incorporated dynamic events such as new collecting requirements and vehicle breakdowns, aiming to minimize both transportation costs and carbon emissions. Madhan and Vasumathi (2020) proposed a financial sustainable clustered dynamic vehicle routing optimization method for solid waste management in developing countries. They addressed the challenges of implementing effective solid waste management services while ensuring the financial stability of the country. The method utilized clustering and dynamic vehicle routing to optimize waste collection, moving waste from cities to depots for disposal. There was only one paper considered DVRP in the area of hazardous material. Ouertani et al. (2022) suggested the dynamic variant of the hazardous materials vehicle routing problem with time windows. The objective was to find the best routes that minimize both the transportation cost and the travel risk in order to meet the customers' demands or needs, within predefined time windows. The paper designed a bi-population genetic algorithm and a hybrid approach combining the genetic algorithm and the variable neighborhood search as solution approaches for the dynamic hazardous material vehicle routing problem. A decision support system was developed to generate the best routes based on these algorithms.

## 2.5 Research gaps

The aforementioned works have contributed to the literature in different directions. However, despite these efforts, several research gaps persist. First, research on hazardous waste management under uncertain conditions is still in its early stages. Many studies have focused on uncertainties related to demand, costs, and risks. However, there is significant variability in the amount of waste available, leading to uncertainties in scheduling pickups. Additionally, different locations may have varying available pickup dates, adding another layer of complication to the uncertainty in the management of hazardous waste. Last but not least, the dynamics of these uncertainties, such as the constantly changing conditions that affect pickup schedules, have largely been ignored in existing studies.

The two-stage problem is a fundamental method for formulating the location-routing problem in hazardous waste management. In the first stage, the locations of the facilities are determined and generation nodes are assigned to selected facilities. Then, in the second stage, routing decisions are made based on the result of the first stage. This approach effectively integrates facility placement and waste collection routes, optimizing the overall management and disposal of hazardous waste. Tasouji Hassanpour et al. (2023b) is the most closely related paper to our works; however, there are notable differences in focus and approach. They mainly concentrated on minimizing various types of risk associated with hazardous waste management. In contrast, our paper adopts a more holistic approach by considering all three aspects of sustainability: economic, environmental, and social. Specifically, our objective function integrates cost, emission, and risk into our considerations. Economically, we

account for the costs related to the establishment and operation of facilities, as well as the transportation of waste. Environmentally, our model includes the emissions generated by facility construction, waste processing, and transportation, ensuring that environmental impact is minimized. Socially, by evaluating and minimizing exposure risk, we address the safety concerns and potential hazards affecting communities and stakeholders involved in the waste management process. Furthermore, our research contributes to addressing a significant gap in the existing literature by being the first to consider the DMPVRP in hazardous waste management. This addition allows us to dynamically adapt routing decisions based on changing conditions, improving the overall efficiency and effectiveness of hazardous waste management operations.

# Chapter 3

## Model Development

### 3.1 Problem statement

The model in this thesis involves a sustainable two-stage multi-period for location routing hazardous waste problem. Figure 3.1 shows the two stage decision framework of our problem. To be more specific, the first stage of our problem is a location-allocation problem where the optimal location for establishing facilities is determined and then generation nodes are assigned to selected facilities. This stage aims to minimize costs, including the fixed cost of establishing facilities and the variable cost associated with processing waste. The result of this stage forms the basis for the routing decisions to be made in the second stage. Following this, the second stage problem is a DMPVRP to address the complexities of hazardous waste management over an extended planning horizon. This DMPVRP develops a dynamic routing plans over multiple periods for smaller networks. Each network consists of one facility and the generation nodes allocated to it in the first stage. The planning horizon for this

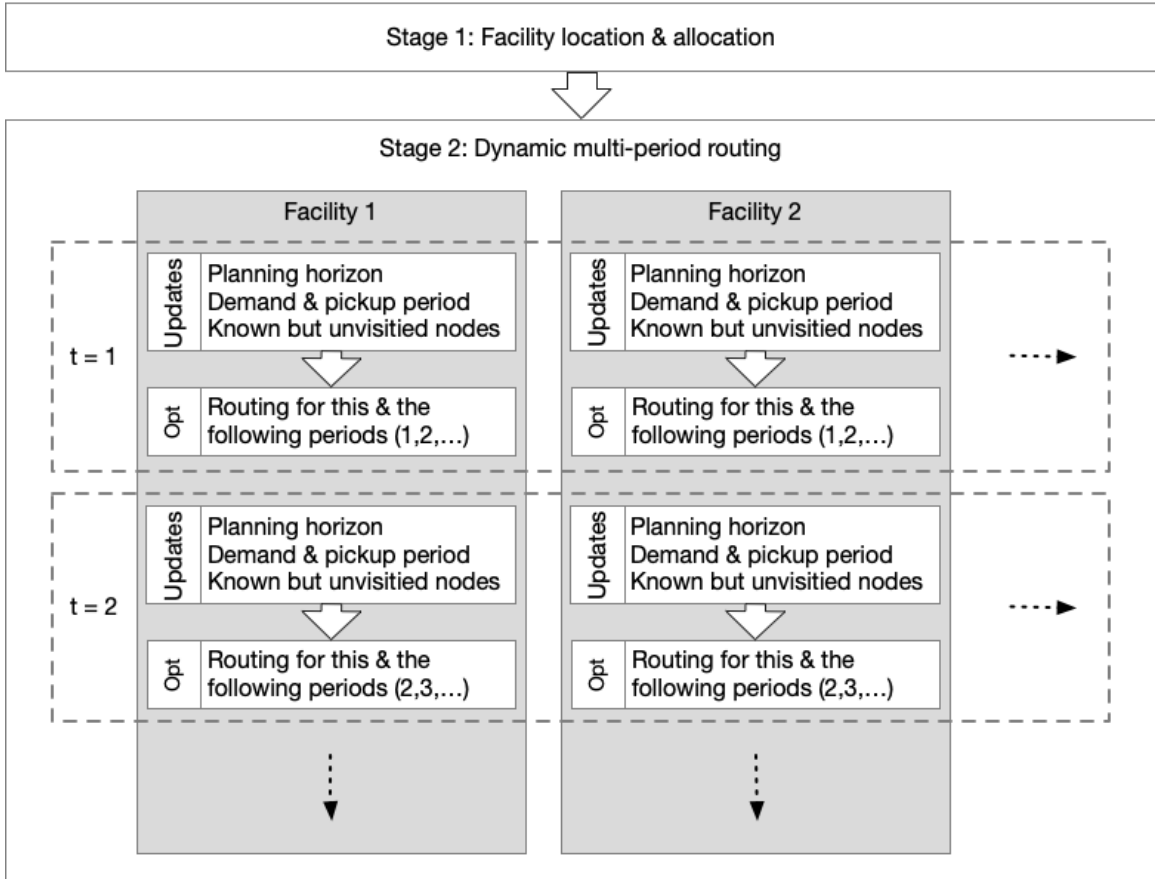


Figure 3.1: A two-stage decision framework for hazardous waste management.

DMPVRP is defined as  $\mathcal{T} = \{1, 2, \dots, t, \dots, \tau\}$ , where  $\tau$  is the total number of days. Each generation node has a unit visit frequency, meaning it must be picked up exactly once within the planning horizon. Once becoming available, generation nodes can be picked up on any day within the planning horizon but must be serviced by the last period.

At the beginning of each period, input parameters such as amount and dates for pickup are updated. This dynamic updating process allows the model to adjust routing plans in every planning day on the most current information. For example, while some nodes might be eligible for pickup from the first day, the model might decide to

service them on a later day within the planning horizon if such an arrangement leads to a more efficient overall routing plan. The flexibility of DMPVRP ensures that the system can respond to evolving conditions, such as variations in waste generation rates and the availability of vehicles. This approach minimizes the total costs, CO<sub>2</sub> emission, fuel consumption, and exposure risk associated with the waste collection network, achieving a balance between economic, environmental, and social objectives. The two-stage framework addresses different decision levels—strategic (Stage 1) and operational (Stage 2)—which justifies modelling and solving them separately. Stage 1 (Location-Allocation) focuses on long-term strategic decisions like selecting facility locations and allocating generation nodes. The objective is to minimize overall costs and emissions. This is a static problem, where decisions are made once and remain fixed throughout. Stage 2 (Dynamic Multi-period Vehicle Routing Problem-DMPVRP) handles daily operational decisions, adjusting vehicle routes every day to minimize costs, emissions, and risks. This is a dynamic problem, solved periodically based on updated data, such as pickup schedules and amount of generated waste.

Figure 3.2 illustrates a sample network over a planning horizon of three days. This network includes many candidate locations for establishing treatment centers tasked with processing hazardous waste alongside multiple generation nodes distributed throughout the region, with different service days. The service days represent the allowable time frame for waste pickup from each node. Nodes with service days of  $\{1, 2, 3\}$  indicate that the earliest available pickup day is day 1, and these nodes can be serviced until the end of the time period, which is day 3. Each generation nodes can be serviced from the first available date of pickup until the end of the planning horizon. Pickup dates are revealed at the beginning of each period, highlighting the

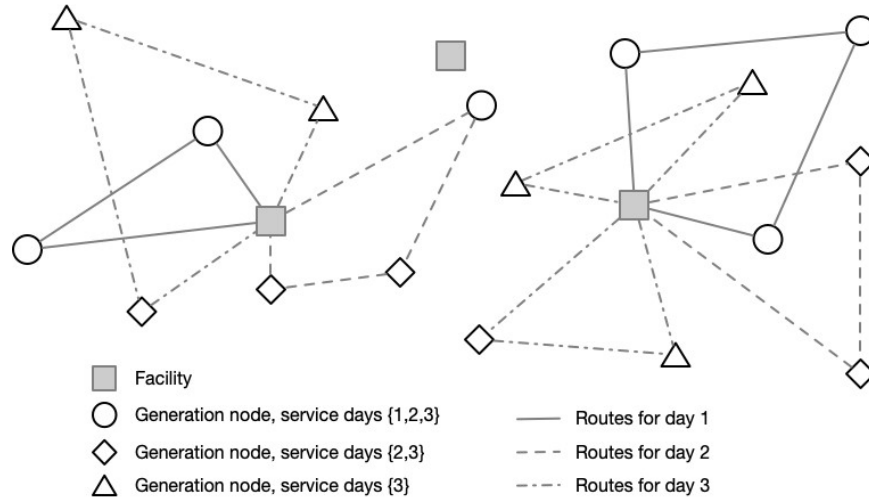


Figure 3.2: A sample two-tiered network with a planning horizon of 3 days

dynamic nature of the problem.

The multi-period aspect of our model arises because the pickup dates for different generation nodes vary across the entire time horizon, from day 1 to the last day of the planning period. To effectively handle this uncertainty, we employ a DMPVRP model. This means that at the start of each time period, the model identifies nodes with a pickup date of that day and schedules waste collection from these nodes first. However, it is important to note that the model does not necessarily collect waste from all nodes within that specific period. Instead, the model can decide to postpone the pickup from some nodes to future days, optimizing the overall collection strategy by minimizing costs, risks, and emissions objectives. For instance, in Figure 3.2 although one of the nodes has a pickup date of 1, the model decides to service this node on day 2, as indicated by its inclusion in the routes for day 2. This DMPVRP model adapts to the uncertain available pick up date for each generation node over multiple periods, ensuring the responsiveness of our waste management system to evolving conditions.

## 3.2 Model development for the decision framework

This section provides detailed elaborations and mathematical models for the decision framework.

### 3.2.1 Stage 1: Location-allocation

The mathematical formulation of the first stage problem is presented in this section. Our primary objective in this stage is two-fold: 1) to minimize the overall costs associated with the facility locations and their operations, and 2) to minimize emissions produced by these facilities during construction and daily processing. In more detail, to comprehensively evaluate the emissions resulting from the waste management, we connect the facility emission to a set of technologies  $\mathcal{M}$ , where better technologies lead to higher facility costs (both fixed and variable cost) and lower emissions (from both facility construction and processing). By integrating costs and emissions considerations into our decision-making process, we aim to develop a solution that not only optimizes the economic aspects of facility placement but also promotes environmental sustainability within our network. This approach allows us to strike a balance between economic efficiency and environmental impact, ensuring that our facilities are both cost-effective and environmentally friendly. Table 3.1 lists the notation used in the first-stage location-allocation model.

Then, the overall emissions of the system can be written as

$$Z_e^0 = \min \sum_{i \in \mathcal{F}} \sum_{m \in \mathcal{M}} FE_i^m o_i^m + \sum_{i \in \mathcal{F}} \sum_{m \in \mathcal{M}} PE_i^m r_i, \quad (3.1)$$

where the first part of this objective minimizes the fixed emission rate produced during the construction of each facility  $i$  and the second part minimizes variable processing

Table 3.1: Stage 1 notation

<b>Sets</b>	
$\mathcal{G}(\mathcal{N}, \mathcal{A})$	A complete graph, where $\mathcal{N}$ and $\mathcal{A}$ are respectively the sets of nodes (indexed by $i, j, h$ ) and arcs. We have $\mathcal{N} = \mathcal{C} \cup \mathcal{F}$ , where $\mathcal{C}$ is the set of generation nodes, and $\mathcal{F}$ is the set of candidate treatment facilities.
$\mathcal{M}$	Set of technologies, indexed by $m$ .
<b>Parameters</b>	
$\bar{W}_j$	Average amount of waste generated at node $j \in \mathcal{C}$ over the planning horizon.
$FC_i^m$	Fixed cost of opening treatment facility $i \in \mathcal{F}$ with technology $m$ .
$PC_i^m$	Processing cost of each unit waste at treatment facility $i \in \mathcal{F}$ with technology $m$ .
$FE_i^m$	Fixed facility emission rate at location $i \in \mathcal{F}$ with technology $m$ .
$PE_i^m$	Variable processing emission rate at location $i \in \mathcal{F}$ with technology $m$ .
$FCAP_i^m$	Facility capacity at location $i \in \mathcal{F}$ with technology $m$ .
$L_{ij}$	Distance between nodes $i$ and $j$ .
<b>Variables</b>	
$o_i^m$	1, if location $i \in \mathcal{F}$ is positioned with technology $m$ ; 0, otherwise.
$r_i$	Amount of waste handled at $i \in \mathcal{F}$ .
$z_{ij}$	1, if generation node $j \in \mathcal{C}$ is assigned to location $i \in \mathcal{F}$ .

emission which is associated with the amount of waste processed at each facility using technology  $m$ . Correspondingly, the cost objective is

$$Z_c^0 = \min \sum_{i \in \mathcal{F}} \sum_{m \in \mathcal{M}} FC_i^m o_i^m + \sum_{i \in \mathcal{F}} \sum_{m \in \mathcal{M}} PC_i^m r_i, \quad (3.2)$$

where this objective aims to minimize the total costs associated with each facility  $i$  including the fixed cost of opening the facility and the processing cost of each unit of waste at treatment facility  $i$  using technology  $m$ .

To effectively manage both objectives, we utilize a scalar method, where both

objectives are integrated into a single composite objective function. This is achieved by assigning a weight factor  $w$  to the costs objective  $Z_c^0$  and a complementary weight factor  $(1 - w)$  to the emission objective  $Z_e^0$ . The composite objective function can be expressed as:

$$Z_0 = wZ_c^0 + (1 - w)Z_e^0, \quad (3.3)$$

where  $0 \leq w \leq 1$ . This approach allows for a flexible balancing of costs and emissions objectives, depending on the value of  $w$  chosen. The above objective functions are subject to the following constraints.

$$\sum_{m \in \mathcal{M}} o_i^m \leq 1, \quad \forall i \in \mathcal{F}; \quad (3.4)$$

$$\sum_{i \in \mathcal{F}} z_{ij} = 1, \quad \forall j \in \mathcal{C}; \quad (3.5)$$

$$r_i = \sum_{j \in \mathcal{C}} \bar{W}_j z_{ij}, \quad \forall i \in \mathcal{F}; \quad (3.6)$$

$$r_i \leq \sum_{m \in \mathcal{M}} o_i^m FCAP_i^m, \quad \forall i \in \mathcal{F}; \quad (3.7)$$

$$o_i^m, z_{ij} \in \{0, 1\}, r_i \geq 0, \quad \forall i \in \mathcal{F}, j \in \mathcal{C}, m \in \mathcal{M}. \quad (3.8)$$

Constraint (3.4) sets that at most one technology can be implemented in each facility. Constraint (3.5) guarantees that each customer (generation node) is assigned to exactly one facility. Constraint (3.6) calculates the processing amount at each facility. Constraint (3.7) ensures the processing and technology capacity of the facility. The variable domains are defined in Constraint (3.8).

### 3.2.2 Stage 2: Dynamic multi-period VRP (DMPVRP)

In this stage, we build upon the optimal solution obtained in the first stage to make routing decisions. We create several networks, each with one facility and the generation nodes assigned to that facility in the initial stage. Mathematically, each facility is considered as node 0 for the corresponding network, and the node set  $\mathcal{N}'$  is updated to include a built facility and those customers assigned to this facility. These networks are used for the multi-period routing planning.

Now, to delve deeper into the second stage problem, we employ a DMPVRP to determine the best multi-period routing plans. Specifically, the planning for each period can be seen as a periodic DVRP with unit visit frequency and consecutive allowable pickup periods. Without loss of generality, we present the formulation for the planning problem on day  $t \in \mathcal{T}$ , where  $\mathcal{T} = \{1, 2, \dots, t, \dots, \tau\}$  is the planning horizon. Each generation node  $j$  can be picked up in any days in the available pickup period (and must be picked up by the end of the planning horizon). Hence, we have the available pickup period  $\mathcal{P} = \{p_j, \dots, \tau\}$ . At the beginning of each period  $t$ , several input parameters are updated in terms of new pickup dates. The first available time of each demand becomes  $p_j^t = \max\{p_j, t\}$  and hence the updated available pickup period is  $\mathcal{P}^t = \{p_j^t, \dots, \tau\}$ ; the updated planning horizon is  $\mathcal{T}^t = \{t, t + 1, \dots, \tau\}$ ; and the set of known but unvisited generation nodes is also adjusted to  $\mathcal{C}^t$ . Then, the optimization model is run for the next  $\tau - t + 1$  period. The decision framework for this stage is demonstrated in Figure 3.1. Other additional notation for stage 2 is given in Table 3.2.

Table 3.2: Stage 2 notation for the sub-network associated with each built facility

<b>Sets</b>	
$\mathcal{C}'$	Set of customers assigned to the corresponding facility.
$\mathcal{N}'$	Set of nodes, where $\mathcal{N}' = \mathcal{C}' \cup 0$ .
$\mathcal{K}$	Set of vehicles, indexed by $k$ .
$\mathcal{T}$	Set of periods in the planning horizon ( $\mathcal{T} = \{1, 2, \dots, \tau\}$ ), indexed by $t$ .
$\mathcal{T}^t$	Set of periods to be planned in period $t$ , $\mathcal{T}^t = \{t, t + 1, \dots, \tau\}$ .
$\mathcal{C}^t$	Set of known but unvisited generation nodes in period $t$ .
<b>Parameters</b>	
$W_j$	Amount of waste generated at node $j \in \mathcal{C}$ .
$p_j$	First available date for pickup at node $j \in \mathcal{C}$ .
$R_i^m$	Risk at facility $i \in \mathcal{F}'$ with technology $m$ .
$R_{ijk}$	Risk along arc $(i, j)$ with vehicle $k$ .
$R_j$	Risk at generation node $j \in \mathcal{C}$ .
$C_k$	Cost of transporting one unit of hazardous waste per distance using vehicle $k$ .
$TC$	Cost of hiring a third party's per node.
$VCAP_k$	Vehicle $k$ 's capacity.
$E_k$	CO <sub>2</sub> emission of vehicle $k$ per distance per unit fuel consumption.
$F_k$	Vehicle fuel consumption rate per distance for vehicle $k$ .
<b>Variables</b>	
$r_{il}^t$	Amount of waste processed at facility $i \in \mathcal{F}$ in period $l$ .
$x_{ijkl}^t$	1, if vehicle $k$ traverses between nodes $i$ and $j$ in period $l$ ; 0, otherwise.
$y_{ijkl}^t$	Load on vehicle $k$ on arc $(i, j)$ in period $l$ .
$u_{ikl}^t$	1, if vehicle $k$ is used starting from and ending at facility $i \in \mathcal{F}$ in period $l$ ; 0, otherwise.
$\delta_{jkl}^t$	Auxiliary variable to eliminate sub-tours in period $l$ .

Based on the fuel consumption, we can compute the route CO<sub>2</sub> emission as

$$\sum_{(i,j) \in \mathcal{A}} \sum_{k \in \mathcal{K}} E_k F_k L_{ij} x_{ijkl}^t$$

by adapting the approach proposed by Abdullahi et al. (2021), where  $E_k$  is an activity based emission factor (McKinnon et al., 2015) that relates the CO<sub>2</sub> emission to fuel consumption (kg-CO<sub>2</sub>/liter). Hence, the emissions objective for period  $t$  in this stage can be written as:

$$Z_e^t = \min \sum_{l \in \mathcal{T}^t} \sum_{i \in \mathcal{F}'} \sum_{m \in \mathcal{M}} P E_i^m r_{il}^t + \sum_{l \in \mathcal{T}^t} \sum_{(i,j) \in \mathcal{A}} \sum_{k \in \mathcal{K}} E_k F_k L_{ij} x_{ijkl}^t. \quad (3.9)$$

The first part of this objective focuses on minimizing the variable processing emission at facility  $i$  using technology  $m$ , while the second part aims to reduce the transportation emission generated by vehicles.

For the risk objective, let  $IR_i^m$  be the incident rate at facility  $i \in \mathcal{F}$  with technology  $m$ . Different technology may induce different probabilities of incidents. The unit risk at  $i$  is

$$R_i^m = POP_i IR_i^m,$$

where  $POP_i$  is the exposed population around node  $i$ . The risk affecting the population around node  $i$  is modeled by considering the exposure of the nearby population to hazardous waste operations and incident rate at that node. Similarly, the unit risk for link  $(i, j)$  is

$$R_{ijk} = POP_{ij} IR_{ijk},$$

where  $IR_{ijk}$  is the incident rate of vehicle  $k$  running on  $(i, j)$ , and  $POP_{ij}$  is the exposed population around link  $(i, j)$ .

Hence, given the load of vehicle  $k$  on  $(i, j)$ ,  $y_{ijkl}^t$ , the total risk objective for period  $t$  can be computed as:

$$Z_r^t = \min \sum_{l \in \mathcal{T}^t} \sum_{i \in \mathcal{F}'} \sum_{m \in \mathcal{M}} R_i^m r_i^m + \sum_{l \in \mathcal{T}^t} \sum_{(i,j) \in \mathcal{A}} \sum_{k \in \mathcal{K}} R_{ijk} y_{ijkl}^t + \sum_{l \in \mathcal{P}^t} \sum_{j \in \mathcal{C}^t} (lx_{ijkl}^t - p_j) R_j W_j. \quad (3.10)$$

Note that the last term of the risks objective computes the penalty risk caused by late pickups, where  $R_j$  is the population risk at node  $j$ , and  $lx_{ijkl}^t$  is the day when node  $j$  is visited and  $p_j$  is the first available pickup date of node  $j$ . Therefore, the term  $(lx_{ijkl}^t - p_j)$  calculates the number of days of delay in servicing node  $j$ .

The third objective is to minimize costs, encompassing waste processing cost, transportation cost for waste collection, and cost for hiring a third party to collect any remaining waste in the last period. Given potential vehicle capacity constraints, some waste may remain uncollected, requiring third-party assistance in the last period. Thus, we must first assess the necessity of hiring a third party and then calculate the associated costs. To do so, a variable is defined to calculate the amount of generated waste that remains to be picked up at the beginning of the last period. To compute this amount, we first determine all the unvisited nodes that need to be visited in the last period ( $\mathcal{C}^\tau$ ) and then sum all the waste that is generated by all those nodes. We call this parameter  $AW_\tau$  (Accumulated Waste at the beginning of last period), which is calculated as:

$$AW_\tau = \sum_{j \in \mathcal{C}^\tau} W_j, \quad (3.11)$$

where  $W_j$  is the amount of waste generated by node  $j$  and  $\mathcal{C}^\tau$  is the set of all unvisited nodes in the last period.

Then, we define a binary variable  $\lambda$  as follows:

$$\lambda = \begin{cases} 1, & \text{if } AW > \sum_{k \in \mathcal{K}} VCAP_k; \\ 0, & \text{otherwise.} \end{cases} \quad (3.12)$$

The variable  $\lambda$  indicates whether the accumulated waste in the last period surpasses

the vehicle's capacity. When  $\lambda = 1$ , the demand cannot be fully satisfied within the capacity constraints, and we need to hire a third party to collect the remaining waste.

We assume the third-party cost is per customer (node) they service, and hence define  $n_\tau$  to represent the number of nodes remaining unvisited at the last period and need to be collected by a third-party.

Hence, the costs minimization is computed below:

$$Z_c^t = \min \sum_{i \in \mathcal{F}'} \sum_{m \in \mathcal{M}} \sum_{l \in \mathcal{T}^t} PC_i^m r_{il}^t + \sum_{i \in \mathcal{C}^t} \sum_{j \in \mathcal{C}^t} \sum_{k \in \mathcal{K}} \sum_{l \in \mathcal{T}^t} L_{ij} C_k x_{ijkl}^t + \lambda n_\tau TC \quad (3.13)$$

The first part involves the processing cost of waste. The second part pertains to using regular vehicles for waste collection. The third part calculates the cost of hiring a third party where  $n_\tau$  is the number of unvisited node at the last period and  $TC$  is the cost of hiring the third party per node.

Similar to first stage, we apply the scalar method, assigning weights 1,  $w_1$ , and  $w_2$  to the objectives  $Z_r^t$  (risks),  $Z_e^t$  (emissions), and  $Z_c^t$  (costs), respectively. This allows us to work with the combined objective  $Z^t = Z_r^t + w_1 Z_e^t + w_2 Z_c^t$ . This approach transforms our multi-objective optimization problem into a single aggregate objective function, enabling us to find a balanced solution that considers all three objectives, adjusted by their respective weights. More specifically, a weight of 1 is assigned to the risk objective. This is because the risk in this stage is considered the highest propriety, and hence should be taken into account in any cases. The other two weights are defined so as to 1) integrate the emission and cost objectives along with the risk consideration, and 2) convert the other two objectives into risk-equivalent values. To serve these two purposes, the weight values are tested and particularly determined in line with the scales of different objectives. Thus, by varying the values of  $w_1$  and  $w_2$ ,

the importance of emission and cost in the overall consideration can be respectively adjusted, and the trade-offs among objectives can be obtained accordingly.

Constraints for the second stage problem are listed below:

*s.t.*

$$\sum_{l \in \mathcal{T}^t} \sum_{j \in \mathcal{N}'} \sum_{k \in \mathcal{K}} x_{ijkl}^t = 1, \quad \forall i \in \mathcal{C}^t; \quad (3.14)$$

$$\sum_{l \in \mathcal{T}^t} \sum_{i \in \mathcal{N}'} \sum_{k \in \mathcal{K}} x_{ijkl}^t = 1, \quad \forall j \in \mathcal{C}^t; \quad (3.15)$$

$$\sum_{j \in \mathcal{N}'} x_{ijkl}^t = \sum_{j \in \mathcal{N}'} x_{jikl}^t, \quad \forall l \in \mathcal{T}^t, i \in \mathcal{N}', k \in \mathcal{K}; \quad (3.16)$$

$$\sum_{i \in \mathcal{N}'} y_{ijkl}^t + \sum_{i \in \mathcal{N}'} W_j x_{jikl}^t = \sum_{i \in \mathcal{N}'} y_{jikl}^t, \quad \forall l \in \mathcal{T}^t, j \in \mathcal{C}^t, k \in \mathcal{K}; \quad (3.17)$$

$$\sum_{j \in \mathcal{C}^t} \sum_{k \in \mathcal{K}} y_{0jkl}^t = 0, \quad \forall l \in \mathcal{T}^t; \quad (3.18)$$

$$y_{i0kl}^t \leq VCAP_k x_{i0kl}^t, \quad \forall l \in \mathcal{T}^t, i \in \mathcal{C}^t, k \in \mathcal{K}; \quad (3.19)$$

$$y_{ijkl}^t \leq (VCAP_k - W_j) x_{ijkl}^t \quad \forall l \in \mathcal{T}^t, i \in \mathcal{N}', j \in \mathcal{C}^t, i \neq j, k \in \mathcal{K}; \quad (3.20)$$

$$y_{ijkl}^t \geq W_j x_{ijkl}^t \quad \forall l \in \mathcal{T}^t, i \in \mathcal{N}', j \in \mathcal{C}^t, i \neq j, k \in \mathcal{K}; \quad (3.21)$$

$$\delta_{ikl}^t - \delta_{jkl}^t + |\mathcal{C}^t| x_{ijkl}^t \leq |\mathcal{C}^t| - 1, \quad \forall l \in \mathcal{T}^t, (i, j) \in \mathcal{A}, k \in \mathcal{K}; \quad (3.22)$$

$$\sum_{j \in \mathcal{C}^t} x_{0jkl}^t \leq u_{0kl}^t, \quad \forall l \in \mathcal{T}^t, k \in \mathcal{K}; \quad (3.23)$$

$$\sum_{k \in \mathcal{K}} u_{0kl}^t \leq |\mathcal{K}|, \quad \forall l \in \mathcal{T}^t; \quad (3.24)$$

$$r_{0l}^t = \sum_{i \in \mathcal{C}^t} \sum_{k \in \mathcal{K}} y_{i0kl}^t, \quad \forall l \in \mathcal{T}^t; \quad (3.25)$$

$$x_{ijkl}^t \in \{0, 1\}, y_{ijkl}^t \geq 0, \quad \forall l \in \mathcal{T}^t, (i, j) \in \mathcal{A}, k \in \mathcal{K}; \quad (3.26)$$

$$r_{0l}^t \geq 0, \quad \forall l \in \mathcal{T}^t; \quad (3.27)$$

$$u_{0kl}^t \in \{0, 1\}, \delta_{ikl}^t \geq 0, \quad \forall i \in \mathcal{C}^t, k \in \mathcal{K}, l \in \mathcal{T}^t. \quad (3.28)$$

Equations (3.14) and (3.15) ensure that each known but unvisited generation node is visited exactly once during the planning horizon. Equation (3.16) presents the flow conservation. Equation (3.17) states that the load in a vehicle arriving at a generation node plus the waste amount at that node equals the vehicle load after serving the node. Constraints (3.18)-(3.21) compute the vehicle load at each link. To be specific, Constraint (3.18) ensures that the vehicle starts from a facility with full capacity. Constraint (3.19) is the vehicle capacity limit. The following two constraints, (3.20) and (3.21), respectively give the lower and upper bounds of vehicle  $k$  running between  $i$  and  $j$ . Constraint (3.22) serves for sub-tour elimination, i.e., determines the sequence of nodes and hence removes sub-tours among generation nodes. Constraint (3.23) shows that only those selected vehicles can be used, and the maximum number of vehicles is assured not to be exceeded in Constraint (3.24). Constraint (3.25) calculates the total amount of waste being process in a certain treatment facility. Constraints (3.26)-(3.28) define the domains for variables.

# Chapter 4

## Numerical Case Study

A real-world case study is conducted within the healthcare sector to validate our model. All computational experiments in this case study, are carried out on a computer with Intel(R) Core(TM) i5-9300HF CPU @ 2.40GHz and 8 GB RAM, using Python with Gurobi Optimizer version 10.0.1.

Medical waste has emerged as a significant concern due to its production of high levels of hazardous and infectious materials. The recent outbreak of COVID-19 has highlighted the critical importance of efficient and safe management of this kind of waste. The pandemic has led to a significant increase in the volume of healthcare waste, necessitating robust systems for its transportation and collection to prevent secondary contamination and ensure public health safety. Proper management of medical waste is essential not only for controlling emissions but also for reducing the risk of infection and environmental contamination.

This case study is based on the actual healthcare waste management network in Shanghai, a city in China. As illustrated in Figure 4.1, the network consists of 50

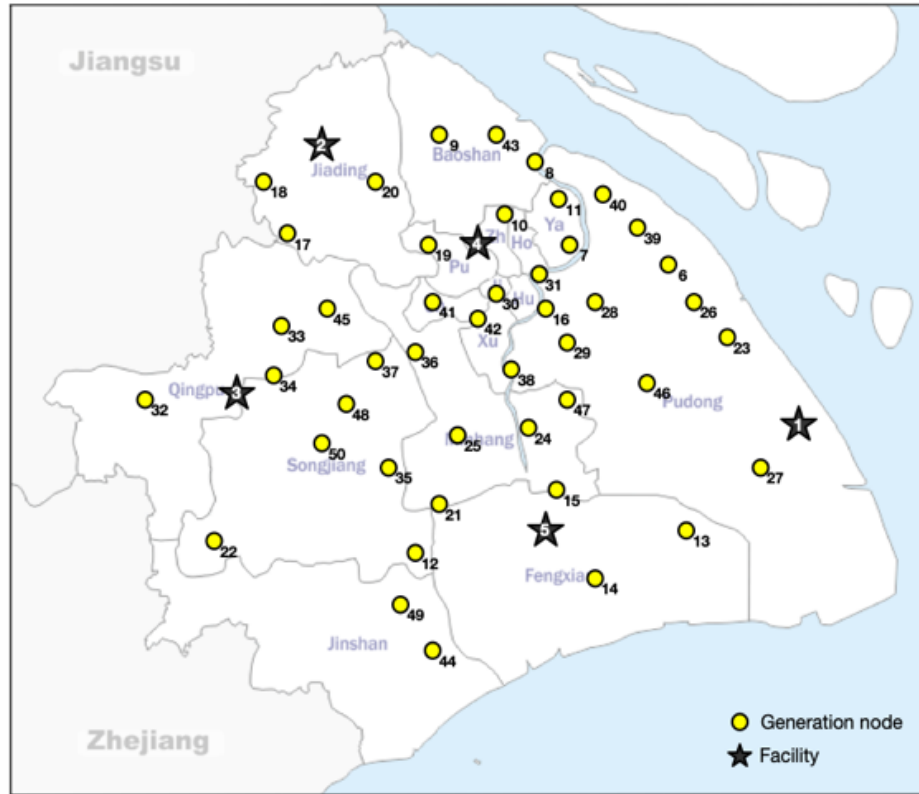


Figure 4.1: The medical waste management network in Shanghai, China.

nodes, which includes 45 generation nodes (nodes C5 - C49) and five potential locations for establishing treatment facilities (nodes F0 - F4). Each facility can be opened with either Technology 1 or Technology 2. These technologies differ mainly in terms environmental impacts. As a more advanced technology, Technology 2 improves the other technology in terms of producing less GHG emission, yet induces higher cost resulted from more up-to-date equipment and cutting-edge processes. Incorporating multiple technologies into waste management reflects the global emphasis on sustainable development, and how to upgrade the current system accordingly. In this context, our study focuses on optimizing the healthcare waste management network in Shanghai, considering all economic, social and environmental factors.

## 4.1 Relevant data

All data for the case study are shown in Tables 4.1-4.3. The network data are estimated based on the real-world medical network of Shanghai. Distances, population, etc. are obtained with GIS. The amount of waste is estimated based on the number of sickbed in each hospital. Table 4.1 provides detailed information about the hazardous waste generated for all generation nodes. Each node is identified with a unique code (e.g., C5, C6), and the table lists the waste amount in tonnes, the exposed population and the pickup dates. In the real world problem pickup dates are updated at the beginning of each day (period). However, for testing our model, these pickup dates are randomly generated. For example, Node C5 generates 2.002 tonnes of waste, exposes a population of 4,762 people, and has a scheduled pickup date on day 5. Similarly, Node C7 generates a significantly higher amount of waste at 12.453 tonnes, exposes a population of 7,836 people, and has a pickup date on day 1.

Table 4.2 outlines the emissions data for different treatment facilities using two technologies. Each facility is assessed for fixed facility emissions and variable processing emission, both measured in kilograms of CO<sub>2</sub> per tonne. For instance, Facility F0 has no fixed emission for Technology 1 but emits 600 kg CO<sub>2</sub> per tonne for Technology 2, and the variable processing emission for Technology 1 is 300 kg CO<sub>2</sub> per tonne while for Technology 2 it is 154 kg CO<sub>2</sub> per tonne (GHGProtocol, 2011). Similarly, Facility F2 has fixed emission of 6,460 kg CO<sub>2</sub> per tonne for Technology 1 and 5,168 kg CO<sub>2</sub> per tonne for Technology 2. Table 4.3 provides information on the construction costs, capacity, and processing costs for treatment facilities using two different technologies. The fixed construction cost is presented in RMB per week, and the

capacity is in tonnes per week, indicating how much waste each facility can handle. For example, Facility F0 has no fixed construction cost for Technology 1 but incurs a cost of 3,150 RMB per week for Technology 2.

Facility F0 has a capacity of 105 tonnes per week for both technologies. The processing cost for Facility F0 is 1,248 RMB per tonne for Technology 1 and 1,872 RMB per tonne for Technology 2. Similarly, Facility F2 requires 8,400 RMB per week for Technology 1 and 10,185 RMB per week for Technology 2, with a capacity of 59.5 tonnes per week for both technologies, and processing costs of 1,560 RMB per tonne for Technology 1 and 2,340 RMB per tonne for Technology 2.

Within the framework of this study, the impact radius for site risk is 0.8 km (Alumur and Kara, 2007). The corresponding exposed population near each generation node and facility are listed in Tables 4.1 and 4.2. As previously noted, Technology 2 leads to lower emissions and reduced risks. Consequently, the site risk radius for Technology 2 is adjusted to 20% lower, that is, 0.64km. Moreover, the arc risk is determined by exposed population in the area between the two connected nodes, within 0.8 km radius.

## **4.2 The first stage result (location-allocation)**

In this stage, two objectives are considered: costs minimization and emissions minimization. By incrementing  $w$  from 0 to 1 in steps of 0.1, the model is solved 11 times for a range of solutions, showing trade-offs between costs and emissions.

Based on the results, Table 4.4 below summarizes the optimal objective function for both costs and emissions, selected facilities, and amount of waste handled at

Table 4.1: Data for generation nodes.

Node #	Waste Amount (tonne)	Exposed population	Pickup date	Node #	Waste Amount (tonne)	Exposed population	Pickup date
C5	2.002	4762	5	C28	2.6635	4832	3
C6	3.1115	30701	2	C29	3.794	21536	6
C7	12.453	7836	1	C30	5.2045	22803	5
C8	3.0345	7958	1	C31	2.429	1802	2
C9	2.73	8661	6	C32	2.1035	1856	1
C10	4.9945	8462	4	C33	6.4645	1991	7
C11	5.145	1330	2	C34	5.313	2993	3
C12	5.159	1579	3	C35	12.936	3098	2
C13	2.8525	1685	4	C36	11.382	3308	1
C14	3.0345	1746	6	C37	4.5535	19338	4
C15	9.863	30575	1	C38	6.9055	19476	5
C16	3.794	3746	2	C39	11.0775	20489	2
C17	2.73	3868	1	C40	7.21	17209	2
C18	2.4675	4141	1	C41	2.6635	19202	1
C19	6.069	4025	5	C42	3.794	8264	1
C20	2.7685	1420	3	C43	5.2045	1425	3
C21	1.5785	1398	5	C44	2.429	1879	1
C22	3.1885	4578	7	C45	2.1035	4721	4
C23	2.3905	6808	2	C46	6.4645	7252	3
C24	1.7815	6987	1	C47	5.313	3108	7
C25	0.728	4685	4	C48	12.936	1463	2
C26	2.4115	4911	3	C49	11.382	3185	6
C27	6.069	4681	4				

Table 4.2: Emission data for treatment facilities for each technology.

Facilities #	Exposed Population	Fixed facility construction emission (kg CO <sub>2</sub> /tonne)		Variable processing emission (kg CO <sub>2</sub> /tonne)	
		Tech 1	Tech 2	Tech 1	Tech 2
F0	4872	0	600	300	154
F1	3946	0	400	300	154
F2	3182	6460	5168	300	154
F3	4022	3800	3040	300	154
F4	1400	3800	3040	300	154

Table 4.3: Construction costs and capacity data for treatment facilities

Facilities #	Fixed construction cost (RMB/week)		Capacity (tonnes/week)		Processing cost (RMB/tonnes)	
	Tech 1	Tech 2	Tech 1	Tech 2	Tech 1	Tech 2
F0	0	3150	105	105	1248	1872
F1	0	1890	63	63	1248	1872
F2	8400	10185	59.5	59.5	1560	2340
F3	5040	6090	35	35	1560	2340
F4	5040	6090	35	35	1560	2340

each selected treatment facility for different values of  $w$ . Increasing  $w$  to 0.1 slightly reduces the costs to 641,890.62 while keeping the emissions constant at 92,294.13. This is because, for  $w = 0$ , the model entirely focuses on emissions reduction, and after incrementing  $w$  to 0.1, costs is taken into consideration. However, the facilities

Table 4.4: Optimization results for stage 1 for different  $w$

Weight ( $w$ )	Objectives		Selected facilities		Amount of waste handled
	Cost	Emission	Tech 1	Tech 2	
0.0	645,371.37	92,294.13	F0, F1	F4	F0: 104.7585, F1: 58.625, F4: 33.2115
0.1	641,890.62	92,294.13	F0, F1	F4	F0: 104.888, F1: 62.958, F4: 28.749
0.2	641,868.78	92,294.13	F0, F1	F3	F0: 104.9405, F1: 62.9335, F3: 28.721
0.3	641,797.80	92,294.13	F0, F1	F3	F0: 104.965, F1: 63.000, F3: 28.630
0.4	641,797.80	92,294.13	F0, F1	F3	F0: 104.965, F1: 63.000, F3: 28.630
0.5	640,747.80	93,054.13	F0, F1, F3	-	F0: 104.965, F1: 63.000, F3: 28.630
0.6	640,747.80	93,054.13	F0, F1, F3	-	F0: 104.965, F1: 63.000, F3: 28.630
0.7	640,747.80	93,054.13	F0, F1, F3	-	F0: 104.965, F1: 63.000, F3: 28.630
0.8	640,747.80	93,054.13	F0, F1, F3	-	F0: 104.965, F1: 63.000, F3: 28.630
0.9	640,747.80	93,054.13	F0, F1, F3	-	F0: 104.965, F1: 63.000, F3: 28.630
1	640,747.80	93,054.13	F0, F1, F3	-	F0: 104.965, F1: 63.000, F3: 28.630

selected remain the same (F0, F1, and F4), but the allocation of waste to these facilities changes, optimizing for costs without adding emissions. For  $w = 0.3$ , the costs drops slightly to 641,797.80 because the weight for the costs objective is higher. As  $w$  increases to 0.5 and beyond, the model prioritizes costs minimization more strongly. The costs declines to 640,747.80, but the emissions climbs to 93,054.13. Three facilities (F0, F1, and F3) are opened, with Technology 1 being more cost-effective but less efficient in reducing emissions compared to Technology 2. Technology 1 is generally cheaper but emits more pollutants compared to Technology 2. When  $w$  increases, the model tends to favor costs reduction, leading to the selection of facilities using Technology 1 despite its higher emissions. Conversely, with lower  $w$  values, the

Table 4.5: Allocation of generation nodes to selected facilities for  $w = 0.4$

Facility	Assigned generation nodes
F0	C5, C6, C8, C9, C10, C11, C12, C13, C14, C15, C16, C17, C18, C20, C22, C25, C26, C28, C29, C30, C31, C32, C33, C34, C35, C36, C37, C38, C39, C40, C41, C46
F1	C7, C19, C23, C24, C27, C42, C43, C45, C48
F3	C21, C44, C47, C49

model chooses to build facilities with Technology 2 to minimize emissions.

In Table 4.5, the assignment of generation nodes to selected facilities for the optimal solution is presented where both the costs and emissions are minimized. In this table, we choose the solution with  $w = 0.4$  as it shows a well-balanced result. Table 4.5 indicates that 32 nodes are assigned to facility F0, 9 to facility F1, and 4 to facility F3. Results from this table is used in the second stage for routing decisions.

### 4.3 The second stage result (routing decision)

In the second stage, the model builds on the results from the first stage to optimize DMPVRP. As mentioned in the previous stage the result for  $w = 0.4$  shown in Table 4.5 are selected to run the model in the second stage.

This stage is divided into three smaller networks, each comprising one treatment facility which is selected in the previous stage (facilities F0, F1, and F3) and their assigned generation nodes. The available pickup date for each node starts from its first available pickup date and extends to the end of the planning horizon. The randomly

Table 4.6: Data for vehicles and third-party

Transportation cost per (km)	Vehicle's capacity (tonnes)	Vehicle's emission (g CO <sub>2</sub> /km/litre)	Third party hiring cost per node per node (RMB)
20	15	119	3500

generated first available pickup date for each generation node is shown in Table 4.1. Please note that data in Table 4.1 are used only for computation purpose. In reality, the pickup information is received and updated every day.

Table 4.6 shows the data for vehicles and third-party hiring costs. The transportation cost is 20 units per kilometer (Tasouji Hassanpour et al., 2023a). We consider homogeneous vehicles each with a capacity of 15 tonnes. The CO<sub>2</sub> emission of the vehicle per distance per unit fuel consumption is 119 unit (g). The third-party hiring cost per node is calculated based on the longest link between the facility and its farthest customer.

The results for all three facilities across various days are presented in Table 4.7, demonstrating each objectives value, amount of waste processed as well as the selected routes for each day. Each facility's performance is evaluated over seven days, and the optimal routes are determined. This distribution of nodes in each network results in higher risks, emissions, and costs objective values for facility F0 in each day compared to the other two facilities.

For facility F0, in day 1 (i.e.,  $t = 1$ ), the objective risks value is 9,098,315.805, emissions value is 26,809.350, and the costs value is 33,314.154. The selected routes for this day include F0-C15-C41-C18-F0, F0-C36-C32-C17-F0, and F0-C8-F0 , indicat-

Table 4.7: Result of the second stage problem for  $w_1 = 50$  and  $w_2 = 50$

Facility	time period	Best Obj			Amount of waste	Selected route
#	$t$	Risk	Emission	Cost	processed(tonnes)	
F0	$t = 1$	9,098,315.805	26,809.350	33,314.154	24.055	F0-C15-C41-C18-F0 /F0-C36-C32-C17-F0/F0-C8-F0
	$t = 2$	8,715,782.175	35,444.463	34,530.708	23.859	F0-C31-C11-F0 /F0-C6-C39-C35-F0/F0-C40-F0/F0-C16-F0
	$t = 3$	5,973,991.241	35,222.324	31,706.007	21.532	F0-C46-C28-F0 /F0-C26-C12-C20-C34-F0
	$t = 4$	4,309,104.970	27,051.760	18,005.515	11.238	F0-C37-C13-F0/F0-C25-C10-F0
	$t = 5$	4,945,914.368	21,136.935	15,544.391	10.013	F0-C38-C5-F0/F0-C30-F0
	$t = 6$	3,315,499.739	20,477.336	14,888.636	9.558	F0-C29-C9-F0/F0-C14-F0
	$t = 7$	1,373,476.549	19,681.390	8,945.403	4.707	F0-C33-F0/F0-C22-F0
F1	$t = 1$	6,923,485.094	24,627.408	28,927.765	20.698	F1-C24-C42-F1/F1-C7-F1
	$t = 2$	2,801,643.990	15,928.444	18,806.054	13.468	F1-C23-C48-F1
	$t = 3$	1,000,926.658	11,589.483	8,310.554	5.313	F1-C43-F1
	$t = 4$	5,952,402.566	27,341.185	25,494.122	17.451	F1-C27-F1 /F1-C45-F1
	$t = 5$	315,189.850	3,462.921	7,850.115	6.069	F1-C19-F1
	$t = 6$	-	-	-	-	-
	$t = 7$	-	-	-	-	-
F3	$t = 1$	1,691,261.126	8,175.765	31,309.504	12.936	F3-C44-F3
	$t = 2$	-	-	-	-	-
	$t = 3$	-	-	-	-	-
	$t = 4$	-	-	-	-	-
	$t = 5$	312,326.123	10,659.754	5,444.390	1.578	F3-C21-F3
	$t = 6$	968,498.271	6,321.455	17,747.217	7.21	F3-C49-F3
	$t = 7$	752,745.744	5,751.588	15,080.457	6.9055	F3-C47-F3

ing three vehicles used in this day using three different route to collect waste from available nodes. For example, for the first route vehicle starts from facility F0, travels to node C15, then to node C41, and then C18 before returning to the facility F0. Each of these routes is served by one vehicle.

In day 2 (i.e.,  $t = 2$ ), the objective risks value decreases to 8,715,782.175, emissions value increases to 33,718.269 and the costs value increases to 34,530.708. The values of risks, emissions, and costs vary in each day affected by several factors. For example, at facility F0 in days 6 and 7, although less waste is processed in day 7, the emissions

values are higher than in day 6. This increase in emissions is due to the higher vehicle emission in day 7, resulting from greater total distance traveled by the vehicles, leading to increased emissions despite the lower volume of waste processed.

In certain days, such as day  $t = 6$  for facility F1 and day  $t = 3$  for facility F3, no routes are selected and no waste is processed. There are two main reasons for this occurrence. First, there might be no nodes available for collection during that specific day. Second, the collection of waste from available nodes might be postponed to subsequent days. This postponement can be due to strategic planning to optimize the overall efficiency and risk management of the waste collection process. In the following analyses, the sub-network for facility F0 is selected because 32 generation nodes are assigned to it, which can show a greater complication and variation than the other two networks. Additionally, the network demand for F0 is distributed across the entire planning horizon, and thus can better demonstrate our computational results.

## 4.4 Trade-off between objectives

To perform the trade-offs, we vary  $w_1$  and  $w_2$  from 0 to 500 and to observe their effects on the objectives. These values are chosen according to the scale difference among the three objective values. Table 4.8 displays the values of the risks, and emissions, with different values of  $w_1$  ranging from 0 to 500. Columns ‘Risk’ and ‘Emission’ represent the total risks and total emissions for each day over the planning horizon, respectively. The last row ‘Total’ list the total values for the 7 days. As  $w_1$  increases from 0 to 500, emissions reduces by almost 30 percent (28.5%), while risks increases by nearly 20 percent (18.5%). Figure 4.2a shows the relative changes of total risks

Table 4.8: Risk and Emission values with different wight  $w_1$  assigned to Emission.

Time period	$w_1 = 0$		$w_1 = 50$		$w_1 = 100$		$w_1 = 150$	
(t)	Risk	Emission	Risk	Emission	Risk	Emission	Risk	Emission
1	8,890,147.713	33,737.635	9,098,315.805	26,809.35	9,098,315.805	26,809.35	9,098,315.805	26,809.35
2	8,596,891.566	39,979.226	8,803,641.044	33,718.269	8,803,641.044	33,718.269	8,803,641.044	33,718.269
3	5,689,958.41	41,179.228	5,973,991.241	35,222.324	5,973,991.241	35,222.324	5,973,991.241	35,222.324
4	4,309,104.97	27,051.76	4,309,104.97	27,051.76	4,309,104.97	27,051.76	4,309,104.97	27,051.76
5	4,945,914.368	21,136.935	4,945,914.368	21,136.935	5,566,660.469	13,967.678	5,566,660.469	13,967.678
6	3,315,499.739	20,477.336	3,315,499.739	20,477.336	3,978,409.477	14,748.88	3,978,409.477	14,748.88
7	1,373,476.549	19,681.39	1,373,476.549	19,681.39	1,373,476.549	19,681.39	1,373,476.549	19,681.39
<b>Total</b>	<b>37,120,993.32</b>	<b>203,243.51</b>	<b>37,819,943.72</b>	<b>184,097.364</b>	<b>39,103,599.56</b>	<b>171,199.651</b>	<b>39,103,599.56</b>	<b>171,199.651</b>
	$w_1 = 200$		$w_1 = 250$		$w_1 = 300$		$w_1 = 350$	
1	9,569,668.974	24,642.615	9,569,668.974	24,642.615	9,569,668.974	24,642.615	9,569,668.974	24,642.615
2	8,803,641.044	33,718.269	8,803,641.044	33,718.269	10,396,136.7	28,263.633	10,396,135.53	28,263.633
3	5,973,991.241	35,222.324	5,973,991.241	35,222.324	5,973,991.241	35,222.324	6,284,362.473	31,494.126
4	5,732,573.301	19,716.315	5,732,573.301	19,716.315	5,732,573.301	19,716.315	5,860,398.321	15,692.276
5	5,566,660.469	13,967.678	5,566,660.469	13,967.678	5,566,660.469	13,967.678	5,566,660.469	13,967.678
6	3,978,409.477	14,748.88	3,978,409.477	14,748.88	3,978,409.477	14,748.88	3,978,409.477	14,748.88
7	1,373,476.549	19,681.39	1,668,816.547	18,494.919	1,668,816.547	18,494.919	1,668,816.547	18,494.919
<b>Total</b>	<b>40,998,421.061</b>	<b>161,697.471</b>	<b>41,293,761.473</b>	<b>160,511</b>	<b>42,886,256.71</b>	<b>155,056.364</b>	<b>433,244,51.803</b>	<b>147,304.127</b>
	$w_1 = 400$		$w_1 = 450$		$w_1 = 500$			
1	9,569,668.974	22,583.407	9,569,668.974	22,583.407	9,569,668.974	22,583.407		
2	10,396,136.7	28,263.633	10,396,136.7	28,263.633	10,396,136.7	28,263.633		
3	5,973,991.241	33,275.284	5,973,991.241	33,275.284	5,973,991.241	33,275.284		
4	6,437,894.506	17,463.739	6,437,894.506	16,783.748	6,437,894.506	17,463.739		
5	5,566,660.469	13,967.678	5,566,660.469	13,967.678	5,566,660.469	12,248.385		
6	3,978,409.477	14,748.88	3,978,409.477	14,748.88	4,395,673.716	14,748.88		
7	1,668,816.547	16,617.843	1,668,816.547	16,617.843	1,668,816.547	16,617.843		
<b>Total</b>	<b>43,591,577.91</b>	<b>146,920.464</b>	<b>43,591,577.91</b>	<b>146,240.473</b>	<b>44,008,842.15</b>	<b>145,201.171</b>		

and total emissions as a function of  $w_1$ .

Similar results can be obtained for risks and costs with increasing values of  $w_2$  from 0 to 500. Table 4.9 presents the values of the risks and costs, with different values of  $w_2$ . Columns ‘Risk’ and ‘Cost’ represent the total risks and total costs over the planning horizon, respectively. The last row ‘Total’ shows the total values for the 7 days. As  $w_2$  increases from 0 to 500, As shown Figure 4.2b, the costs decreases by

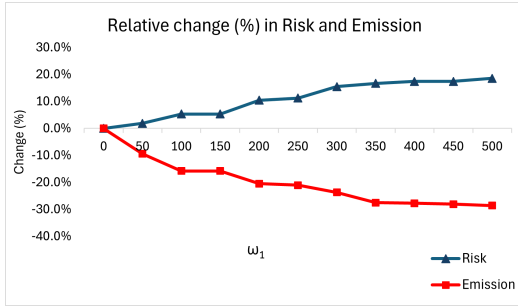
Table 4.9: Risk and Cost values with different wight  $w_2$  assigned to Cost.

Time period	$w_2 = 0$		$w_2 = 50$		$w_2 = 100$		$w_2 = 150$	
(t)	Risk	Cost	Risk	Cost	Risk	Cost	Risk	Cost
1	9,098,315.805	33,314.154	9,098,315.805	33,314.154	9,098,315.805	33,314.154	9,849,340.372	32,631.741
2	8,803,641.044	34,240.592	8,803,641.044	34,240.592	8,803,641.044	34,240.592	8,803,641.044	34,240.592
3	5,973,991.241	31,706.007	6,012,537.241	29,817.007	5,973,991.241	31,706.007	5,973,991.241	31,706.007
4	4,309,104.97	18,005.515	4,309,104.97	18,005.515	4,810,966.096	16,581.361	4,810,966.096	16,581.361
5	5,566,660.469	14,339.474	5,566,660.469	14,339.474	5,566,660.469	14,339.474	5,861,312.607	13,719.473
6	3,315,499.739	14,888.636	3,315,499.739	14,257.636	3,978,409.477	13,925.87	3,978,409.477	13,925.87
7	1,373,476.549	8,945.403	1,373,476.549	8,945.403	1,165,453.782	8,283.391	1,165,453.782	8,283.391
<b>Total</b>	<b>38,440,689.825</b>	<b>155,439.781</b>	<b>38,479,235.532</b>	<b>152,919.781</b>	<b>39,397,437.91</b>	<b>152,390.849</b>	<b>40,443,114.62</b>	<b>151,088.435</b>
	$w_2 = 200$		$w_2 = 250$		$w_2 = 300$		$w_2 = 350$	
1	9,849,340.372	32,631.741	9,849,340.372	32,631.741	9,849,340.372	32,631.741	9,849,340.372	32,631.741
2	8,803,641.044	34,240.592	9,143,286.429	34,240.592	9,143,286.429	32,419.56	9,143,286.429	29,516.263
3	5,973,991.241	31,706.007	5,973,991.241	31,706.007	5,973,991.241	31,706.007	5,973,991.241	31,706.007
4	5,189,371.296	16,341.835	5,189,371.296	16,341.835	5,189,371.296	16,341.835	5,189,371.296	16,341.835
5	5,861,312.607	13,719.473	5,861,312.607	13,719.473	5,861,312.607	13,719.473	5,861,312.607	13,719.473
6	3,978,409.477	13,925.87	3,978,409.477	13,925.87	3,978,409.477	12,645.873	3,978,409.477	13,925.87
7	1,165,453.782	8,283.391	1,165,453.782	8,283.391	1,165,453.782	8,283.391	1,165,453.782	8,283.391
<b>Total</b>	<b>40,821,519.82</b>	<b>150,848.909</b>	<b>41,161,165.267</b>	<b>149,027.877</b>	<b>41,161,165.267</b>	<b>147,747.88</b>	<b>41,749,341.591</b>	<b>146,124.58</b>
	$w_2 = 400$		$w_2 = 450$		$w_2 = 500$			
1	9,849,340.372	32,631.741	9,849,340.372	30,371.739	9,849,340.372	32,631.741		
2	9,731,462.812	29,516.263	9,143,286.429	29,516.263	9,143,286.429	32,419.56		
3	5,973,991.241	29,759.375	5,973,991.241	31,706.007	6,328,643.738	29,371.294		
4	5,189,371.296	16,341.835	5,189,371.296	16,341.835	5,189,371.296	16,341.835		
5	6,714,943.634	11,345.476	5,861,312.607	13,719.473	5,861,312.607	13,719.473		
6	3,978,409.477	13,925.87	3,978,409.477	13,925.87	3,978,409.477	13,925.87		
7	1,165,453.782	8,283.391	1,165,453.782	8,283.391	1,759,376.371	7,462.912		
<b>Total</b>	<b>42,014,796.23</b>	<b>144,707.248</b>	<b>42,014,796.23</b>	<b>143,864.578</b>	<b>42,697,916.674</b>	<b>142,969.388</b>		

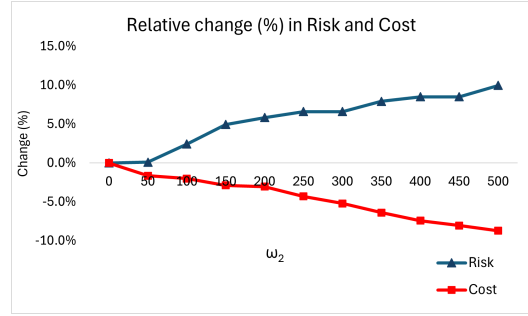
10 percent (8.8%) and the risks also increases by 10 percent.

## 4.5 A comparison with the current system

To further illustrate the advantages of implementing the two-stage location-routing waste management system with multiple facilities and generation nodes, we compare



(a) Risk vs Emission



(b) Risk vs Cost

Figure 4.2: Relative changes in Risk, Cost, and Emission as a function of weights  $w_1$  and  $w_2$ .

our proposed system with the existing one across both stages. In the first stage, we focus on comparing costs and emissions, while in the second stage, we evaluate risks, costs, emissions, and the number of vehicles used. To be specific, the current waste management system is comprised of only two operational facilities, both equipped with Technology 1. Each generation node is picked up by direct routes conducted by a dedicated vehicle. The comparison results are summarized in Table 4.10, where  $\Delta\%$  represent the improvements over the current system.

The facility utilization rate of the current system is 117.8%, indicating that the demand exceeds the capacity of the current facilities, leading to overutilization and potentially increased operational strain. In contrast, the proposed system introduces additional facilities, which significantly increases overall capacity and reduces the facility utilization to 65.4%–73.1%, depending on the weight ( $w$ ) given to costs versus emissions in the optimization process. This reduction in utilization shows that the proposed system not only meets the current demand more effectively but also provides a buffer for future increases in demand, reducing the strain on individual facilities.

Table 4.10: A comparison with the current system in stage 1.

		Facility	Processing	Total	Facility	Processing	Total	Facility
		cost	cost	cost	emission	emission	emission	utilization
Current system		-	535,658.038	535,658.038	-	117,538.27	117,538.27	117.8%
	$w = 0$	6,090.000	639,281.370	645,371.370	3,040.000	89,254.130	92,294.130	65.4%
	$\Delta\%$	-	+19.3%	+20.5%	-	-24.1%	-21.5%	-44.5%
Proposed system	$w = 0.4$	6,090.000	635,707.800	641,797.8	3,040.000	89,254.130	92,294.130	73.1%
	$\Delta\%$	-	+18.7%	+19.8%	-	-24.1%	-21.5%	-37.9%
	$w = 1$	5,040.000	635,707.800	640,747.800	3,800.000	89,254.130	93,054.130	73.1%
	$\Delta\%$	-	+18.7%	+19.6%	-	-24.1%	-20.8%	-37.9%

From Table 4.10, it is evident that the proposed system achieve mixed results compared to the current system. While there is a significant reduction in processing and total emissions, with a decrease of 24.1% across all weights for processing emission and 20.8%-21.5% for total emissions, the processing and total costs are increased by 18.7%–19.3% and 19.6%–20.5% respectively. The increase in processing and total cost is primarily due to the establishing a new facility equipped with Technology 2. This new facility has a higher processing cost compared to the existing two facilities with Technology 1. On the other hand, the improvement in processing and total emissions can be attributed to the new facility with Technology 2. This facility has a significantly lower processing emission rate compared to the existing facilities with Technology 1. By assigning some of the waste to this new facility, the overall emissions can be reduced by 20.8%-21.5% for different  $w$ , showcasing the environmental benefits of integrating advanced Technology into the waste management system.

The most significant benefit of the proposed system is observed in the second stage, where it utilizes much fewer vehicles to collect waste. The current system uses

Table 4.11: A comparison with current system in stage 2 for network with facility F0.

	Time period	Objective			No. Veh	Max No. Veh
	( <i>t</i> )	Risk	Emission	Cost		
Current system	<i>t</i> = 1	12,345,678.901	74,321.876	59,876.543	7	-
	<i>t</i> = 2	11,234,567.890	98,765.432	62,962.963	7	-
	<i>t</i> = 3	7,654,321.098	98,321.876	57,777.438	6	-
	<i>t</i> = 4	5,543,210.987	75,432.109	33,950.617	4	-
	<i>t</i> = 5	6,358,024.691	58,024.691	29,629.630	3	-
	<i>t</i> = 6	4,271,604.938	56,790.123	28,395.062	3	-
	<i>t</i> = 7	1,763,271.235	54,691.235	14,353.086	2	-
	<b>Total</b>	<b>49,170,679.74</b>	<b>516,347.342</b>	<b>286,945.339</b>	<b>32</b>	<b>7</b>
Proposed system	<i>t</i> = 1	9,098,315.805	26,809.350	33,314.154	3	-
	<i>t</i> = 2	8,715,782.175	35,444.463	34,530.708	4	-
	<i>t</i> = 3	5,973,991.241	35,222.324	31,706.007	2	-
	<i>t</i> = 4	4,309,104.970	27,051.760	- 18,005.515	2	-
	<i>t</i> = 5	4,945,914.368	21,136.935	15,544.391	2	-
	<i>t</i> = 6	3,315,499.739	20,477.336	14,888.636	2	-
	<i>t</i> = 7	1,373,476.549	19,681.390	8,945.403	2	-
	<b>Total</b>	<b>37,731,084.847</b>	<b>185,823.558</b>	<b>156,934.814</b>	<b>17</b>	<b>4</b>
$\Delta\%$	-23.3%	-%64	-45.3%	-46.9%	-42.9%	

one vehicle for each node, which results in many unnecessary trips. By optimizing the routes and dividing the long direct routes between each facility and generation nodes, the proposed system greatly reduces the number of vehicles required. This not only decreases the risks by eliminating unnecessary or repetitive connections but also significantly lowers transportation cost and emission by reducing the travel distances.

As Table 4.11 shows, the proposed system achieves a 23.3% reduction in risks by eliminating redundant routes and reducing vehicle use. Emissions are slashed by

64%, thanks to shorter, more efficient routes, and cost savings amount to 45.3% due to fewer vehicles being needed and more efficient routing. Even, when comparing the daily performance across the planning horizon, the proposed system consistently outperforms the current system, with lower values for all three objectives—risks, emissions, and costs—on each day. Furthermore, The proposed system requires only 17 vehicles in total, with a maximum of 4 vehicles needed on day 2, compared to 32 vehicles in the current system—a 46.9% reduction in fleet size. This decrease is possible because, unlike the current system where each node must be served by a dedicated vehicle, the proposed system allows a single vehicle to serve multiple nodes. Additionally, by reusing the same vehicles across different days, the proposed system can operate effectively with just 4 vehicles on its busiest day.

Table 4.12 provides a comprehensive comparison between the current system and the proposed system across both stages. The values for emissions and costs are obtained by summing the total value of both objectives from stage 1 ( $w = 0.4$ ) and the entire planning horizon of stage 2 ( $w_1 = 50$  and  $w_2 = 50$ ). The risks value represents the cumulative risks over the entire planning horizon of stage 2. As illustrated in Table 4.12, the proposed system achieves a 23.3% reduction in total risks and a significant 63.4% decrease in total emissions. Although the costs of the proposed system increases in stage 1 due to the establishment of a new facility, the overall costs is greatly reduces by 43.2% due to savings realized in stage 2. Additionally, the current system suffers from a 17.8% unsatisfied demand due to limited facility capacity. By adding a new facility, the proposed system effectively increases capacity, fully satisfying all demand.

Overall, the proposed system provides a comprehensive improvement over the cur-

Table 4.12: An overall comparison with current system for both stages.

	Objectives			Unsatisfied
	Risk	Emission	Cost	demand (%)
Current system	49,170,679.740	516,347.342	286,945.339	17.8%
Proposed system	37,731,084.847	188,863.558	163,024.814	0%
$\Delta\%$	-23.3%	-63.4%	-43.2%	-

rent system. It integrates enhanced route optimization, reduces vehicle requirements, and lower operational costs to deliver a safer, more environmentally friendly, and cost-effective solution for waste collection.

## 4.6 Sensitivity analyses

In this section, sensitivity analyses are performed to evaluate the impact of various parameters on the optimization results. By varying these parameters, we can identify which factors have the most significant influence on the decision-making process and the overall performance of the system.

### 4.6.1 Varying the capacity of vehicles

In this section, we investigate the impact of altering vehicle capacity on our three objectives—risks, emissions, and costs—as well as the number of vehicles used. We consider five different vehicle capacities: 10, 12, 15, 17, and 20 tonnes. Our analysis reveals how these changes influence each objective and the number of vehicles deployed in each day. A summary of the results is provided in Table 4.13.

Table 4.13: Sensitivity analysis for vehicle capacity.

VCAP	Objective	Time period ( <i>t</i> )							Total
		1	2	3	4	5	6	7	
10	Risk	12,635,516.99	8,783,270.709	5,962,845.749	4,309,104.97	4,945,914.368	3,978,409.477	1,373,476.549	<b>41,988,538.81</b>
	Emission	30,108.928	34,471.904	42,056.899	27,051.76	21,136.935	14,748.88	19,681.39	<b>189,256.696</b>
	Cost	33,868.705	34,367.253	32,854.675	18,005.515	15,544.391	13,925.87	8,945.403	<b>157,511.812</b>
	No. Veh	4	4	3	2	3	1	2	<b>19</b>
	Max No. Veh	-	-	-	-	-	-	-	<b>4</b>
12	Risk	10,911,026.06	8,327,941.912	5,689,958.41	4,309,104.97	4,945,914.368	3,978,409.477	1,373,476.549	<b>39,535,832.74</b>
	Emission	29,177.494	33,718.269	41,179.228	27,051.76	13,967.678	14,748.88	19,681.39	<b>179,524.699</b>
	Cost	33,712.162	34,240.592	32,707.167	18,005.515	14,339.474	13,925.87	8,945.403	<b>155,876.183</b>
	No. Veh	3	4	3	2	2	1	2	<b>17</b>
	Max No. Veh	-	-	-	-	-	-	-	<b>4</b>
15	Risk	9,098,315.805	8,161,376.583	5,689,958.41	4,309,104.97	4,735,762.627	3,978,409.477	1,373,476.549	<b>37,346,404.42</b>
	Emission	26,809.35	33,718.269	35,222.324	27,051.76	13,967.678	14,748.88	19,681.39	<b>171,199.651</b>
	Cost	33,314.154	34,240.592	31,706.007	18,005.515	14,339.474	13,925.87	8,945.403	<b>154,477.015</b>
	No. Veh	3	3	2	2	1	1	2	<b>14</b>
	Max No. Veh	-	-	-	-	-	-	-	<b>3</b>
17	Risk	9,098,315.805	8,161,376.583	5,286,548.386	4,309,104.97	4,735,762.627	3,978,409.477	1,373,476.549	<b>36,942,994.4</b>
	Emission	26,809.35	33,718.269	34,876.735	27,051.76	13,967.678	14,748.88	19,681.39	<b>168,331.084</b>
	Cost	33,314.154	34,240.592	31,706.007	18,005.515	14,339.474	13,925.87	8,945.403	<b>154,477.015</b>
	No. Veh	3	3	2	2	1	1	2	<b>14</b>
	Max No. Veh	-	-	-	-	-	-	-	<b>3</b>
20	Risk	9,098,315.805	8,161,376.583	4,925,841.652	4,309,104.97	4,735,762.627	3,978,409.477	1,373,476.549	<b>36,582,288.66</b>
	Emission	26,809.35	33,718.269	34,876.735	27,051.76	13,967.678	14,748.88	19,681.39	<b>165,999.066</b>
	Cost	31,186.736	34,240.592	31,706.007	18,005.515	14,339.474	13,925.87	8,945.403	<b>152,349.597</b>
	No. Veh	2	2	2	2	1	1	2	<b>12</b>
	Max No. Veh	-	-	-	-	-	-	-	<b>2</b>

The number of vehicles used decrease from 19 to 12 as the vehicle capacity increase from 10 to 20 tonnes. This is because higher-capacity vehicles can collect more waste, reducing the need for multiple trips and thus the total number of vehicles required. We also determine the maximum number of vehicles required for each capacity during the entire panning horizon. This maximum number represents the peak demand for vehicles, helping us determine the fleet size required to meet the highest daily demand.

Table 4.13 illustrates this analysis by showing the number of vehicles used each day (denoted as “No. Veh”) and identifying the maximum number of vehicles required on any single day within the planning horizon. The maximum number of vehicles deployed is 4 when the capacity is 10 or 12 tonnes, while it drops to 3 at 15 and 17 tonnes, and further decreases to 2 when the capacity grows to 20 tonnes.

The risks associated with waste collection decrease by approximately 12.9% when the vehicle capacity increase from 10 to 20 tonnes. This reduction in risks is logical, as fewer trips and can lead to a lower risks. Emissions show a notable decrease with increased vehicle capacity. Specifically, the total emissions from day 1 to 7 drop from 189,256.696 units at 10 tonnes capacity to 165,999.066 (12.9% decrease) units at 20 tonnes capacity. This reduction is due to fewer trips needed to collect the same amount of waste, leading to lower fuel consumption and, consequently, lower emissions. Similarly, the costs objective also see a decrease. The total costs goes down from 157,511.812 units at 10 tonnes capacity to 152,349.597 units at 20 tonnes capacity. The reduction in costs can be attributed to lower transportation cost associated with fewer trips.

Overall, the sensitivity analysis shows that increasing vehicle capacity from 10 to 20 tonnes positively impacts the number of vehicles used, the risks, emissions, and costs objectives. Larger vehicle capacities allow for more efficient waste collection by reducing the number of trips and vehicles needed, thereby lowering the associated risks, emissions, and costs.

## 4.6.2 Varying first available pickup date

The first available pickup date is a dynamic parameter in our hazardous waste management model that plays a crucial role in determining the efficiency of the system. It dictates when each generation node can start waste collection, directly affecting the routing strategy, vehicle usage, and the overall balance between costs, risks, and emissions. Due to its significant impact on the model's performance, it is vital to conduct a sensitivity analysis on this parameter. For this analysis, the model is run with a maximum of 5 vehicles available each day, which allows us to observe how the system responds. To explore how changes in the first available pickup date influence the system, we propose analyzing four scenarios:

- **Normal Distribution:** Pickup dates are generated with Normal distribution with a mean of 0.4 and a standard deviation of 1.5 for first available date, introducing moderate variability around the original schedule.
- **Uniform Distribution:** Pickup dates are evenly spread across the planning horizon, generated from 1 to 7, simulating a consistent distribution of waste collection opportunities.
- **Left-Skewed Binomial Distribution:** Pickup dates are delayed, with most concentrated towards the end of the planning horizon (closer to 7), simulating a scenario with later demand. A left-skewed binomial distribution is generated using parameters  $n = 32$  (number of trials) and  $p = 0.7$  (probability of success).
- **Right-Skewed Binomial Distribution:** Most pickup dates are earlier, concentrated towards the beginning of the planning horizon (closer to 1), simulating

a scenario with higher initial demand. Similarly, a right-skewed binomial distribution is generated with parameters  $n = 32$  and  $p = 0.3$ .

Table 4.14 details how the demand (first available pickup dates) is allocated across different time periods for each distribution type. The model is executed with four vehicles available each day, each having a capacity of 15 tonnes. The objective function of the model is formulated as a weighted sum of emissions and costs, with equal weights assigned to both objectives ( $w_1 = 50$ ,  $w_2 = 50$ ), while the risk component is directly included without any additional weighting.

As Table 4.15 shows, with the uniform distribution, the pickup dates are evenly distributed throughout the entire planning horizon, leading to a balanced workload over time. This distribution results in the absence of any delays or third-party costs, as the pickups can be managed within the available resources and time without requiring external assistance. Consequently, the transportation risk, cost, and emissions are minimized. Specifically, the total transportation risk is 32,318,011.987, which is the lowest among all distributions. The transportation cost amounts to 23,727.398, and the total emissions are 133,077.034, both of which are also at their lowest. The uniform distribution provides the most efficient and cost-effective results due to the even spread of operations across the time periods. Under the normal distribution, pickup dates tend to cluster around the middle of the planning horizon, leading to a concentration of pickups during certain periods. This clustering results in some nodes being postponed from the fourth day to the fifth, which in turn causes a delay risk penalty at this day. Transportation risk, cost, and emissions are also increase compared to a uniform distribution. The total transportation risk rises to 34,969,018.556.

Table 4.14: First available pickup dates distribution for all four scenarios

Distribution	Time period (t)	Demand (first available pickup dates)
Normal	1	-
	2	C12, C14, C15, C37
	3	C16, C20, C25, C28, C33, C34
	4	C6, C10, C18, C29, C30, C31, C35, C40, C41
	5	C5, C8, C13, C22, C32, C36, C38, C39, C46
	6	C9, C11, C17
	7	C26
Uniform	1	C12, C36, C41
	2	C10, C18, C20, C28, C40
	3	C5, C6, C8, C25, C34
	4	C13, C15, C22, C33, C35, C38
	5	C11, C14, C31, C32
	6	C16, C29, C37, C39
	7	C9, C17, C26, C30, C46
Left-Skewed Binomial	1	-
	2	-
	3	C14, C30, C31, C32, C39
	4	C9, C11, C15, C18, C20, C46
	5	C6, C10, C13, C16, C25, C26, C34, C36, C40
	6	C5, C8, C17, C22, C28, C29, C35, C41
	7	C12, C33, C37, C38
Right-Skewed Binomial	1	C6, C29, C34, C37
	2	C5, C8, C9, C10, C12, C15, C17, C18, C26, C32, C38, C39
	3	C11, C20, C28, C30, C31, C35, C36, C40, C41
	4	C16, C22, C33, C46
	5	C13, C25
	6	C14
	7	-

Table 4.15: Result of varying first available pickup date

Pickup dates	Time period	Risk		Cost			Emission		No. Veh	
		Transportation	Delay	Processing	Transportation	Third-party	Transportation	Facility		
Uniform	$t = 1$	2,430,321.891	-	17,082.533	3,670.247	-	21,837.973	2,371.550	2	
	$t = 2$	4,652,397.017	-	23,025.648	3,099.236	-	18,440.454	3,461.286	3	
	$t = 3$	4,105,491.671	-	21,749.463	3,029.646	-	18,026.393	3,392.451	2	
	$t = 4$	9,053,991.554	-	28,463.634	2,303.370	-	13,705.057	3,829.173	4	
	$t = 5$	3,808,482.747	-	20,529.841	3,461.561	-	20,596.292	2,761.330	2	
	$t = 6$	3,303,122.229	-	19,317.582	3,234.494	-	19,245.240	3,074.628	2	
	$t = 7$	4,965,203.878	-	21,452.391	4,928.844	-	21,226.625	3,306.782	2	
	<b>Total</b>		<b>32,318,011.987</b>	-	<b>151,621.092</b>	<b>23,727.398</b>	-	<b>133,077.034</b>	<b>22,197.200</b>	<b>17</b>
Normal	$t = 1$	-	-	-	-	-	-	-	-	
	$t = 2$	10,351,755.486	-	28,618.257	4,332.339	-	25,777.422	3,718.470	4	
	$t = 3$	2,335,297.117	-	18,496.848	3,402.021	-	20,242.029	2,855.671	2	
	$t = 4$	10,223,350.932	26,278.374	33,825.326	5,093.246	-	30,304.817	4,087.920	4	
	$t = 5$	8,785,036.516	-	27,615.386	5,577.029	-	33,183.322	4,180.773	4	
	$t = 6$	1,661,161.419	-	18,931.372	2,437.311	-	14,502.004	2,094.521	2	
	$t = 7$	1,613,417.086	-	19,463.058	3,511.410	-	20,892.890	2,206.498	2	
	<b>Total</b>		<b>34,969,018.556</b>	<b>26,278.374</b>	<b>146,950.247</b>	<b>24,353.356</b>	-	<b>144,902.484</b>	<b>19,143.853</b>	<b>18</b>
Left-Skewed	$t = 1$	-	-	-	-	-	-	-	-	
	$t = 2$	-	-	-	-	-	-	-	-	
	$t = 3$	1,908,158.773	-	18,572.628	986.855	-	5,871.791	3,146.593	2	
	$t = 4$	8,633,679.190	-	22,426.382	4,476.480	-	26,635.056	3,391.548	4	
	Binomial	$t = 5$	10,089,836.193	46,382.543	35,169.264	6,617.960	-	45,326.862	4,587.246	5
	$t = 6$	9,297,849.524	78,375.316	33,473.628	5,229.965	-	34,118.297	3,848.179	4	
	$t = 7$	9,271,928.635	89,691.235	28,640.318	5,082.407	17,500.000	32,390.325	4,064.372	4	
	<b>Total</b>		<b>39,201,452.315</b>	<b>214,449.094</b>	<b>145,282.220</b>	<b>22,393.667</b>	<b>17,500.000</b>	<b>144,342.331</b>	<b>19,037.938</b>	<b>19</b>
Right-Skewed	$t = 1$	1,962,40.170	-	13,529.294	1,537.024	-	7,456.293	1,938.065	2	
	$t = 2$	11,818,888.994	48,354.531	33,529.183	5,014.425	-	29,835.829	4,632.945	2	
	$t = 3$	12,221,736.780	124,656.342	34,225.639	7,663.068	-	45,595.257	4,832.178	5	
	$t = 4$	6,415,773.462	93,489.392	24,592.295	6,063.742	-	36,079.269	4,263.305	3	
	Binomial	$t = 5$	4,239,437.536	51,185.067	22,416.046	3,991.649	-	27,800.313	3,492.421	3
	$t = 6$	1,143,364.265	20,477.336	14,629.372	1,251.659	-	18,764.291	2,197.234	3	
	$t = 7$	842,639.680	-	7,317.328	739.312	-	13,682.417	1,592.846	1	
	<b>Total</b>		<b>38,644,280.887</b>	<b>338,162.668</b>	<b>150,239.157</b>	<b>25,260.879</b>	-	<b>178,213.669</b>	<b>22,956.994</b>	<b>19</b>

Although most periods experience no delays, the fourth period shows a notable risk delay of 26,278.374 due to the postponed pickups. The transportation cost increases slightly to 24,353.356, and the total emissions rise to 144,902.484. Additionally, the

total number of vehicle used increases from 17 to 18 compared to uniform distribution. Despite these increases, all demand is satisfied by the last period, and there is no need to hire a third party. This is why no third-party cost are incurred. The lack of third-party cost indicates that the system manages the workload internally without external support. However, the clustering effect contributes to higher overall risks and cause delays in handling pickups, impacting the system's efficiency compared to the uniform distribution.

When pickup dates follow a left-skewed binomial distribution, the majority of pickup dates are actually delayed, with most of them concentrated towards the end of the planning horizon (closer to period 7), simulating a scenario with later demand. This skew leads to a significant increase in both transportation risk and the need for third-party intervention. The total transportation risk jumps to 39,201,452.315, and delays begin to accumulate, with a total delay risk of 214,449.094. The use of third-party resources is required in the final period, because five generation nodes remain unprocessed and adding a cost of 17,500.000. Additionally, the total number of vehicles used in this scenario increases from 17 to 19 compared to the uniform distribution. However, the transportation cost remains relatively controlled at 22,393.667, and total emissions amount to 144,342.331. Although the transportation cost is slightly lower than in the normal distribution, the increased risks and additional costs make this distribution less desirable.

For a right-skewed binomial distribution, the majority of pickup dates are concentrated towards the beginning of the planning horizon, leading to a scenario where most pickups occur earlier in the planning horizon. This results in a pronounced increase in transportation risk and cost. The total transportation risk reaches 38,644,280.887,

with delays accumulating to a total of 338,162.668. A total of 19 vehicles are used in this scenario, which is 2 more than the number used in the uniform distribution. Consequently, transportation cost rise to 25,260.879, and the highest emission levels are recorded at 178,213.669. Despite these challenges, there are no third-party cost, indicating that while the system faces significant internal strain, it does not yet require external assistance. Overall, the concentration of activities earlier in the period contributes to inefficiencies and heightened risks, making this distribution the least desirable. Please note that there is little change in the processing cost and facility emission across all four scenarios. This is primarily because these factors are closely tied to the amount of waste generated, which remains constant in each scenario regardless of the changing available date.

# Chapter 5

## Conclusions and Future Directions

### 5.1 Conclusion

In this thesis, we develop a two-stage framework for sustainable hazardous waste management, incorporating location optimization and dynamic multi-period vehicle routing decisions. The first stage identifies optimal locations for waste treatment facilities using a multi-objective optimization model aimed at minimizing both costs and emissions. Once the locations are determined, generation nodes are assigned to the selected facilities. This allocation forms the basis for the second stage. The second stage addresses the dynamic multi-period vehicle routing problem (DMPVRP) by using the allocation results from the first stage. The overall network is divided into smaller sub-networks, each associated with a specific treatment facility and those generation nodes assigned to it in the first stage. Routing decisions are then made for each sub-network, dynamically adjusting routes in each period based on real-time data to ensure optimal performance throughout the planning horizon.

To validate the proposed model, it is applied to a real-world healthcare waste management network in Shanghai, China. Analysis comparing the current system with the proposed framework demonstrates significant improvements in cost efficiency, environmental impact, and risk reduction. The results highlight that the proposed system is more resilient and sustainable, offering valuable insights for policymakers and waste management authorities. Additionally, tests are conducted by varying vehicle capacities and demand distributions to assess their impact on the results. The analysis shows that adjusting vehicle capacity directly influences operational efficiency, with higher capacities generally leading to lower overall risk, costs, and emissions. Similarly, varying demand distribution scenarios reveals that more balanced demand patterns contribute to greater stability and efficiency in the system.

## **5.2 Managerial insights**

Effective hazardous waste management is a critical concern for both industrial and healthcare sectors, as improper handling can pose severe risks to human health and the environment. The dynamic multi-period decision framework which is presented in this thesis offers a comprehensive approach to optimizing hazardous waste management systems, with particular focus on cost efficiency, emission reduction, and risk minimization. For managers overseeing hazardous waste operations, this framework provides a valuable tool to enhance efficiency in their decision-making processes.

Our analysis demonstrates that opening an additional facility and integrating Technology 2, despite the initial cost increase in the first stage, leads to significant reductions in total risks, emissions, and costs for the entire proposed system. Accord-

ing to Table 4.12, the proposed system achieves a 23.3% reduction in risks, a 63.4% reduction in emissions, and a 43.2% reduction in overall costs compared to the current system. These substantial improvements highlight the importance of investing in newer technologies and additional facilities. Although the upfront costs are higher, this investment results in a more resilient and sustainable system with long-term environmental, social, and economic benefits. Policymakers and waste management authorities should prioritize such investments to enhance both operational efficiency and environmental performance.

The results from Table 4.11 indicates that implementing DMPVRP within the proposed system leads to a 46.9% reduction in the total number of vehicles required, which correlates with a 64% reduction in emissions and a 45.3% decrease in costs. By optimizing the routing dynamically based on real-time data, waste management operations become more efficient and less risky. This highlights a key takeaway for managers and policymakers: adopting dynamic routing solutions can lead to significant cost and environmental savings, particularly in complex urban environments like Shanghai.

In hazardous waste management, uncertainty in pickup dates can significantly disrupt operations, leading to inefficiencies and increased risks. The proposed dynamic multi-period vehicle routing problem offers a robust solution to these challenges by enabling real-time adjustments to waste collection schedules (see Section 4.3). Managers should recognize the value of this adaptive approach, as it allows for continuous optimization, ensuring that operations remain efficient and resilient even under unpredictable conditions. By dynamically managing routes, the framework minimizes the environmental impact, reduces operational costs, and mitigates risks associated with

hazardous waste transportation, ensuring high standards of safety and sustainability in hazardous waste logistics.

### **5.3 Future research**

For future research, several promising directions can be pursued to further enhance this study.

Firstly, the integration of advanced predictive analytics and machine learning techniques could be explored in greater depth. By incorporating methods such as deep learning, reinforcement learning, and time-series forecasting, the model could be more adept at predicting and adapting to real-time data, including traffic conditions, weather forecasts, and dynamic waste generation rates. This would enable the model to make more informed routing decisions and further improve its performance in dynamic environments.

Additionally, expanding the framework to handle multiple types of hazardous waste presents another important research avenue. The compatibility of different types of hazardous waste will be taken into account. Different types of hazardous waste may have varying levels of risk, transportation requirements, and treatment processes. Developing a multi-faceted framework that can accommodate these variations would provide more comprehensive solutions applicable to a broader range of scenarios. This could also involve the integration of multi-modal transportation networks, where different transportation modes (e.g., road, rail, or waterways) are used in combination to optimize the efficiency and sustainability of waste transportation.

Finally, future studies could focus on the development and application of more

effective and efficient solution methods, particularly for large-scale instances. While the current study utilizes existing optimization techniques, there is significant potential in using an exact methods, such as branch-and-bound or cutting-plane methods, to solve complex problem instances more efficiently. Research could also exploring advanced algorithms, such as the metaheuristics, hybrid approaches, or parallel computing techniques, to reduce computation times and improve solution accuracy.

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