



An-Najah National University
Faculty of Graduate Studies

**SUSTAINABLE SOLID WASTE MANAGEMENT
VEHICLE ROUTING PROBLEM CONSIDERING
DRIVERS HEALTH STATE AND
RISK OF ACCIDENTS**

By

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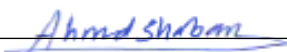
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Dedication

This thesis is dedicated to my beloved wife and kids, you have been the unwavering support and the guiding light that led me through my Master's degree journey. You have sacrificed, believed in me, and provided boundless love and encouragement. To my parents, for your endless sacrifices and the values you instilled in me; to my siblings, for the laughter and companionship on this journey; to my extended family, for your constant love and encouragement; and to my children, who inspire me to be the best version of myself.

Acknowledgment

﴿ قَالُوا سُبْحَانَكَ لَا عِلْمَ لَنَا إِلَّا مَا عَلَّمْتَنَا إِنَّكَ أَنْتَ الْعَلِيمُ الْحَكِيمُ ﴾

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Lastly, I offer my sincere thanks to the thesis defense committee for dedicating their time and efforts to review and provide invaluable recommendations for this thesis.

Declaration

I, the undersigned, declare that I submitted the thesis entitled:

**SUSTAINABLE SOLID WASTE MANAGEMENT VEHICLE ROUTING
PROBLEM CONSIDERING DRIVER'S HEALTH STATE AND RISK OF
ACCIDENTS**

I declare that the work provided in this thesis, unless otherwise referenced, is the researcher's own work, and has not been submitted elsewhere for any other degree or qualification.

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SUSTAINABLE SOLID WASTE MANAGEMENT VEHICLE ROUTING PROBLEM CONSIDERING DRIVER'S HEALTH STATE AND RISK OF ACCIDENTS

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Abstract

Due to the rapid growth of urbanization, the issue of solid waste management has drawn the attention of society and all stakeholders, because of the harm that will affect citizens and the environment if waste is not managed properly. Our research aims at solving a solid waste management vehicle routing problem that integrates the three pillars of sustainability; environmental, economic, and social. More specifically, our approach intends to investigate the effect of different drivers' health state on the different parameters in solid waste management networks, by estimating the probability of suffering from work-related injuries, using Markov's Chain model. In addition, our approach extends the reality of the model by considering different parameters and variables that will improve its practicality, such as including different cost functions. Furthermore, to ensure sustainable business practices, our model aims at minimizing the CO₂ emissions resulting from different types of waste vehicles. Also, the social factor was studied by considering drivers' health condition, minimizing the risk of accidents facing drivers, and minimizing any deviation from balanced workload between drivers. The Non-dominated Sorting Genetic Algorithm (NSGA) was used to solve the developed model, due to its ability to tackle multi-objective vehicle routing problems in general, and Solid Waste Management Vehicle Routing Problems in particular. After solving the proposed model, results revealed the effect of driver's health states on different cost functions, in addition to the negative impact of high travel distance and waste vehicle load on the health condition of drivers. Sensitivity analyses illustrated how different model variables and parameters interact with each other, in addition to the effect of travel distance and vehicle load on drivers' health conditions. The execution of this model in

the waste management sector yields many advantages for service providers, due to its ability to monitor the health condition of drivers at each node in the network. This results in productive healthy drivers carrying out operations, who can achieve financial success along with a healthy and safe working environment.

Keywords: Vehicle Routing Problem; Solid Waste Management; Health State; Sustainability; Risk of Accidents.

Chapter One

Introduction and Literature Review

1.1 Overview

Waste management is collecting, transporting, processing, recycling, disposing, and monitoring waste materials. Such processes and practices have drawn the attention of authorities, different industries, and even researchers due to the significant impact of waste on all stakeholders, including citizens, the environment, and the economic revenues of profitable companies. Also, rapid urbanization, population growth, and the industry transformation in materials used and process flow have thrown waste management into a catastrophic situation, which must be planned carefully, especially for developing markets where sustainable development must be achieved (Ismagilova et al., 2019). Recently, the concept of smart cities has gained the interest of governments and researchers. The concept of smart cities lies in the idea of creating a sustainable lifestyle that preserves the environment and the well-being of people and develops the economy, as well as improves the quality of life using different means of Information and Communication Technology (ICT), especially Internet of Things (IoT). Waste management is one of the seven main dimensions that create and support the idea of smart cities (Ismagilova et al., 2019). The importance of waste management in such cities lies in its significant role in protecting the health of citizens and the environment from different types of waste, as well as creating a civilized form of collecting waste bins that creates aesthetic views for citizens rather than visual pollution.

In waste management, collecting and transporting waste is considered to be the primary and most important process since it accounts for 80% of costs associated with waste management systems (Rabbani et al., 2018); such costs are due to the massive use of trucks, labor and the required time for planning and scheduling. In addition to costs, the harm that will affect the environment and citizens caused by harmful and hazardous emissions is significant and must be minimized. Industrial facilities worldwide produce vast quantities of waste in the form of solids, liquids, and gases. A considerable amount of these wastes affects the environment, living organisms, and humans (Misra & Pandey, 2005). An ineffective waste management system leads to a polluted environment and substantially harms human health (Herva et al., 2014). Therefore, it is important to plan

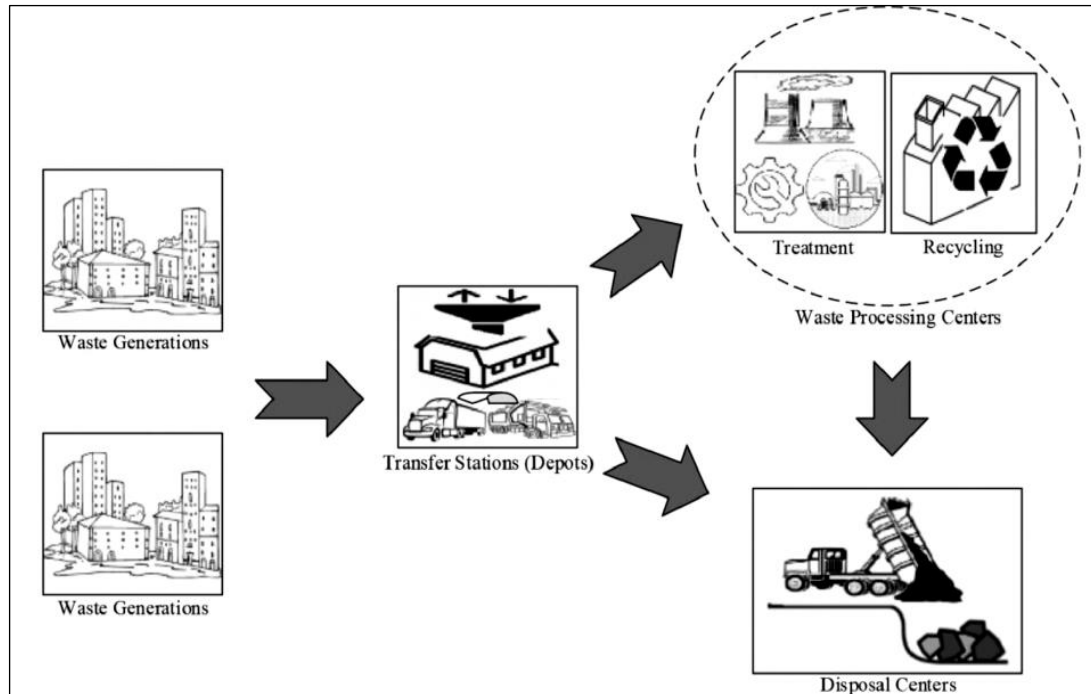
the procedure of collecting such hazardous wastes to protect the environment, eco-system, and the well-being of people (Misra & Pandey, 2005).

Similarly, the Solid Waste Management (SWM) process includes collecting, transporting, recycling, treating, and disposing of different types of waste, which are generated due to daily typical domestic and industrial activities (Mojtahedi et al., 2021). A rapid growth in the generation and accumulation of Solid Waste (SW) was noticed in the last few decades, certainly because of population growth and urbanization, as well as the industrial revolution to Industry 4.0, which will result in additional manufacturing and production plants. According to (Assaf & Saleh, 2017), a positive direct proportion relationship exists between population and industrial growth and the quantity of generated SW. The process of SWM faces many challenges, including transportation network complexities (Asefi & Lim, 2017), high operational and environmental costs (Rabbani et al., 2018), limitations and regulations regarding the location of waste facilities (Fathollahi-Fard et al., 2020), and other regulations related to recycling and treatment technologies. Although SWM is an essential service that every government provides for its citizens, many worldwide concerns were raised regarding the effectiveness and efficiency of carrying out the process due to the major impact on people and the environment if the process is not planned wisely (Vecchi et al., 2016). This is especially important with regards to SW collection, which consumes nearly 50% of the overall operating costs, and waste trucks that produce around 1.24 kg of CO₂/km while travelling between different nodes (Vecchi et al., 2016).

In a classic SWM system, specially-designed trucks travel from a depot (start node) to many nodes to collect and transport waste. Such nodes include waste generation nodes (where waste is generated due to various activities such as industrial ones), recycling nodes (to convert waste to useful materials and objects), treatment nodes (to reduce the impact of waste on the environment and citizens), and disposal centers (to ensure a good and safe disposal process) (Mojtahedi et al., 2021). Figure 1 shows a general SWM system that includes different nodes, waste processing facilities, and the possible routing direction between nodes, which was adopted from the work of (Mojtahedi et al. 2021). As mentioned, collecting and managing waste consumes many resources, including waste collection trucks and labor. Each aspect related to these resources, such as fuel for trucks,

working hours for labor, and the population's safety, must be considered and planned carefully.

Figure 1
General SWM system



Source: (Mojtahedi et al., 2021)

Moreover, a great deal of attention must be given to the selection of routes for trucks to collect waste from geographically distributed bins. Many complexities appear in route planning, mainly due to the use of many waste trucks, bins, and labor. Therefore, many researchers treated waste collection as a Vehicle Routing Problem (VRP). Indeed, such a process must be planned carefully to fulfill and achieve the three pillars of sustainability (economic, environmental, and social).

The complexities above usually do not address the drivers of waste trucks in terms of performance, skills, productivity, job satisfaction, and the possibility of improving driver-related factors. Although truck driver physical condition in terms of fatigue and awareness levels were investigated in the literature (Bowden & Ragsdale, 2018), other factors, including performance and productivity, were not addressed before in SWM models, regardless of the possible gains to the system's utility if worker (in our case waste truck driver) productivity and performance are measured and improved (Sayin & Karabati, 2007).

This research aims to develop a novel sustainable vehicle routing problem model for SWM systems. This model considers the three pillars of sustainability by implementing the Triple Bottom Line (TBL) concept. While TBL's economic and environmental aspects are frequently addressed in research, the social aspect is usually ignored (Vega-Mejía et al., 2019). Therefore, this research highlights and presents social factors such as the drivers' performance, work-related risk factors facing drivers, and the risk of accidents. In addition, workload balance is another key factor that should be considered to minimize subjective bias since the workload is a significant factor affecting drivers' satisfaction levels. Finally, improving drivers' productivity through minimizing the possible risk factors facing drivers while routing, including physical injuries and fatigue, is analyzed and studied by assuming two different driving states: health state and pain state. Therefore, including the three pillars of sustainability in a comprehensive, well-defined approach will positively contribute to waste collection VRP.

1.2 Research Problem

The issue of SW has drawn society's attention lately due to the possible impacts and harm if waste is not properly collected and treated. In addition, the rapid growth of urbanization and the increasing demand for establishing smart-sustainable cities expanded the work scope in the waste management field. By 2030, the waste management business market share is expected to hit the 3-trillion-dollar mark (Chinchane & Mutreja, 2023). Such global growth in the waste management market is due to many reasons, including governmental and business sector initiatives to reduce the illegal disposal of waste and increase the adoption of recycling and treatment techniques for different types of waste. However, this demand growth will increase the operations in the field to meet the escalating requests for proper waste management. This means more trucks in service for collecting waste and more workforce working intensively in collecting, transporting, and recycling/treating waste. Thus, more costs will be incurred (operation costs and wages), and a heavy workload on laborers (including drivers) will be borne as well. This is an issue that can be crucial if ignored due to the possible results of employee dissatisfaction and the risks of work accidents and health issues. In a typical SWM system, specially-designed trucks driven and operated by specialized drivers travel from one or more depots to collect waste from different waste bins in different locations. As the fleet of waste trucks, drivers, and waste bins grows, the complexity of operations increases. This

complexity results from the many routes that must be covered to collect waste from containers and the parameters that should be considered, such as traveled distance, fuel consumption, working hours, overtime, and safety concerns. This is why many researchers study the issue of SWM as a VRP (SWMVRP), which must be planned carefully. In addition to route planning, different social factors strongly affect the execution of the waste collection process; at the same time, while many drivers have high-performance rates, others may have lower productivity rates. In addition, workload distribution among drivers must be planned carefully without bias. Such social factors are typically ignored in the literature on waste management VRP. However, adequate planning of these factors may result in many benefits in the form of cost reduction (cost of accidents, poor performance, and workload imbalance). According to The Royal Society for the Prevention of Accidents, an accurate estimation of the number of accidents caused by fatigued or injured drivers is not possible, however, research shows that fatigued and/or injured drivers cause up to 20% of road accidents, which contribute to one-quarter of fatal accidents (The Royal Society for the Prevention of Accidents Road, 2020).

Moreover, considering the aforementioned social factors creates a healthy work environment where drivers are satisfied and willing to offer their best performance, which are the main motivation to carry out this research. This research aims to integrate SWM with sustainable VRP to develop a Sustainable Solid Waste Management Vehicle Routing Problem (SSWMVRP) model. Two social-related aspects are considered in this research (along with economic and environmental aspects): first, the productivity level of drivers and the possibility of suffering from work-related injuries while traveling between different waste nodes; second, balanced workload distribution among drivers. Although drivers' productivity can be considered as an economic indicator, since it affects profitability, however in this research we consider it as a social indicator to highlight its effect on SWM systems. In addition, we link productivity with health (work-related injuries) in this research, therefore productivity is directly related to the social pillar of sustainability more than the economic one. The objectives of the proposed model are minimizing operational costs (fixed and variable), minimizing harmful emissions of CO₂, minimizing workload imbalance, minimizing the risk of accidents, and minimizing the effect of work-related risk factors facing drivers, approached as a cost function in our research. Therefore, developing a realistic and comprehensive model considering the

three pillars of sustainability, which emphasize social aspects, is a worthy and innovative contribution to the literature on SWMVRP.

1.3 Research Significance

From what has been discussed earlier, a model integrating SWM with sustainable VRP while focusing on the social pillar of sustainability is expected to improve and fill a research gap in the current models in the literature. Since logistical activities in general and waste collection, in particular, are rapidly growing industries, planning the routes that vehicles must follow to serve different areas becomes more and more complicated over time. Therefore, including different variants with rich constraints of VRP to simulate real-life scenarios, which result in a practical model, is the first contribution of the model. In addition, the concept of TBL is addressed in this model by reducing the emissions of greenhouse gases (GHG) and minimizing the resulting operational costs, including fixed and variable ones, such as fuel, maintenance, depreciation, insurance, etc. Moreover, studying and focusing on the social aspect, mainly the driver, improves this research's significance. According to Sayin & Karabati (2007), enhancing the work environment of workers (similarly drivers) leads to improving the efficiency of the workforce in their assignments, which results in higher productivity. Moreover, analyzing drivers' productivity by considering the possibility of facing work-related risks of injuries resulting from long driving periods such as spinal compression, muscle strain, and fatigue, has not been considered before in the literature of SWMVRP, which we believe is a significant and notable contribution. To the best of our knowledge, a model that investigates sustainable VRP in SWM, especially the social pillar, was not considered before in the literature. Our model digs deep into the social aspect of sustainability by integrating drivers' health conditions, productivity, and satisfaction levels along with economic and environmental pillars, which is the main contribution of this research.

1.4 Research Objectives

This research aims at achieving the following objectives:

1. To develop a theoretical SWM framework to integrate the following social dimensions in waste collection VRP; note that those dimensions are either ignored (driver's productivity and health condition) or inadequately addressed in previous research:

- a. The workload on drivers.
 - b. Drivers' productivity.
 - c. Drivers' health condition and the possibility of transiting from health to pain state and visa-versa.
 - d. Drivers' job satisfaction.
 - e. The risk of accidents.
2. To develop a SWMVRP model that considers integrating the concept of TBL in waste collection VRP.

1.5 Research Questions

To clearly understand the research problem under study, the following proposed questions must be answered and discussed after solving the developed mathematical model. In addition, the relationship between different aspects and dimensions of the model are explored.

1. How can drivers with different productivity levels affect routing costs and CO₂ emissions?
2. What is the effect of drivers' health conditions on different routing costs and CO₂ emissions?
3. What is the effect of workload balance on different routing costs and CO₂ emissions?
4. How can drivers with different health conditions affect the process of SWM?

1.6 Research Methodology

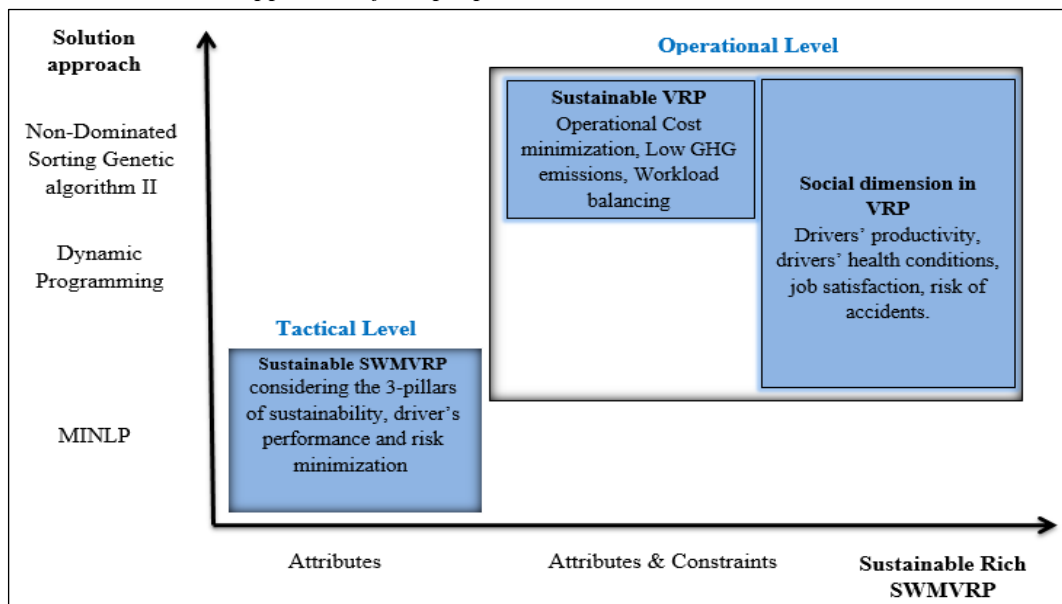
This research starts with identifying a problem in the literature; here, it is critically important to find a real problem and determine the scope of the study to fill a specific existing research gap. While identifying a problem, research objectives, questions, and their corresponding constraints must be set. Next, the data are computed from previous instances in the literature of SWMVRP or generated randomly. After that, a mathematical model is formulated using a Mixed Integer Nonlinear Programming (MINLP) approach considering the pre-defined objectives and constraints. The use of MINLP is justified by the complexity of the developed model and the research problem under study. Then, the proposed model must be solved using heuristic algorithms, mainly Non-Dominated Sorting Genetic Algorithm II (NSGA II), since using an exact methodology is not feasible for multi-objective rich VRP problems. Although many mathematical models can be

solved using exact methods, VRP is an NP-hard problem with many complications. MATLAB software is used to code the developed solution approach and compute results. Finally, the model is validated and implemented in some instances to observe the outcomes and compare them to existing models in the literature of solid waste collection VRP to address the contributions and improvements of this research.

Moreover, each characteristic of the developed model is measured on specific criteria while considering the tradeoffs and conflicts. For example, the issue of sustainability is calculated based on the resulting transportation costs, environmental pollution levels, considerations on the well-being of citizens, and status of satisfaction resulting from workload balance among drivers. Finally, a sensitivity analysis is performed to test the robustness of the developed model and reveal how variables interact with each other, thus providing a better understanding of the effect of a driver's health condition, including health and pain states, on different model variables. Figure 2, adopted from the work of Reyes-Rubiano (2019), illustrates the research problem, the proposed SSWMVRP model, and the planned solution methodology. Note that Reyes-Rubiano (2019) did not include the social dimension in his study. In addition, the strategic level of the developed SSWMVRP model is discussed in the next chapters.

Figure 2

Structure and solution approach of the proposed SSWMVRP model



Source: (Reyes-Rubiano, 2019)

1.7 Thesis Organization

The remaining sections of this thesis are structured as follows: the literature review is discussed in this chapter, including past contributions in classical VRP, waste management VRP, SWMVRP, sustainability dimensions in VRP, risk management in VRP, and finally, the social aspect, including performance and workload balance in VRP are presented. The interaction between the various components of our SSWMVRP model is better understood in this chapter. Additionally, research gaps are identified. The mathematical model is introduced in chapter two. The MINLP model, which comprises indices, definitions, parameters, decision variables, and limitations, is shown and described in detail in this chapter. Chapter three presents the research results and solution methodology, in addition to the conducted sensitivity analysis. Finally, in chapter Four, a brief summary and discussion of the developed model, conclusions and suggestions for further research, and managerial insights are presented.

1.8 Classical Vehicle Routing Problem

Dantzig & Ramser (1959) studied and introduced VRP to operational research literature for the first time in 1959. The authors developed a mathematical model for a gasoline delivery system that transports gasoline to geographically-distributed stations. This model aims to meet customers' needs by minimizing travel distance and reducing costs subject to the following equation:

$$D = \sum_{i,j=0}^n d_{ij}x_{ij} \quad (A)$$

where D presents the overall distance, d_{ij} is the distance covered by trucks from station i to station j , and x_{ij} is a binary (0 or 1) decision variable that indicates if a truck traveled from one node to another or not. According to Liong et al. (2008), VRP can be defined as selecting the best path for vehicles to follow to serve different locations while considering other customer objectives. After a few years, Clarke & Wright (1964) developed a more complicated VRP model that considers more than one truck with different types and capacities to deliver goods to many customers located at different sites. However, as time went by, complexities arose in every business, which led researchers in the field of VRP to study these complications to create comprehensive real-life models. Eksioglu et al. (2009) constructed a detailed taxonomy of VRP research in the literature; 1021 articles

published between 1959 and 2008 were studied, summarized, and analyzed, which provided researchers with a better understanding of VRP models. Although most VRP studies focus on cost parameters by reducing operational costs by minimizing fuel consumption and travel distance, other parameters and VRP variants are introduced in this section. Also, Braekers et al. (2016) developed a study that classifies VRP research from 2009 to 2015 based on many criteria, such as the study's objectives, solution methodology, type of business, and scenario characteristics. The 277 analyzed researches revealed many variants and trends of VRP to meet the complexities created by the rapid development of business operations. In addition, Tan & Yeh (2021) conducted a similar classification using the taxonomic framework from 2019 to 2021. The authors classified VRP research into three main categories: customer-related, vehicle, and depot-related models. Moreover, they argued that due to the recent advancements in the computer industry, which lead to high processing speeds and larger memory capacity, complex VRP models can be solved using different algorithms in a reasonable time.

Capacitated VRP (CVRP) is a well-known variant of VRP that considers the load capacity of vehicles; in a typical CVRP model, a set of different vehicles with the same load capacity are used to service many geographically-distributed customers with varying demands (S. W. Lin et al., 2009). The main goal of CVRP models is to serve customers with a pre-defined set of needs while considering the vehicles' maximum capacity. The routes are planned to minimize delivery costs (Toro O. et al., 2015). Moreover, many other contributions were made in the literature on CVRP, where different solution methodologies were used to solve the NP-hard problem of CVRP. These methodologies have used different algorithms: exact algorithms, such as the branch-and-cut method or the branch-and-price algorithm (Baldacci et al., 2004, 2010; Lysgaard et al., 2004), and heuristics, in particular, metaheuristics to solve large instances (Sacramento et al., 2019). Another variant that enhances the applicability of VRP models is the VRP with Time Windows (VRPTW). VRPTW is a generalization of the VRP that requires customers to be served within pre-specified starting and end times (Desrochers et al., 1992). According to Liong et al. (2008), introducing time windows of service in the VRPTW improves vehicle route planning and makes the developed models more easily applicable in different sectors and industries. Applications such as health services, waste collection, food delivery, the newspaper industry, and others benefit from VRPTW (Golden et al., 2002). Similarly, VRPTW made a notable contribution; Kim et al. (2006) addressed the

critical issue of waste management and collection by considering time windows to conduct the service, multiple vehicles, multiple disposal centers, route capacity, and lunch breaks for drivers. The main objectives were minimizing travel time and several vehicles and maximizing workload balance and route compactness. A variant of VRPTW, which can be used in many applications, such as elderly transportation, cargo delivery, and urban delivery services, is VRP with Pickup and Delivery with Time Windows (VRPPDTW). This variant of VRP studies the situation where different vehicles are used to provide service when there are multiple pickup and delivery points, and each trip is bounded by a timeline (Desaulniers et al., 2002).

Another variant of VRP is Multi-Depot VRP (MDVRP), which can be defined as the situation when there is a pre-defined number of depots where multiple vehicles with limited capacities to load and deliver goods to customers can be based (Ho et al., 2008). Moreover, Montoya-Torres et al. (2015) introduced a deep analysis of the literature on MDVRP by analyzing the articles published between 1988 and 2015 to reveal different variants of MDVRP and discuss solution methodologies using various algorithms. Lahyani et al. (2018) introduced a rich model tackling Multi-Depot, Fleet Size, and Mix VRP (MDFSMVRP) to simulate real-life scenarios. Due to the high collaboration of the model, heuristic algorithms were used to solve the mathematical model.

Furthermore, the Periodic VRP (PVRP) is a variant of VRP where the planning horizon of the problem is set to cover several periods rather than a single day; customers are served based on a pre-determined time horizon, where each customer may be served in two or more periods each day (Campbell & Wilson, 2014; Gulczynski et al., 2011). Beltrami & Bodin (1974) developed the first PVRP model in municipalities to find the best routes and waste collection periods for trucks to follow. Nuortio et al. (2006) discussed a Stochastic Periodic Vehicle Routing Problem with Time Windows and a limited number of vehicles (SPVRPTW), to solve a real-life situation for collecting and transporting municipal SW in Finland. A metaheuristic algorithm approach was used to solve the developed model.

Dynamic VRP (DVRP), developed by Psaraftis (1988), is a variant of VRP that deals with uncertainty regarding a vehicle's routing plan, especially when a change of order or a new request for service arises. In other words, DVRP models assume instances with

evolving information, such as the number of customers, trips, and vehicle load. Pillac et al. (2013) proposed a comprehensive review of DVRP and its applications; the authors suggest that the importance of DVRP lies in the dynamism and uncertainty of requirements in real-life applications, such as health services, delivery of goods, equipment maintenance services, and personal transportation services.

As discussed earlier, real-life applications are complicated and involve many different aspects that need consideration, as well as customers with various needs and requirements, which must be accounted for adequately. However, most VRP models in the literature only consider one variant of VRP without integrating more issues. Some researchers placed much effort into creating comprehensive, realistic models to meet real-world applications. Thus, Rich VRP (RVRP) models were developed to overcome the issues above by considering multi-variants of VRP; these models often account for the dynamism and uncertainties of real-world applications (Caceres-Cruz et al., 2014). Pellegrini et al. (2007) argued that due to the complexity of such models, using exact algorithms is not feasible since large, complicated instances require a lot of time to be solved. Therefore, heuristic and metaheuristic algorithms are used to tackle these models. Osaba et al. (2017) discussed a model for newspaper distribution; they proposed an Asymmetric and Clustered VRP model with Simultaneous Pickup and Deliveries, Variable Costs, and Forbidden Paths (AC-VRP-SPDVCFP). The complexity of the problem is due to the constraints and limitations of simulating the exact real scenario. These limitations include the geographic locations of customers and distribution centers, variable travel time, type of routes, and different types of customers. A metaheuristic approach was developed to solve the model using the Discrete Firefly Algorithm (DFA). Other variants of VRP are found in the literature, each derived from the classic VRP to solve an existing problem that serves a real-life application. While some VRP variants are simple, such as Open VRP (OVRP) (Braekers et al., 2016), and Heterogeneous VRP (HVRP) (Koç et al., 2016), other variants are complicated and result from the integration between two or many VRP variants, such as fleet size, and mix VRP (FSMVRP) (Renaud & Boctor, 2002) and AC-VRP-SPDVCFP (Osaba et al., 2017). Many other modified forms of VRP exist, where each developed model is used to solve an existing real-world problem.

1.9 Sustainable Vehicle Routing

The Industrial Revolution and new urbanization trends forced authorities and society to adopt practices and lifestyles that ensure citizens healthy and safe habitats. Therefore, sustainability has received significantly more attention in recent years. Sustainability has three main pillars, which are economic, environmental, and social pillars, where a set of practices are adopted to ensure the future for all and support the evolution and success of society without threatening the existence of the next generation by draining natural resources and damaging the environment (WCDE, 1987). Similarly, sustainability in routing received attention and interest from researchers and companies. Thus, many efforts are undertaken to ensure that VRP practices are efficient and environmentally-friendly and protect society's well-being (Mojtahedi et al., 2021).

1.9.1 Economic Dimension

The economic dimensions of the VRP are essentially related to the costs and profits of the vehicle routing planning process. Such costs mainly revolve around operational expenses, including fixed and variable ones, associated with performing the required service. Zhang et al. (2015) developed a VRP model that considers transportation costs, such as fuel, maintenance, insurance, salaries, and penalties for violating environmental policies. The main objective of this model was minimizing costs. Moreover, Kramer et al. (2015) proposed a model that aims at reducing costs by considering the travel time of vehicles. The authors argued that the cost of routing could be minimized by altering the travel time of vehicles, mainly by increasing the speed of vehicles to a specific limit to minimize travel time and thereby reduce fuel consumption. Other authors suggest that reducing costs can be achieved by planning the load capacity of vehicle containers to minimize the number of vehicles used to deliver service and reduce costs (Z. Wang et al., 2008). Wang et al. (2019) also developed a multi-depot VRP model considering time dependency and a piecewise penalty. The proposed model aims at minimizing CO₂ emissions and minimizing costs by penalties due to early or late service delivery rather than conducting the service in the pre-determined agreed time. In addition, Archetti et al. (2016) developed a CVRP model that considers occasional drivers ready to deliver the required service using their vehicles. The developed model aims to minimize costs resulting from using the company's drivers and vehicles, as well as the compensation paid to occasional drivers, which is set depending on the distance between the occasional

driver and the service delivery location. Results showed a substantial cost saving when hiring occasional drivers due to the great flexibility in service delivery when using such drivers. However, challenges were present because of the difficulty in planning an adequate compensation system.

Furthermore, concerning operational cost reduction (which is the main idea of the economic dimension), Kucukoglu et al. (2021) introduced a literature review on Electric VRP (EVRP), which depends on using electric vehicles rather than traditional fuel-operated vehicles. EVRP is centered around energy consumption since electric vehicles require significantly less energy than traditional fuel vehicles. The review above shows many EVRP models with different cost minimization objectives; while some models considered transportation costs in terms of travel distance and time, other models studied charging technologies, full and partial battery charging, in addition to other costs such as vehicle cost, depreciation, battery swapping, and the availability of charging stations.

1.9.2 Environmental Dimension

As discussed earlier, ignoring environmental standards and regulations while providing service or doing business damages our habitat and threatens the ecosystem. Many companies adopted decisive policies to reduce fuel consumption and GHG emissions in line with these efforts. Similarly, in the transportation sector, efforts were made to reduce CO₂ emissions caused by burning fuel (Salimifard et al., 2012). The continuous enhancements made by researchers in the field of VRP to create a rich and comprehensive model, allied with efforts to reduce the emissions of CO₂ done by logistics companies, led to the development of a new VRP variant called Green VRP (GVRP). This can be defined as a generalization of the VRP that aims to reduce the consumed fuel and minimize the emissions of harmful gases while balancing the tradeoff between reducing costs and preserving the environment (Erdoğan & Miller-Hooks, 2012; Hooshmand & MirHassani, 2019). Lin et al. (2014) presented a survey on past, current, and possible future research on GVRP. The authors argued that green logistics is a new trend in supply chain systems, which altered the traditional objectives of VRP from minimizing costs to minimizing the harm to the environment resulting from routing and operational costs. The developed survey classifies GVRP into three categories based on their real-world applications rather than solution methodology (algorithms): traditional GVRP, pollution routing, and reverse logistics VRP.

Furthermore, Asghari & Mirzapour Al-e-hashem (2021) introduced a similar state-of-the-art review of GVRP research. The authors pointed out that GVRP research gained great interest recently due to the overuse of energy, which pollutes the environment. The classification was based on many factors such as vehicle engine type, mainly Internal Combustion Engine Vehicles (ICEVs), Alternative-Fuel powered Vehicles (AFVs), and Hybrid Electric Vehicles (HEVs). Also, the classification scheme investigated other factors, including objective functions, real-life scenarios, and solution methodologies. Minimizing fuel consumption is the main objective of many VRP models. However, many factors affect consumption, such as speed, capacity, traffic, and terrain (Kuo, 2010; Poonthilir & Nadarajan, 2018; Xiao et al., 2012).

Kara et al. (2007) proposed a VRP model that minimizes fuel consumption by considering vehicle load and travel distance constraints and how they relate to fuel consumption. Moreover, Niu et al. (2018) developed a comprehensive Green Open Vehicle Routing Problem with Time Windows (GOVRPTW) model, with the option of outsourcing the delivery services to other third-party companies. After solving the model, the results showed a 20% reduction in total costs.

1.9.3 Social Dimension

As mentioned in previous sections, the social pillar of sustainability concerns the well-being of populations, including citizens and employees. Many studies suggest that social dimensions are usually affected and are linked with economic and environmental dimensions. For example, high emissions of CO₂ pollute the environment and risk citizens' health. Also, minimizing different fiscal costs results in more profits for companies, creating more jobs and maintaining current ones. However, social factors are generally neglected in sustainable VRP models (Bhinge et al., 2015; Seuring, 2013).

Nevertheless, some efforts were made in the VRP literature considering social aspects, regardless of the difficulty in measuring such elements. Yang et al. (2015) developed a VRPTW model that maximizes customer satisfaction by ensuring the service is performed on time between time-bounded windows. In addition, other contributions were made concerning this dimension, such as considering passenger safety through travel speed and minimizing the risk of accidents (X. Wang et al., 2015). Also, the social dimension was studied by considering fair workload distribution among drivers without bias to maximize

job satisfaction and protect drivers from work overload (Matl et al., 2018, 2019). Furthermore, Bowden & Ragsdale (2018) introduced a novel approach that considered the driver's fatigue levels. The authors used the Three Process Model of Alertness (TPMA) model that estimates driver's wakefulness (alertness) levels at different periods of the day, enabling decision-makers to alter the schedule and working hours of drivers to maintain acceptable fatigue levels. Such an approach ensures drivers' well-being and health, reflecting on the safety of citizens surrounding the planned route since drivers with high alert levels have a lower risk of accidents than fatigued drivers (Bowden & Ragsdale, 2018).

Moreover, Asrawi et al. (2017) studied the effect of different drivers' behavior on green supply chain management. The authors classify drivers based on their Green Driving Index (GDI), which measures drivers' awareness and responsibility toward protecting and preserving the environment. The model considered three types of driving behavior: calm, aggressive, and eco-driving, where each driving pattern results in different fuel consumption and CO₂ emissions. Also, the model considered the possibility of training to improve drivers' skills and awareness of eco-friendly driving behaviors. Concerning driver's behavior, Abu Al Hla et al. (2019) developed a model that considered different drivers' behavior in terms of risk-taking. The authors suggested that the human factor is usually ignored in VRP models, regardless of its significant influence. The proposed model investigated the effect of different drivers' behavior patterns, i.e., risk-taker, risk-neutral, and risk-averse, on the optimal solution.

Indeed, the effect of the human factor in logistics is significant and strongly affects the performance of companies. As discussed earlier in this section, different drivers' behaviors and skills affect the operational costs and CO₂ emissions, which are considered the main objectives of VRP models. Our research supports the suggestions above regarding the human factor in VRP and investigates the effect of drivers' productivity and skill improvement on the proposed SWMVRP model.

1.10 Solid Waste Management VRP

SW is generated due to human activities, including residential, industrial, commercial, and institutional facilities, such as universities, living compounds, and factories (Staley & Barlaz, 2009). SW includes municipal SW, green waste, plastic and paper waste, and

food waste (Assaf & Saleh, 2017). According to Ayuba et al. (2013), the issue of SW management is worldwide in developed and developing countries (especially in third-world countries) due to industrialization, the growing population, and the change in consumer behavior. Therefore, SWM must be planned carefully for citizens' well-being, the environment, agricultural and financial profits, and, as a result, ensuring sustainable living (Nwofe, 2015). Moreover, the study of Samiha (2013) highlighted the importance of SWM and the resulting harm that may occur if appropriately managed. The author argued that SW generation is inevitable due to the nature of human life, where waste is generated continuously daily because of many different activities. However, efforts should be made to manage such waste and reduce environmental pollution. Therefore, the author investigated using the 3R principle to achieve sustainability in reducing pollution and preserving natural resources in the field of SW. According to Samiha (2013), the 3R (Reduce, Reuse, Recycle) principle in SWM starts with reducing the generated waste by adopting eco-friendly behaviors; then, specific materials are separated to be reused. Finally, when waste can't be reduced or reused, recycling efforts are made using the appropriate recycling technique on secondary materials such as glass, paper, steel cans, and many other materials.

Similarly, Kanat & Erguven (2020) spotlighted the importance of SWM. They argued that SW is unavoidable and must be planned carefully for the sake of citizens and authorities, especially in large cities with high population and urbanization rates. The authors considered the use of waste composting in order to reduce the environmental pollution caused by biological and chemical materials that result from the generated waste, as well as using refined and recycled organic materials from waste in agriculture as low-cost fertilizers. Thus, ensuring sustainable development and minimizing the effect of SW on the environment.

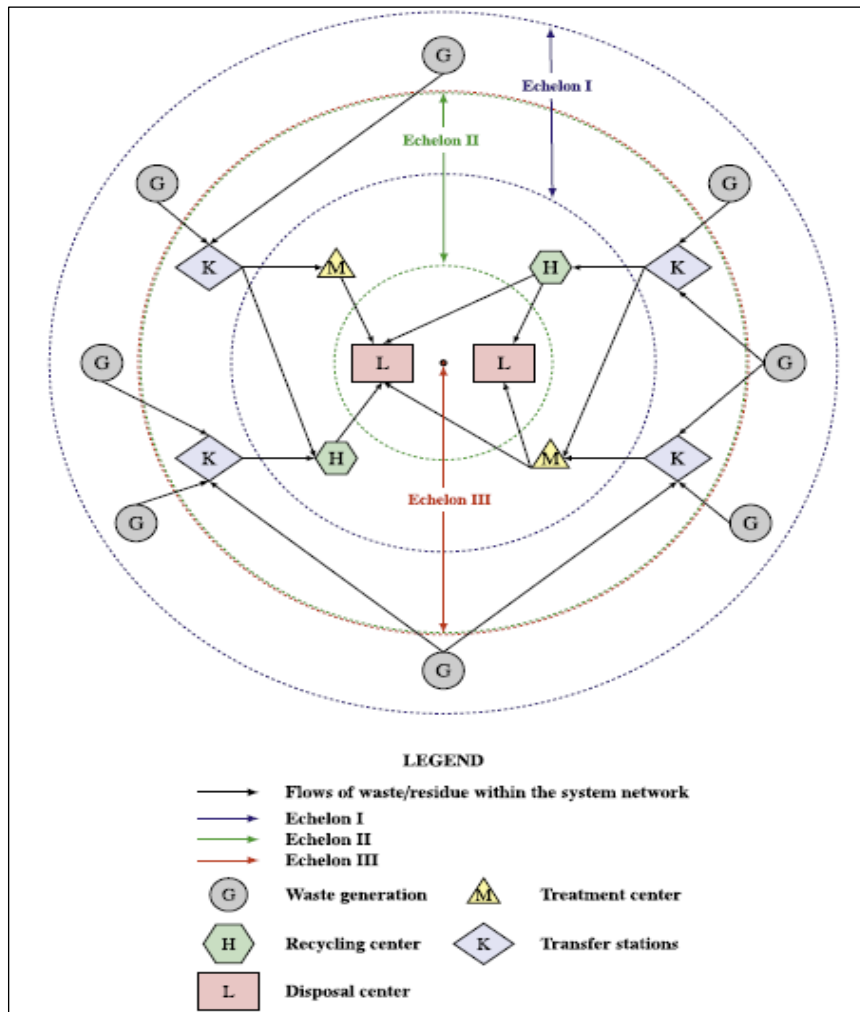
Many researchers studied SWM as a VRP with different variables and settings to optimize the current practices regarding cost, pollution, and, rarely, social aspects. The research on municipal SWMVRP dates back to the work of Beltrami & Bodin (1974), where different techniques were presented to tackle practical problems in waste collection. Li et al. (2008) developed a SW and truck scheduling model to find the optimal schedule and routes for the trucks to follow. The trucks are assumed to have a fixed capacity and must serve a pre-defined set of nodes to minimize operational costs. In addition, the authors considered

penalty costs resulting from overloading waste at recycling facilities. Therefore, the model aimed at minimizing such costs by balancing the unloading of waste vehicles.

On the other hand, Bianchi-Aguiar et al. (2012) studied PVRP in the SW collection sector with constraints that force waste trucks to visit one of many disposal centers before returning to the initial node. Two decisions must be made in the developed model: first, the schedule and how many times each waste node must be visited; second, the optimum route for the waste vehicles to follow with a primary objective of minimizing the travel distance of vehicles. Furthermore, other researchers considered VRPTW to solve SW problems by adding start and end service constraints to improve the service and increase satisfaction levels in parallel with finding an optimum route to follow (Buhalkal et al., 2012). Similarly, in VRPTW, Moon et al. (2012) developed a model considering constraints related to outsourcing the service to third-party waste collection companies and constraints dealing with drivers' overtime. The proposed VRPTW with Overtime and Outsourcing Vehicles (VRPTWOV) model aims to minimize different types of costs, including travel costs, regular workforce costs, overtime costs, and fixed vehicle costs. The authors solved the model using a Genetic Algorithm and a hybrid Simulated annealing algorithm to solve the complex problem in a reasonable time.

Asefi et al. (2019) discussed an integrated SWM model to solve the challenging problem of growing volumes of municipal SW. Integrated SWM systems combine different waste management components, including collection, transporting, recycling, treatment, and disposal, to achieve sustainable waste management practices, as well as reduce operational costs. The formulated model considered a three-echelon SWM network with a heterogeneous fleet of waste vehicles, different waste facilities, and different waste processing technologies as shown in Figure 3. The main objectives were minimizing operational costs (fixed and variable costs) and minimizing any variation from fair load balance, which also balances workload among workers i.e., drivers.

Figure 3
Integrated SWM network



Source: (Asefi et al., 2019)

Moreover, Mojtahedi et al. (2021) developed a coordinated SWM model that considers the TBL concept of sustainability to solve practical problems in SW while ensuring sustainable development. The authors argued that the issue of SWM is crucial and challenging due to the transformation of industries, the rapid increase in population, and the tendency to move to cities rather than rural areas. The suggested coordinated SWM problem considered a heterogeneous fleet of waste vehicles operating in a network with different waste facilities to achieve the following objectives:

- Minimizing total costs, including fixed and variable costs, based on the total distance covered by waste trucks and the load on each truck.
- Minimizing CO₂ emissions, based on travel distance and truckload, affects fuel consumption and CO₂ emissions.
- Minimizing any deviation from fair load distribution.

A novel adaptive memory social engineering optimizer was used to solve the NP-hard SWMVRP model, which showed better results than other metaheuristic algorithms. In addition, Mahdavi et al. (2022) integrate SWM with sustainable development to solve a sustainable, multi-trip, and multi-period SWMVRP model. In this research, the waste transfer station is considered due to its significant effect on the optimal solution to redesign those stations to obtain better results. The main objectives of the model are minimizing economic costs such as fixed costs, maintenance costs, routing costs, transferring costs between different waste facilities, and relocation costs between different waste transfer stations, minimizing environmental costs resulting from CO₂ emissions, and developing a social life-cycle assessment methodology to reduce the impact of citizens when routing and relocating transfer stations. The developed model was applied to a real-life practical problem and showed promising results in reducing costs, travel distance, and CO₂ emissions and improving the social score, reflecting the SWM network's impact on citizens.

Despite the similarity between our work and the work of Mojtahedi et al. (2021) and Mahdavi et al. (2022) in economic pillars, environmental pillars, and the topology of the SWM system, our research highlights and digs deep on the effect of the social pillar on SWM systems from the point of view of both drivers and companies.

As mentioned in previous sections, smart cities seek to ensure a high-quality, sustainable, and resourceful life for citizens. Therefore, from the perspective of smart cities, Akbarpour et al. (2021) developed an innovative municipal SWM model that promotes the use of technology in the waste collection process. The authors highlighted the importance of municipal SWM in smart cities and suggested that the main challenge of SWM in such cities is high operational costs, which must be minimized. The research problem was solved using the sub-model approach; the first sub-model was solved as a VRP that minimizes the travel distance of vehicles from waste generation nodes to waste separation nodes, where volume sensors were used to transmit data regarding the amount of waste in bins. The second sub-model deals with resource allocation, mainly from waste separation to waste recovery facilities, to maximize recovery value from the collected and recovered different types of waste. Note that revenues from SWM systems are correlated with the recovered waste. Therefore, the second objective of the discussed model maximized revenues as well. Four metaheuristic algorithms were used to solve the model

due to the uncertainty in some model variables and parameters.

Furthermore, Hrabec et al. (2019) introduced a waste collection VRP model that employs technology to predict bin waste amounts. The proposed model assumes dynamism in waste generation rate and uses volume sensors in waste bins to provide data about waste accumulation. The main idea of such an approach is that some data in the waste collection system is both deterministic regarding current waste level in bins and stochastic since the future amount of waste cannot be predicted accurately since the accumulation rate is random. Therefore, the model is solved by collecting waste from full bins and leaving partially full bins to be served later while predicting the accumulation rate of those partially full bins. The main objective of the model is to minimize total traveled distance, penalty costs due to exceeding the waste bin allowed capacity, and penalty costs resulting from driving the obligatory extra distance to collect waste.

1.11 Risk Management in VRP

Preparing businesses for eventualities that may hinder success and growth, mitigating possible threats, and supporting the decision-making process with adequate data are benefits of employing a suitable risk management plan in any business. Today, all sorts of companies are applying risk management plans while developing strategies for the financial profits and the safety and well-being of employees and staff. Moreover, employing risk management plans reflects the welfare of citizens, especially those living or located near possible danger or unhealthy environments due to carrying out different businesses such as waste management facilities, chemical industries, and logistics that involve transporting hazardous materials. Indeed, integrating risk management into business practices supports achieving sustainable development.

The logistics sector, in general, and vehicle routing, in particular, are no different from those businesses. Recently, risk management has been embedded in scheduling and planning commodity delivery. Van Raemdonck et al. (2013) analyzed the risk of transporting hazardous materials. The authors presented an evaluation framework for estimating the risk in hazardous materials transportation along different routes by estimating possible risks in operation and calculating the probability of occurrence of accidents. In the presented framework, two risk maps were discussed to estimate the probability of accident risk. A local risk map to estimate the probability of accidents, based on the local infrastructure of different routes and the available local data on

accidents, in addition to a global risk map based on international data on accidents in transporting hazardous materials. A Geographic Information System was used in risk maps, where each used data must have a geographic reference to be used.

Similarly, Bula et al. (2019) considered the environmental, social, and economic aspects of distributing and collecting hazardous materials. The authors discussed the tradeoff between cost-efficient and safe transportation by proposing a bi-objective model to minimize the routing cost and the entire routing risk. The routing risk was calculated using the accident rate of different truck types (since different types of trucks have different probabilities of having an accident) and the probability of releasing hazardous materials in case of accidents. Note that the risk-minimizing objective considered the well-being of both drivers and citizens by including the probability of accidents and the probability of being exposed to hazardous materials, respectively. Furthermore, Holeczek (2021) analyzed different risk models in hazardous materials transportation while considering a network of urban roads. The author investigated the effect of different factors on the risk of hazardous materials VRP, such as truck fleet size and load. The main objectives were minimizing travel distance, risk of population exposure to hazardous materials, risk of accidents, and traditional risk value.

Additionally, load-dependent and load-independent risk models were compared and analyzed to reveal the effect of truckload on transportation risk. Also, in the field of hazardous materials VRP, B. Wang et al. (2020) proposed a model that considered a multi-depot, heterogeneous fleet of trucks, risk analysis, and different routing scenarios. In their research, the risk coefficient is calculated based on the occurring accident scenario which is related to the type of transportation route, hazardous material carried, and the probability of accidents. The main objectives of the model were minimizing transportation costs, risk costs, and overtime costs. Away from hazardous materials models, Ji et al. (2022) developed a workforce scheduling and VRPTW model that integrates risk analysis and stochastic events. In the proposed model, the author assumes different risks related to the service delivery: risk of arriving late from the pre-defined time of service, risk of uncertainties such as travel time and service duration time, and risk of not conducting the required service due to the technician's skill level. The model aimed at minimizing such risks and delivering the needed service on time between the agreed start and end times of service. In another approach, Ghannadpour & Zandiyeh

2020) introduced a real-life case of the cash transit VRPTW model that considered the risk of delivering cash from the central treasury to different banks. The risk in cash in transit was estimated using Equation (B).

$$R_{ij}^k = \mathbb{P}_i^k \cdot p_{ij} \cdot v_{ij} \cdot D_{ij}^k \quad (\text{B})$$

where R_{ij}^k is the risk in transporting cash from between nodes i and j using vehicle k , p_{ij} and v_{ij} are the probability of robbery occurrence and the probability of robbery success between nodes i and j , respectively. D_{ij}^k the severity of risk reflects the amount of the stolen cash if the robbery was successful. Finally, \mathbb{P}_i^k shows the probability of not having a robbery between nodes. Note that the discussed formula is general and can be applied in different applications to estimate the resulting risk. The authors mentioned that the objectives were minimizing travel distance and risk on cash transit. In addition, the main research contributions were developing a novel cash-in-transit VRP model that considers risk, estimating the probability of robbery while routing, estimating the likelihood of success of the robbery, periodic review of routes to prevent link repeatability in case of possible robbery, and developing a hybrid genetic algorithm to solve the model. Another contribution to risk management in VRP was introduced by Abdullahi et al. (2021) by developing a multi-objective sustainable VRP model. The authors tackled the social dimension of sustainability by considering the risk of accidents while routing since it involves the well-being of drivers and citizens. The risk of accidents was computed based on the travel distance, the load of the vehicle, and a coefficient to monetize accidents, which are measured by USD/kg-km. On the other hand, Soeanu et al. (2020) introduced a study in multi-depot vehicle routing of commodity distribution with risk mitigation. In their approach, two types of risk were considered: the risk of not reaching the destination node and failing to deliver the commodity and the risk on vehicles due to breakdown or loss.

In the field of SWMVRP, Govindan et al. (2021) researched one type of municipal SW, which is infectious medical waste generated by the COVID-19 virus. The authors developed a novel location-routing model that considered realistic scenarios and many variants, such as time windows, different types of costs, risk management, vehicle failure, vehicle load, and split delivery. The main objectives of the model were minimizing costs and risks to the population caused by exposure to hazardous medical waste. The risk

function was calculated based on the possibility of vehicle failure and the probability of citizens' exposure to infectious waste. Thus, the model was solved to select routes with low population density to lower the probability of exposure to infectious medical waste. In addition, vehicles with a low probability of failure, i.e., high reliability, were assigned to collect infectious waste, whereas vehicles with low reliability and high probability of failure were assigned to collect non-infectious medical waste.

Most of the reviewed VRP articles in risk mitigation studied risk either as minimizing the risk of losing cash or valuable commodities or minimizing the risk of exposing the population to hazardous or any other harmful materials. In most scenarios, the risk was estimated using either Failure-Mode-and-Effects-Analysis (FMEA) methodology, Multi-Criteria Decision-Making (MCDM) methods, or game theory. Similarly, in the field of SWMVRP, most risk management efforts were directed toward minimizing the effect and harm on citizens living near waste facilities or along the route that waste trucks follow between waste generation nodes and other waste facilities. However, analyzing the risk of accidents, which involves the well-being and safety of drivers and the population, was not considered in SWMVRP as far as our knowledge goes. Also, considering the safety of drivers in risk analysis improves the sustainable performance of SWM companies.

1.12 Productivity Improvement and Drivers' Health State in VRP

Improving the skills of the workforce results in many benefits for all stakeholders. For instance, improving workers' skills increases their productivity and added value, thereby increasing revenues for business owners. On the other hand, training workers and enhancing their skills can develop self-confidence and create a healthy environment and satisfied workers (Sayin & Karabati, 2007). In the manufacturing sector, Qu et al. (2016) developed a mathematical model for optimizing manufacturing systems to meet the technological advancement and the revolution of Industry 4.0. The aim was to develop an efficient, adaptive, and optimal workforce schedule manufacturing system consisting of multiple manufacturing stages, various products, different workers' skill levels, and different types of machines. Maximizing workers' productivity by planning an adequate schedule and minimizing workforce costs were the main objectives of the model.

Moreover, Arashpour et al. (2018) formulated an optimization model for prefabrication in the construction sector. The authors argued that due to uncertainty in demand, change order, and resource availability, efforts should be made to utilize the available resources

and train the workforce to have multi-skilled workers with high productivity. This research aims to incorporate the needed time and money for workforce cross-training, with resource planning, to minimize costs associated with utilizing a multi-skilled workforce. The authors stated that the main contributions of the developed model were analyzing the deployment of multi-skilled workers to improve productivity and production flexibility and using a hybrid methodology in model formulation, which integrated linear, integer, and probabilistic modeling. Furthermore, Othman et al. (2012) developed a model that considers workers' productivity using the Ability, Motivation, and Opportunity (AMO) theory. The proposed model studied human aspects such as worker abilities, training, personalities, capacity, motivation, learning rates, and fatigue levels, intending to minimize firing rates of high-performance work and cost minimization objectives. AMO framework is derived from psychological concepts, which measure the performance of employees based on their motivation to do the job, the available opportunities for success, and their skills and abilities (Hughes, 2007). The author suggested that motivation directly affects employees' performance (behavior) and the moderate influence of abilities and opportunities. On the other hand, before the development of the AMO framework, Blumberg & Pringle (1982) argued that estimating and predicting employee performance was not an easy job, and many systems faced failure due to neglecting important dimensions related to employee performance and productivity. The authors suggested a three-dimension interactive model that measures the expected work performance of employees:

1. Capacity: which reflects the employee's ability, skills, education, health, knowledge, and intelligence to accomplish the needed physical or mental task.
2. Willingness: This is related to the employee's motivation to perform the tasks, which is affected by job satisfaction, attitude, values, and personality.
3. Opportunity: based on the availability of tools, machines, healthy work conditions, and a fair incentives system. Note that this dimension is beyond the employee's control and does not relate to other personality factors.

Similarly, in logistics and VRP, improving drivers' skills results in business success and plays an essential role in achieving sustainability goals (Dubey & Gunasekaran, 2015). The authors suggest that driving skills include technical skills (such as mechanical skills and the ability to handle the vehicle while driving) and behavior skills (such as awareness of environmentally-friendly driving habits). Martinussen et al. (2014) argued that drivers'

skills must be considered to support the efforts to minimize CO₂ emissions. The research aimed to spotlight the effect of drivers who drive dangerously and analyze their characteristics regarding gender, age, involvement in accidents, and annual driving distance. The authors used a research tool that analyzed the link between drivers' driving skills and their driving behavior. Results showed that drivers with high driving skills (in terms of handling the vehicle and safe-driving skills) reflect lower driving aberrations, and vice versa. Also, Schneider et al. (2010) studied a stochastic VRP model considering driver learning. Their model examined the effect of drivers' familiarity with routes and customers on routing efficiency. The proposed approach eliminates any fixing of delivery locations to avoid losing routing flexibility. Instead, the model considered drivers' knowledge through driver-specific travel and service times, encouraging drivers to stay in familiar areas and routes.

Moreover, in the production industry, Sobhani et al. (2015) developed a mathematical model in a production assembly line that investigates the effect of the working environment and work-related health risks on workers' productivity. The 2-state Markov chain model supported their approach to measure the economic impact of work-related injuries that hinder workers' productivity. The developed model was based on the idea that workers may have a healthy state and a pain state while working, and the transition between the two states causes a variation in unit production in a certain time horizon. To estimate the workers' state, a formula was developed to estimate the probability of transiting from health state and pain state and vice versa. The model had one objective function that aimed at minimizing total costs related to production rate, inventory, overtime, and Occupational Health and Safety costs.

Moreover, like all other industries, waste management workers (including drivers) face daily work-related conditions that may cause injury or affect their health. Such work-related injuries may include physical and mental injuries (such as fatigue) caused by stress and long working hours; such injuries affect workers and the surrounding population and could result in catastrophic accidents. According to Jeong et al. (2016), household waste collectors are exposed to many work-related injuries and illnesses to a degree that differs according to the worker's age, health condition, length of employment, and other factors; in addition, their results showed that most of the recorded injuries were musculoskeletal conditions.

Given what had been discussed earlier, assessing drivers' productivity by analyzing the probability of suffering from work-related risks of injury was not considered before in the field of SWMVRP. Therefore, the main contribution of this research is to integrate drivers' health state and productivity into a sustainable SWMVRP model and analyze its effect on different model parameters and variables, which is a novel approach and a worthy research gap to be studied. Note that our research is based on the SWMVRP model developed by Mojtahedi et al. (2021), and in terms of workforce we only consider drivers, although SWM systems have other workers beside the driver.

Chapter Two

Model Formulation

2.1 Chapter Overview

In this chapter, the generated ideas and the defined research gaps in the field of SWMVRP were translated and presented as mathematical equations in order to formulate the mathematical model, solve the research problem, and obtain results. The model formulation process starts with clearly understanding the research problem, to derive mathematical equations that create the proposed model; after that, an adequate solution methodology must be selected to generate results. Moreover, the developed model was solved as an MINLP model. This chapter is presented in the following order: First Section discusses a review of Mixed Integer Non-Linear Programming (MINLP) to gain a general knowledge of linear programming, integer programming, MILP, and MINLP. Next section shows a detailed description of the proposed model, which includes sub-sections that discuss problem presentation, necessary assumptions to solve the developed model, sets, and parameters, defining equation that explains how certain parameters were calculated, decision variables, objective functions and finally model constraints.

2.2 Mixed Integer Non-Linear Programming (MINLP)

Since our optimization and mathematical modeling approach to solve the research problem and the developed model is an MINLP, some terms and modeling approaches must be defined and explained briefly to justify our methodology. Linear Programming (LP) is an optimization technique that aims at maximizing/minimizing a numerical value that presents a pre-defined objective function. However, to solve any optimization problem using LP, some conditions must be met, mainly linearity conditions in terms of constraints and objective functions. In addition, LP may generate solutions with fractional numbers, which is unreasonable and unrealistic since it may generate infeasible results when solving specific real-world applications. Therefore, Integer Linear Programming (ILP) was used to produce integer solutions.

On the other hand, we must deal with the complexity of the developed models, which tackle real-world applications that include multiple objectives and complicated constraints. Therefore, we need a framework that allows an optimization problem to have

continuous and discrete variables; thus, Mixed Integer Linear Programming (MILP) is used. Due to the growing demands to solve real-life problems, we need to find a solution that allows for nonlinear and integer variables. Mixed Integer Non-Linear Programming (MINLP) is an optimization approach that helps to solve such optimization models. It involves collecting data and using mathematical programming to minimize or maximize an objective function while considering nonlinear constraints that involve both discrete (integer) and fractional (continuous) variables. MINLP is widely used across various industries, such as logistics, transportation, supply chain management, waste collection, and manufacturing, due to its ability to include realistic conditions and decision variables. In the proposed SWMVRP model, the complexity of a real-life problem is often addressed by creating a more accurate model of the situation. This model is composed of several decision variables with unique values, making the task of addressing the issue more complex. However, the increased complexity of the model can also lead to better and more comprehensive solutions. For example, variables like the amount of CO₂ emissions are presented as fractional numbers. In contrast, variables such as the compatibility of the type of waste for treating or recycling are shown as a binary number ($\in [0,1]$). Therefore, using MINLP is more practical and should generate more accurate results.

2.3 Model Description

In order to present the research problem and model that had been developed, this section discusses the model assumptions, as well as provides a comprehensive description of the parameters, variables, constraints, and objective functions that are part of the model. This allows for a better understanding of the problem and model.

2.3.1 Problem Presentation

The need for adequate municipal SWM services is an inevitable requirement nowadays. Possibly, because of the danger and damage that may touch the environment and the surrounding forms of life, in addition to the high expenses of treating and restoring any pollution or damage to the infrastructure caused by municipal SW. Moreover, the recent emergence of smart cities promoted the idea of a green lifestyle without accumulated waste or pollution. No doubt, managing municipal SW properly results in many benefits to the environment and society. However, many challenges and difficulties arise, especially when collecting, treating, and disposing SW. Such challenges include

transporting costs, personnel management (drivers' productivity, overtime, etc.), and possible environmental and societal risks. In recent years, researchers have delved into the SWMVRP, integrating various variants and objectives of the VRP into their models, such as cost minimization, reduction of GHG, travel time optimization, and considering different economic, environmental, and social aspects. Additionally, researchers have explored a range of scenarios, including single-depot, multi-depot, multi-vehicle, and scenarios with uncertainty in travel times and services. As time passes, the complexity of our research topic (SWMVRP) models increases, making it better suited to address real-life problems. Nevertheless, none of the prior attempts in solving SWMVRP considered measuring and monitoring the health state of waste truck drivers, which affects significantly the performance, compared to other industries such as manufacturing and healthcare, where many efforts were made to plan and improve the workforce adequately. Moreover, there is no indication from the researched literature on SWMVRP that there is a direct metric for the risk facing waste truck drivers while traveling in a waste management network. Therefore, in our approach, the main goal is to spotlight the integration of the pillars of sustainability with drivers' health state and performance, in addition to the risk of accidents facing drivers while performing their route. Regarding drivers' health state and performance, our approach relies on mathematical and statistical models to predict the health state (condition) of drivers at/after each node in the proposed waste management network, mainly using Markov chains. Moreover, the health state of drivers is predicted based on suffering from work-related injuries, and since we are studying a VRP model, the most common work-related injuries in driving include fatigue, lower back pain, spinal compression, etc. Markov chain is a stochastic statistical model that predicts the occurrence of an event based on the current state (not the past state) using probabilities of transiting from one state to another (Ching et al., 2013). In this research, for the purpose of reaching a steady-state probabilities of health and pain states, we use Ergodic Markov chain to make it possible to reach from one state to another with positive probability. Equation (1) shows the transition probability (P_{ij}) of transiting from state i to state j .

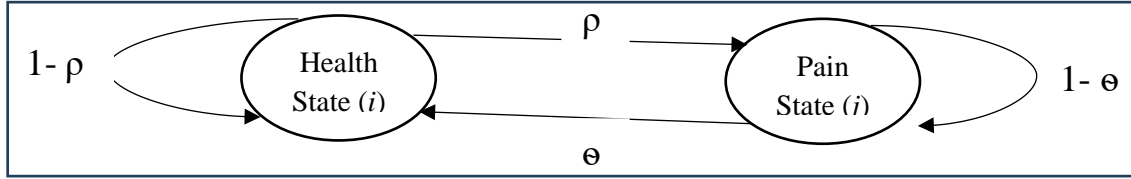
$$P_{ij} = \mathbb{P} \left(X_{t+1}=j \mid X_t=i \right) \quad (1)$$

In this research, we consider two health states describing the drivers, which are the health state and pain state. Using the Markov chain, we develop two transition probabilities,

which are the probability of transiting from the health state to the pain state (ρ) and the probability of transiting from the pain state to the health state (θ). Figure 4 shows the probability of transiting between the two states. Note that the sum of probabilities at each node must equal one, therefore, the probability of keeping a health state is $(1 - \theta)$, whereas the probability of staying in a pain state is $(1 - \rho)$.

Figure 4

Two-state Markov chain probabilities of the developed model



Using the transition probabilities in Figure 4, we can develop the transition matrix shown in Equation (2), where the current state is shown in the rows and the new state is shown in the columns.

$$P_{ij} = \begin{bmatrix} 1 - \rho & \rho \\ \theta & 1 - \theta \end{bmatrix} \quad (2)$$

Finally, we need to solve the transition (probability) matrix shown above to find the stationary (steady-state) distribution probability, which is a property of the Markov chain when probability distribution remains unchanged as time goes as shown in Equation (3) that must be satisfied to reach stationary distribution.

$$\pi = \pi P_{ij} \quad (3)$$

Equation (4) shows the final formula to find the steady-state probabilities of the driver's health state in our proposed model, where the steady-state (stationary) probabilities of the healthy state are (π) and for the pain state is (μ) , and (m) is the number of steps from the current state. Note that in our model each step illustrates traveling between different nodes in the network including generation nodes and waste processing facilities. To find the steady-state probability of health state the initial state vector (i.e.. $[\pi \ \mu]$) is set to $[1 \ 0]$, and to find the steady-state probability of pain state it is set to $[0 \ 1]$. Keep in mind the sum of all steady-state probabilities must equal to 1 (i.e.. $\pi + \mu = 1$).

$$[\pi \ \mu] = [\pi \ \mu] \begin{bmatrix} 1 - \theta & \rho \\ \theta & 1 - \rho \end{bmatrix}^m \quad (4)$$

According to Ching et al. (2013), after solving the probability matrix for the long run the steady-state probabilities of a 2-state Markov chain can be described as shown in Equations (5) and (6).

$$\pi = \frac{\theta}{\theta + \rho} \quad (5)$$

$$\mu = \frac{\rho}{\theta + \rho} \quad (6)$$

Therefore, in our research, we introduce and study a multi-objective SWMVRP model with the following objective functions: (1) minimizing total costs in the SWM network that includes two main costs, which are fixed costs for vehicles and transportation (variable) costs, (2) minimizing the costs incurred due to drivers' loss of productivity caused by suffering from work-related injuries or illness, which can be considered as both economic and social costs, (3) minimizing the emissions of CO₂ resulting from burning fuel, subject to the traveled distance and the amount of load carried by waste vehicles, (4) minimizing any bias or deviation from the fair allocation of load among drivers, which results in improving drivers' job satisfaction levels, (5) minimizing the risk of accidents while traveling between different waste management nodes in the proposed routing network. The novelty of the developed model mainly consists of two main contributions to the literature of SWMVRP; first, investigating and improving driver's productivity level, and including the probability of suffering from work-related injuries in the SWMVRP model for the first time. Secondly, our model studies and aims at minimizing the risk of accidents facing drivers based on the traveled distance and vehicle's load rather than only considering the risk of exposing people to harmful materials. In addition, developing a rich SWMVRP model that integrates the three dimensions of sustainability with risk of accident minimization, along with analyzing drivers' health condition, yields a comprehensive scenario that simulates real-world applications. Given the earlier discussion, the developed model can be defined as follows. In a SWM network that consists of different (multi-depot) geographically distributed waste nodes, which are waste generation nodes, waste treatment facilities, recycling facilities, and disposal facilities, a heterogeneous fleet of waste vehicles that vary in type, load capacity, transportation costs, and the amount of CO₂ are used to transport waste from one node to another. The selection of different waste vehicles is determined by the type of the carried

waste, which also determines the transportation activity in terms of which waste facilities can be visited and which cannot be based on the type of waste. The model assumed three different types of waste trucks (shown in appendix A) based on the classification in the work of Mojtahedi et al. (2021), specifically residue-transferring trucks, waste-transporting semi-trailers, and waste collection trucks; as mentioned earlier, each type of truck has different specifications regarding fuel consumption, load capacity, and travel destinations. Note that choosing among different trucks will affect the results of the model and will alter the objective functions of cost and CO₂ emissions, which support the idea that different waste types yield different costs for managing them (treating/recycling/disposing). This model considers different types of waste, including garbage, recyclable, and hazardous waste, which are generated with different volumes in waste-generated nodes before collection by trucks. In the proposed waste management network, a waste collection truck travels from a specific transfer station to collect different types of waste from various waste generation nodes. Each waste generation node can generate any type of waste and with different volumes. After collection, trucks move back to the transfer station, where they start the route to unload the collected waste. After that, in the transfer station, collected waste will be sorted using different processing technologies to create sub-types of waste, which, on the other hand, will be transported to the appropriate waste facilities in the network to continue the procedure of SWM. After processing waste, a waste transportation semi-trailers transport different types of waste from transfer stations to its appropriate waste facility, whether it is a recycling, treatment, or disposal facility. Those facilities then process the waste by recycling and/or treating it, which will result in recoverable and/or treated materials. However, recycling, treating, and disposing of waste results in different types and amounts of residues that must be managed. Therefore, residue transferring trucks are used to transport residues from waste processing facilities to disposal unless some of the residues can be recycled. Note that the three types of waste vehicles incur two types of costs, fixed and variable (transportation costs), as shown in the first objective function of the model. Figures (1-3), shown in Appendix A, illustrate the developed SWMVRP model, which is structured as a three-level echelon waste collection / transporting network with three main nodes, which are the initial depot (i.e., transfer station), customer nodes (i.e., waste generation node), destination nodes (i.e., waste processing facilities). Echelon I represents the routing activities between transfer stations and waste generation nodes, whereas Echelon II shows the transportation

network between transfer stations (after waste segregation) to waste processing facilities, including recycling, treatment, and disposal facilities. Finally, Echelon III plays an important role in the network by linking transfer stations, recycling/treatment facilities, and disposal facilities to transport residues. Note that the structure of the developed model is adopted from the work of Mojtahedi et al. (2021). In addition, our approach extends its interest to the human factors by considering the productivity of drivers, by analyzing the probability of suffering from work-related injuries while driving, such as fatigue and musculoskeletal injuries, which results in two health conditions that describe drivers, namely healthy state and pain state. The driver's health condition (state) yields different productivity levels, where healthy drivers can drive more distance to collect and transport waste between waste facilities compared to injured drivers and, thus, higher productivity. Note that due to the nature of the problem under study, the productivity is measured by the driving distance and the required time to drive one kilometer under a healthy / pain state. The probability of suffering from work-related risk of injury is calculated according to the 2-state Markov chain process, which shows the probability of having a health or pain state as adopted from the work of Sobhani et al. (2015). In the developed model, we assume different skills required to operate (drive) waste trucks due to the difference in size and properties of the three types of waste vehicles included in this model. Moreover, the developed model analyzes the risk of traveling and carrying waste from one node to another. In our approach, the risk is considered as a function of cost to minimize the cost of traveling accidents. The studied risk is affected mainly by two factors, which are the travel distance and the amount of carried waste (vehicle load); a coefficient was used to monetize risk based on the work of Delucchi & McCubbin (2011), which is measured using USD/kg-km unit. In most waste management models, the risk is measured based on the possibility of exposing the environment and people to hazardous materials. However, in our approach, the risk function takes into consideration the well-being of drivers.

Appendix B includes the sets, indices, parameters, decision variables, and constraints related to the developed mathematical model.

2.3.2 Model Assumptions

The following necessary key assumptions are set to model and solve model.

1. The model assumes multi-depot (transfer stations), multi-destination points (waste generation and processing facilities), and an echelons network.
2. The locations of waste generation nodes and waste processing facilities are assumed to be fixed in the network.
3. The optimal solution of the model should be a decision on the required number and type of vehicles to visit different nodes in the network, the optimal productivity level of drivers', and the cost of routing risk.
4. The total costs of waste vehicles in the network are the vehicles' fixed costs and variable (subject to the traveled distance and vehicles' load) costs.
5. The environmental emissions are calculated based on the travel distance between different types of nodes, vehicle load, and fuel consumption rates.
6. The fair load balance function is based on any lost capacity.
7. The quantity and type of waste at each generation node are known and pre-specified.
8. The waste volume capacity at different network elements, including generation nodes, vehicles, and processing facilities, is limited and predefined.
9. Each vehicle is allocated to a single depot at any given time.
10. The model assumes three different types of waste vehicles, each one is characterized by different fuel consumption, load capacity, CO₂ emissions, and operational costs.
11. Each waste facility performs only one job (treatment, recycling, or disposal).
12. After collection, each type of sorted waste at transfer stations is only compatible with one technology (treatment, recycling, or disposal).
13. After processing, the generated residue is only compatible with disposal technology.
14. The amount of generated waste, either while collecting or after processing, does not exceed the capacity of the waste vehicles fleet.
15. The different waste vehicles are assumed to be working perfectly and do not affect the productivity of drivers.
16. Drivers described as having a healthy state are assumed to be 100% productive, subject to the categories of health transition probabilities, which is presented in the research results chapter.
17. The model assumes that each driver is allocated to only one waste vehicle.

2.3.3 Objective Functions

- **Description of the first objective function:** this objective function aims to minimize the costs associated with the waste management network, which are fixed and transportation (variable) costs. Fixed costs include license, registration, salaries, insurance, taxes, depreciation, and, in some cases, the cost of housing the vehicles after working hours. In contrast, transportation costs are incurred when waste vehicles travel between waste facilities, such as fuel, maintenance, and toll roads. Note that in our proposed model, transportation costs vary according to the amount of waste carried by waste vehicles (which significantly affects fuel consumption) and the travel distance between different nodes in the waste network. Also, the model considers the fixed and transportation costs for the three types of vehicles used in the 3-level echelon network: collection vehicles, transportation, and transferring semi-trailers.

$$\begin{aligned}
\min Z_1 = & \sum_{q \in V \in Q} FC_q \times \left(\sum_{i \in K} \sum_{j \in G} X_{ij}^q \right) + \sum_{q \in S \in Q} FC_q \times \left(\sum_{i \in K} \sum_{j \in MUHUL} X_{ij}^q \right) \\
& + \sum_{q \in U \in Q} FC_q \times \left(\sum_{i \in K} \sum_{j \in MUH} X_{ij}^q \right) + \sum_{i \in G} \sum_{j \in KUG} \sum_{q \in V \in Q} TC_{ij}^{qW} \times X_{ij}^q \times W_{qi} \\
& + \sum_{i \in G} \sum_{j \in KUG} \sum_{q \in V \in Q} TC_{ij}^{qD} \times X_{ij}^q \times DIS_{ij} \\
& + \sum_{i \in K} \sum_{j \in MUHUL} \sum_{q \in S \in Q} TC_{ij}^{qW} \times X_{ij}^q \times W_{qi} \\
& + \sum_{i \in K} \sum_{j \in MUHUL} \sum_{q \in S \in Q} TC_{ij}^{qD} \times X_{ij}^q \times DIS_{ij} \\
& + \sum_{i \in MUH} \sum_{j \in MUHUL} \sum_{q \in U \in Q} TC_{ij}^{qW} \times X_{ij}^q \times W_{qi} \\
& + \sum_{i \in MUH} \sum_{j \in MUHUL} \sum_{q \in U \in Q} TC_{ij}^{qD} \times X_{ij}^q \times DIS_{ij}
\end{aligned} \tag{7}$$

- **Description of the second objective function:** this objective function shows the main contribution of this research, which investigates the effect of work-related risk of injuries (illness) on drivers' productivity. Therefore, the model assumes that drivers could have two states, which are the health state and pain state (when drivers suffer from injuries such as musculoskeletal injuries and fatigue). Note that the probability

of transiting from health to pain state or vice-versa is calculated subject to equations 1-6 according to the 2-state Markov chain. Due to the nature of the research problem, productivity is measured by the travel distance covered by the driver in one period (shift) and the amount of time needed to travel one kilometer in a health or pain state. Finally, the aim is to minimize the penalty costs resulting from the loss of productivity.

$$\begin{aligned}
\min Z_2 = & \left(\sum_{i \in G} \sum_{j \in KUG} \sum_{Dq \in DV \in DQ} pen^{Dq} \times X_{ij}^{Dq} \times time_{hs}^{Dq} \times DIS_{ij} \times (1 - \pi_{Dq}) \right. \\
& + \left. \sum_{i \in G} \sum_{j \in KUG} \sum_{Dq \in DV \in DQ} pen^{Dq} \times X_{ij}^{Dq} \times time_p^{Dq} \times DIS_{ij} \times \mu_{Dq} \right) \\
& + \left(\sum_{i \in G} \sum_{j \in KUG} \sum_{Dq \in DS \in DQ} pen^{Dq} \times X_{ij}^{Dq} \times time_{hs}^{Dq} \times DIS_{ij} \times (1 - \pi_{Dq}) \right. \\
& + \left. \sum_{i \in G} \sum_{j \in KUG} \sum_{Dq \in DS \in DQ} pen^{Dq} \times X_{ij}^{Dq} \times time_p^{Dq} \times DIS_{ij} \times \mu_{Dq} \right) \\
& + \left(\sum_{i \in G} \sum_{j \in KUG} \sum_{Dq \in Du \in DQ} pen^{Dq} \times X_{ij}^{Dq} \times time_{hs}^{Dq} \times DIS_{ij} \times (1 - \pi_{Dq}) \right. \\
& + \left. \sum_{i \in G} \sum_{j \in KUG} \sum_{Dq \in Du \in DQ} pen^{Dq} \times X_{ij}^{Dq} \times time_p^{Dq} \times DIS_{ij} \times \mu_{Dq} \right) \quad (8)
\end{aligned}$$

- **Description of the third objective function:** this objective function concerns the environmental pillar of sustainability to minimize the CO₂ emissions resulting from waste vehicles while collecting and transporting waste. Similar to the previous objective functions, three types of waste vehicles are considered since each type of vehicle is characterized by different fuel consumption and, thereby CO₂ emissions. Also, the load of the vehicle affects CO₂ emissions, therefore, the current load and the maximum load of waste vehicles are considered for each vehicle type.

$$\begin{aligned}
min Z_3 = & \sum_{i \in G} \sum_{j \in K \cup G} \sum_{q \in V \in Q} CER_q \times \left(ROI_q + \frac{ROF_q - ROI_q}{MXC_q} W_{qi} \right) \times DIS_{ij} \times X_{ij}^q \\
& + \sum_{i \in K} \sum_{j \in K \cup M \cup H \cup L} \sum_{q \in S \in Q} CER_q \times \left(ROI_q + \frac{ROF_q - ROI_q}{MXC_q} W_{qi} \right) \times DIS_{ij} \times X_{ij}^q \\
& + \sum_{i \in M \cup H} \sum_{j \in M \cup H \cup L} \sum_{q \in U \in Q} CER_q \times \left(ROI_q + \frac{ROF_q - ROI_q}{MXC_q} W_{qi} \right) \times DIS_{ij} \\
& \times X_{ij}^q \tag{9}
\end{aligned}$$

- **Description of the fourth objective function:** this objective function tackles the social aspect of sustainability by eliminating any bias in the work environment to minimize the deviation from the fair-load allocation between drivers. The amount of accumulated waste, the capacity of transfer stations, and the amount of processed waste at transfer stations are considered in this objective function to distribute jobs between drivers equally.

$$min Z_4 = \sum_{j \in K} \left| \frac{CPK_j}{\sum_{i \in K} CPK_i} - \sum_{o \in O} YK_{ok} / \sum_{o \in O} \sum_{g \in G} BG_{og} \right|_j \tag{10}$$

- **Description of the fifth objective function:** the fifth and final objective function demonstrates the social pillar of sustainability similar to the second and fourth objective functions, to minimize the risk of driving accidents. The risk of accidents was linked to the amount of waste carried by waste vehicles and the travel distance, as adopted from the work of Abdullahi et al. (2021). Note that the risk of accidents was studied as a cost function, therefore, a constant “A” was used to monetize accidents, measured by USD/kg-km unit.

$$min Z_5 = \sum_{i=0}^n \sum_{j=1}^n \sum_{q \in Q} A \times X_{ij}^q \times (W_{qi} + DIS_{ij}) \tag{11}$$

2.3.4 Constraints

Note that the following equation (65 and 66) shows the calculation of vehicle’s q fuel consumption rate (FCR_q) and the amount of generated CO₂ emissions (GE_{ij}^q) respectively.

$$FCR_q = ROI_q + \frac{ROF_q - ROI_q}{MXC_q} W_{qi} \quad (65)$$

$$GE_{ij}^q = CER_q \times \left(ROI_q + \frac{ROF_q - ROI_q}{MXC_q} W_{qi} \right) \times DIS_{ij} \quad (66)$$

- Description of constraints:** equations (12-19) state limitations necessary for the flow of the model for the three types of waste vehicles and the three-level echelon waste network, for example, equation (12) ensures that waste vehicles travel from transfer stations to waste generation nodes and equation (15) limits the number of trips to the number of transfer stations. Also, equations (13), (16), and (18) show vehicle utilization across the three-echelon waste management network. Equations (20-22) eliminates any sub-tours in the three echelons by stating that the arriving node must be the departure node. On the other hand, equations (23-25) present common constraints used in VRP, which ensures that each waste node in the network containing one of the three types of waste (o, w, f) is visited only once per trip by a compatible waste vehicle (V, S, U). Equations (26-30) state that each vehicle is allocated to only one transfer station and ensure that each vehicle must return to its original depot node. Equations (31-41) show the load limitations of different types of waste vehicles (which have various load capacities) in the three echelons existing in the proposed model. In general, those constraints mean that the load of each vehicle after visiting waste generation nodes or different waste facilities must not exceed the total load capacity of the vehicle.
- Furthermore, equations (42-44) were set to ensure that different waste facilities, namely treatment, recycling, and disposal facilities, only accept and process compatible types of waste. Similarly, equation (45) ensures disposal facilities only receive and process compatible residues. Equation (46) deals with the amount of different types of waste sorted at transfer stations subject to the ratio of sorting and the amount of processed waste, which is ready to be transported to the compatible waste facility. Equations (47-49) direct the demand at different waste processing facilities, where constraints (47) and (48) present the amount of residue generated after processing waste at treatment and recycling facilities. As such, constraint (49) controls the amount of generated residue at treatment and recycling facilities which is ready to be transported to disposal facilities. Also, constraints (50-54) present the

number of different types of waste at their compatible waste facilities, including sorted, treated, recycled, and disposed waste, as well as the resulting residues respectively. Common constraints used in VRP and logistics models are shown in equations (55-57), which state that every customer request must be met and any shortage in service delivery shouldn't exist. Therefore, equation (55) states that all accumulated waste at waste generation nodes must be collected and transported to transfer stations, as such equation (56) ensures that all sorted waste at transfer stations must be transported to treatment, recycling, and disposal facilities to be processed, on the other hand, equation (57) makes sure that all generated residue from treatment and recycling facilities should be delivered to disposal facilities. Moreover, equations (58-61) limit the capacity of waste facilities by stating a fixed capacity for transfer stations, treatment, recycling, and disposal facilities. Equations (62) and (63) ensure the feasibility of variables in the model by forcing every variable to have a binary positive value. Finally, equation (64) is a constraint that allocates each driver to one waste vehicle. Note that our developed model is a MINLP model where all objective functions and constraints are non-linear.

Chapter Three

Research Results and Solution Methodology

3.1 Chapter Overview

In this chapter, the results obtained after solving the proposed SSWMVRP model are presented and discussed. This chapter starts with a presentation of the generated data to solve the model. The results are shown in detail including the routing stage to collect different types of waste, the transportation stage that shows the delivery of processed waste, and residues between different waste facilities, the health state of drivers that shows when they enter a pain state due to different work-related injuries, the results related to the risk of accidents which is presented as a monetary function. Also, this chapter shows and discusses the adopted solution methodology used to carry out this research. Specifically, this chapter demonstrates how the developed MINLP mathematical model will be converted to programming codes, which are then used to draw the needed numerical results. Also, in this chapter, we demonstrate and elaborate on each stage of the process involved in the methodology, which was implemented through a metaheuristic algorithm. Finally,

3.2 Solution Methodology

In optimization, there are two types of problems based on the number of objective functions - single-objective and multi-objective functions. The former aims to find a single optimal solution, while the latter involves multiple objectives, making it harder to find a single optimal solution due to the objectives' interdependence. A non-dominance criterion, which ensures that no solution dominates others, is used to solve the multi-objective problem, generating Pareto optimal solutions in a feasible space. The set of all Pareto-optimal solutions is called the Pareto optimal set. In contrast, the graphically represented Pareto optimal set is known as the Pareto-optimal frontier, which is often used in solving multi-objective optimization problems. Therefore, due to the complexity of this research and the developed model for studying a Multi-Objective Optimization Problem (MOOP) and the number of used constraints, using exact methods is impractical and could generate unfeasible solutions. Therefore, in this research, an approximate optimization methodology was adopted, specifically by using a Non-Dominated Sorting Genetic Algorithm II (NSGA-II). The use of the proposed algorithm is due to the need to

deal with the dynamism of the proposed model (the change in the driver's health state) in addition to being a multi-objective functions problem. The proposed NSGA-II generates near-optimal results in contrast to the optimization approaches offering global-near optimal results (Rader, 2010). The employment of the NSGA-II algorithm is due to its accuracy and excellent results in solving multi-objective complex NP-hard optimization problems such as VRP in general and waste management networks, as presented in many VRP researches (Bagherinejad & Dehghani, 2016; Gupta & Garg, 2017; Kalhor et al., 2011). In addition, the proposed algorithm proved its ability to solve large-scale location-routing problems in a reasonable time (Rabbani et al., 2018). The developed mathematical model and NSGA-II algorithm were coded with Matlab software using a personal computer with the following specifications: windows 10 enterprise operating system, 3.00 GHz CPU, A6-7310 APU AMD processor, and 16.00 GB of RAM.

3.2.1 Non-Dominated Sorting Genetic Algorithm II (NSGA-II)

NSGA-II is an evolutionary algorithm that solves mathematical models by duplicating and emulating the natural behavior of living organisms in surviving. Note that NSGA-II is a variant of the well-known genetic algorithm, which is faster in solving mathematical models and has a better sorting scheme. NSGA-II is a population-based search algorithm that generates a population of many solutions and then selects the fit solution that ensures achieving all objective functions. This algorithm is commonly used to solve VRP optimization problems with multi-objective functions where two or more objective functions have conflicting purposes (Srinivas & Deb, 1994). In VRP multi-objective problems, finding a global optimum solution that optimizes all objective functions simultaneously is nearly impossible. Therefore, the concept of Pareto-optimal solution is adopted in solving such problems. A Pareto solution concept ensures that no single solution that dominates all other solutions is selected; in other words, optimizing one objective function that dominates other objective functions is not feasible. Therefore, Pareto-optimal solutions are generated at each iteration of the model where no objective function can be improved without deteriorating the other objective functions. The resulting Pareto-optimal solutions are led by the best solutions, referred to as Pareto-front solutions. The following subsections present and demonstrate how NSGA-II works, including the main five solution stages: population initialization, non-dominated sorting, crowd distancing, crossover, and finally, mutation.

3.2.1.1 Population Initialization

Population initialization is the first stage in NSGA-II for solving mathematical models; it starts with generating a random initial population P_0 with a size of $N_{\text{population}}$, which is generated based on the complexity of the research problem and the number of constraints. As mentioned in previous sections, the evolutionary algorithms, including NSGA-II, emulate the nature of living organisms. In NSGA-II, the solution methodology imitates genetics, which has chromosomes, genes, and inheritances from parents, where a single chromosome presents one solution to the mathematical problem. In contrast, genes present the components of the model including decision variables. For instance, in a waste management network a chromosome can be presented as a multi-level matrix that presents essential nodes in the developed model, such as waste generation nodes (g), transfer station (k), different waste processing facilities (treatment (m), recycling (h), disposal (l)), different types of waste vehicles (collection vehicles (v), transportation semi-trailers (s), transferring semi-trailers (u)), different types of generated waste in the network (o, w, f), and finally the different types of technologies used in waste processing facilities (t, r, d). Table 1 in Appendix C shows an example of a solution chromosome in a waste management network that includes different genes (input data). Note that if the calculated decision variables comply with the model constraints, a chromosome is formulated, and a solution is generated to calculate the values of the objective functions. Keep in mind that altering the values of the genes in a chromosome will result in different objective function values, which will be shown in the next steps of NSGA-II.

3.2.1.2 Non-dominated Sorting

After generating the initial population of solutions, the algorithm will rank and sort every objective function in every chromosome (solution) according to its fitness function. Note that the sorting procedure is based on a non-dominance technique where the enhancement of an objective function doesn't lead to diminishing another objective function. After sorting the non-dominated solutions only, the algorithm finds the fittest solutions, which, as the name genetic algorithm implies, are the best fit (survival of the fittest) genes and chromosomes (solutions). The fittest solutions in the population are called Pareto front; for example, the non-dominated and fittest solutions are ranked as F_1 , which is the first and best rank of solutions. Then the remaining non-dominated solutions are sorted into other ranks such as F_2, F_3, \dots, F_N . Note that the evaluation of solution fitness is based on

the values of the objective functions, meaning that higher values are fittest in maximization problems and lower values are fittest in minimization problems.

3.2.1.3 Crowding Distance

After sorting the solutions according to the non-dominance rule and the Pareto front solutions are known, it is time to sort the resulting Pareto front solutions according to the crowding distance sorting. Crowding distance sorts solutions based on the density of the Pareto front solutions that surround a particular Pareto front solution; in other words, it measures the closeness of solutions to their adjacent solutions, which is measured according to equation C:

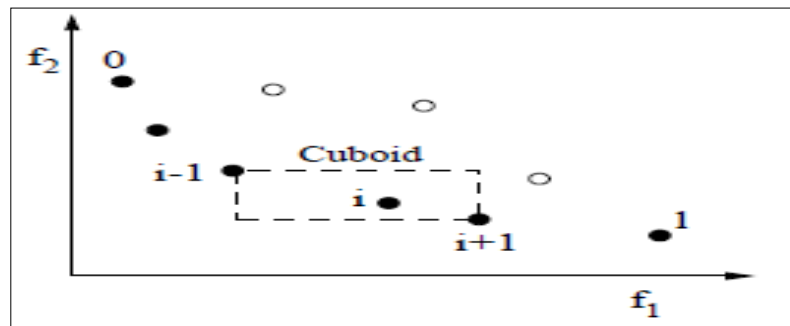
$$d_i^j = \sum_{i=1}^N \frac{f_j^{i+1} - f_j^{i-1}}{f_j^{max} - f_j^{min}} \quad (C)$$

Where f_j^{min} shows the smallest value of the individual objective function j , similarly f_j^{max} is the largest value of j , f_j^{i+1} and f_j^{i-1} are the values of the neighbor objective functions to j , which are $(i + 1)$ and $(i - 1)$ solutions.

The crowding distance aims to improve the diversity of the solutions to ensure a better set of solutions for the developed objective functions, where the larger the crowding distance, the better the diversity of the resulting Pareto fronts solutions. At the end of this stage, the Pareto front solutions with the largest crowding distance factor are chosen and passed to the next population. Figure 5 shows an example of crowding distance as adopted from Deb et al. (2000). Note that the Pareto front solutions, which are in the same rank (close to each other), are sorted in a dashed cuboid to select the solution with the highest crowding distance factor to be in the next generation.

Figure 5

Crowding distance process



Source: (Deb et al., 2000)

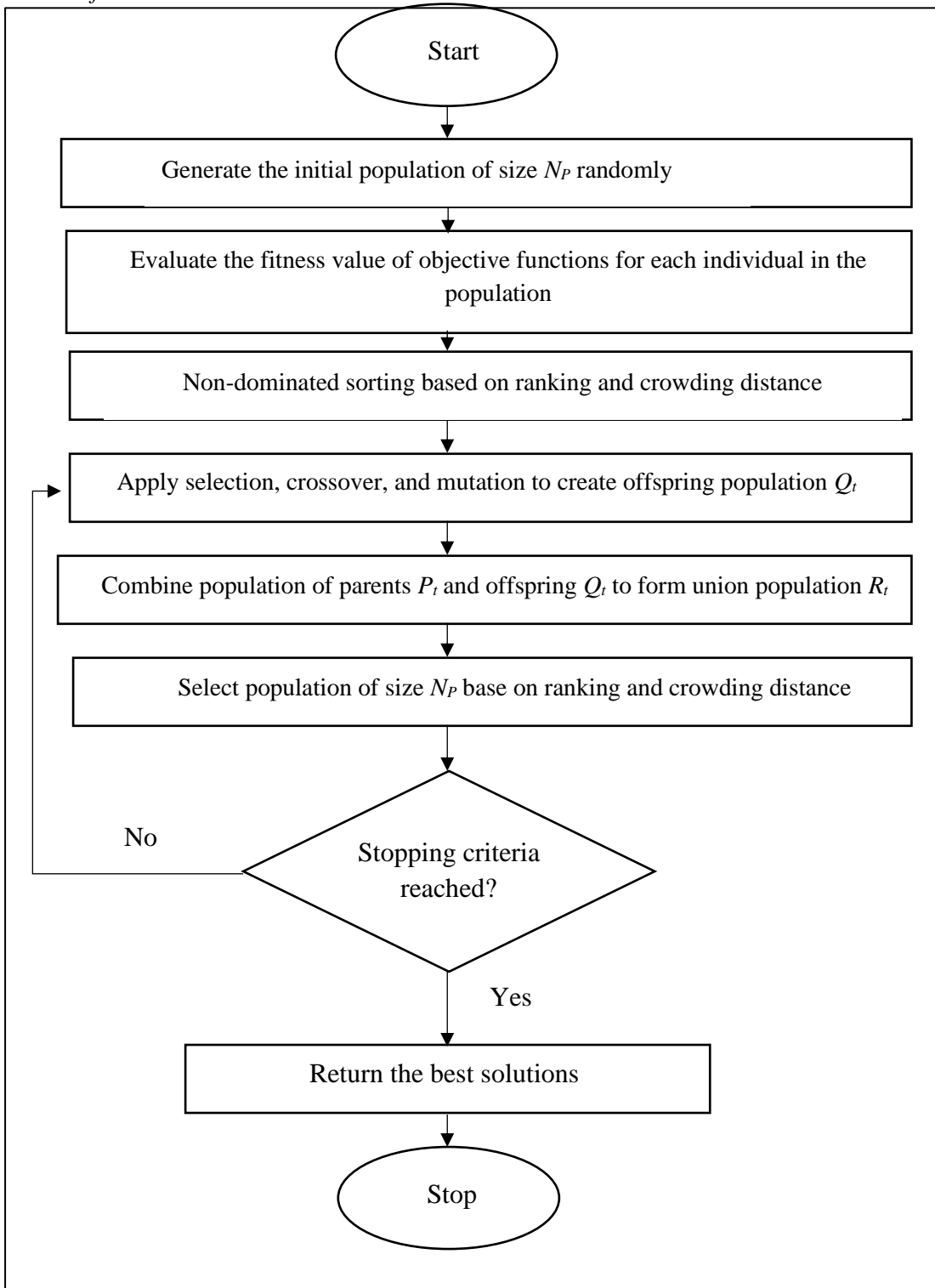
3.2.1.4 Crossover

After finishing the sorting process of the generated population, the algorithm continues enhancing the generated solutions. As mentioned in previous sections, the evolutionary algorithms adopt the nature of living creatures. Therefore, the enhancement process is inspired by the nature of genetics in terms of inheriting the parents' best features to the children (offspring). The process of producing offspring starts with tournament selection, which involves choosing two parents (solutions/chromosomes) randomly from the population of Pareto front solutions and comparing them in a tournament to select the best parent. The selection is based on the rank and the crowding distance of those parents, where higher rank and higher crowding distance parents are selected and ready to produce an offspring solution. Note that this process is repeated two times to choose parent 1 and parent 2 to be ready for the next step in producing an offspring, which is crossover. Crossover is an NSGA-II operator that shares and combines the DNA from the two selected parents to produce offspring, in other words, crossover randomly takes half of the genes in a chromosome (solution) from one parent and changes them with the other half of the genes from the other parent. The result is an offspring that could be better than both parents if it combines the best genes from both parents. Table 2 in Appendix C is an example of the crossover process in the proposed SWM network, where the highlighted genes from each parent are inherited to the offspring, as discussed in this section.

3.2.1.5 Mutation

Before adding the resulting offspring to the final population of solutions and repeating the process to generate different solutions, the final process in NSGA-II occurs, mutation. The mutation process involves randomly picking different genes from the offspring to be subject to altering to enhance the diversity and the applicability of the final solution, where modifying the value of any gene will change the value of the resulting objective functions. Table 3 in Appendix C shows an example of the mutation process. Note that the mutation process can be done by modifying the value of a gene by a percentage or completely reassembling the value of the gene, in addition, the discussed NSGA-II process can be repeated for a certain number of iterations if reached. For example, we can repeat the process for 100 generations and then select the best solutions, or it can be repeated until no significant change is noted. Moreover, Figure 6 shows a flowchart explaining the process of NSGA-II as adopted from Rabbani et al. (2018).

Figure 6
NSGA-II flowchart



Source: (Rabbani et al., 2018)

3.2.2 Solution Representation

As presented previously, in the proposed SWMVRP model, a driver assigned to a waste vehicle will travel from a transfer station to collect different types of waste from a waste generation node, and then travel back to its assigned transfer station. After that, every kind of waste is transported using a specific type of waste vehicle to its compatible waste processing facilities, including treatment, recycling, and disposal facilities. This process is carried out while considering the health state of the driver. Specifically, the developed model will calculate the probability of transiting from health to pain state and vice-versa, due to suffering from a work-related risk of injuries while driving. The solution using NSGA-II was carried out by an order-based encoding methodology, commonly used in mathematical problems to find solutions in the search space.

In our research problem, the chromosome is presented as a $(M + N + Q + HS) G$ matrix that illustrates one solution. The following components M, N, Q, HS, and G show the different types of waste in the network, different waste processing facilities, different types of waste vehicles, the health state of drivers, and waste generation nodes, respectively. Table 4 in Appendix C shows an example of a solution chromosome according to the presented matrix of components. Note that the first 3 rows show the 3 waste types generated at different generation nodes, whereas the next 3 rows show the visited waste processing facilities, which are treatment, recycling, and disposal facilities. Moreover, rows 7-9 show different types of waste vehicles used to collect and transport waste between different nodes in the network. Finally, the last two rows show the health state of drivers (healthy / pain state) after visiting each node in the proposed waste management network. Note that some of the cells in the chromosome are empty because, in some trips, some facilities are not visited, generation nodes are not ready for collection, some waste types are not accumulated, or one type of waste vehicle is not used.

After generating the values of the model parameters and inputs, it's time to extract the values of the decision variables and solve the developed objective functions. The solution procedure is divided into two stages: waste collection and waste transporting while considering drivers' health state and productivity. First, the destination nodes that contain waste generation nodes must be determined; after that, depending on the waste type, the capacity of waste facilities, and the waste processing technology, the destination to a treatment or recycling facility is determined. For example, if a waste vehicle collects one

type of waste, the destination to a waste facility, whether a treatment or a recycling facility, is made depending on the technology used in a waste facility and its available capacity to receive the load of the waste vehicle. This process continues until there are no nodes to visit concerning limitations and capacities set by the model. In the second stage which involves waste transportation, the decision variables concerned with the amount of processed waste and the resulting residues from treatment and recycling facilities are determined and transported to disposal facilities. Like the previous stage, the process continues until all treatment/recycling facilities are drained from residue or the capacity limits of disposal facilities are reached. Note that during the routing and transportation stages, the health state and productivity of drivers are monitored, as well as other model elements such as CO₂ emissions, fixed costs, transportation costs, and risk of accidents.

3.3 Data Generation

Regarding the used data (input data) in terms of model parameters, waste generation nodes for the three types of waste, and the different waste processing facilities that are used to solve the SWMVRP model, our approach depends on using randomly generated data through the random function MATLAB, due to the lack of real-world instances in the field of SWMVRP which simulate our research problem. In addition, the drivers' health state and the probability of changing the health condition between pain and healthy state were not considered before in the literature of VRP, therefore, some data was adopted from the work of Mojtahedi et al. (2021) and Rabbani et al. (2018), while the rest of data was assumed hypothetically in form of categories, mainly the values of the transition probabilities. The transition probability values were categorized into three categories based on the health condition of the driver such as age, unhealthy habits such as smoking, chronic diseases, and any health-related factors that affect driving. Note that unhealthy drivers refer to drivers who have health conditions that could potentially affect their ability to operate a vehicle safely, whereas healthy drivers are those who not only meet the standard health requirements for driving but are also in good overall health. Moreover, the third category of drivers is normal drivers which doesn't necessarily imply optimal health but rather refers to drivers who don't have any severe health conditions that significantly impede their ability to drive safely. Maintaining good health can contribute to better focus, reaction times, and overall safety on the road. The transition probabilities Θ and ρ are categorized as follows, where $\Theta \neq \rho$:

$$\theta = \begin{cases} 66.67\% - 100\% , & \text{for healthy driver} \\ 33.34\% - 66.66\% , & \text{for normal driver} \\ 1.00\% - 33.33\% , & \text{for unhealthy driver} \end{cases}$$

$$\rho = \begin{cases} 66.67\% - 100\% , & \text{for unhealthy driver} \\ 33.34 - 66.66\% , & \text{for normal driver} \\ 1.00\% - 33.33 , & \text{for healthy driver} \end{cases}$$

Table 5 in Appendix D shows different instances of the problem in terms of size (20 test instances), which includes small (P1 to P6), medium (P7 to P12), and large (P13 to P20) instances, which are presented later on this chapter to test the validity of the model. Note that the instances in Table 5 (Appendix D) were adopted from the work of Mojtahedi et al. (2021). In addition, Table 6 in Appendix D presents the parameters used to generate instances in the mathematical model, and their values. Note that the values are adopted from the work of Mojtahedi et al. (2021), and they are presented as random functions.

3.4 Routing Stage Results

This section presents the results related to the routing plan of waste collection vehicles, which will travel from transfer stations to collect different types of waste from waste generation nodes. Table 1 presents the results of the routing stage. It mainly illustrates the route that waste collection vehicles follow, starting and ending from a specific transfer station. In addition, Table 1 shows the amount of collected waste by each vehicle, as well as the total traveled distance. Note that since each generation node may contain different types of waste, each node may be visited once or more, as shown in Table 1. Moreover, nine waste collection vehicles of type v were used in this solution. For example, vehicle no. 1 starts routing from transfer station 9 to collect waste from waste generation nodes 4, 9, 2, and 5, and it is dedicated to collecting waste type 3. Furthermore, Tables 7 and 8 in Appendix D show a detailed description of vehicle waste load, the distance traveled for each vehicle, and its assigned route.

Table 1
Routing stage results

Waste type o	Vehicle type v no.	Transfer station node no.	Collection route	Amount of load (kg)	Travelled distance (Km)
1	7	5	G8-G10-G7-G6	443	272
	3	3	G2-G11-G4-G5	393	243
	5	8	G12-G9-G1-G3	450	268
2	4	2	G12-G4-G6-G8	430	363
	6	6	G1-G11-G10-G2	471	252
	2	7	G5-G9-G7-G3	425	323
3	9	1	G11-G7-G3-G8	364	234
	8	4	G1-G12-G6-G10	316	321
	1	9	G4-G9-G2-G5	484	381

3.5 Transportation Stage Results

In the transportation stage results, the second and the third echelon of the model are discussed and interpreted. In echelon II, waste vehicles of type s were used to collect and transport different types of waste from different transfer stations to one of the waste processing facilities, either treatment, recycling, or disposal facilities. Table 2 shows the results of the waste transportation process in echelon II. As shown in Table 2, each waste vehicle is assigned to transport one type of waste, and it starts from a transfer station to collect the same type of waste from the other transfer station to arrive at one of the waste processing facilities. Note that, as mentioned earlier, (M) refers to a treatment facility, (H) refers to waste recycling facilities, and (L) indicates a waste disposal facility. In addition, the last column shows the total traveled distance by each vehicle, and concerning the vehicle's load, each vehicle must empty the carried waste at its destination. In echelon III of the proposed waste management network, waste vehicles of type u are used to transport residues from different waste treatment and recycling facilities to disposal centers. Like echelon II, the vehicles start from a transfer station and return to the same station. Table 3 below and Table 9 (in Appendix D) show detailed results regarding echelon III of the developed model, which includes the route that wastes vehicles of type u followed to collect and transport residues between different facilities, in addition to the total travel led distance and the total load of waste carried by each vehicle. Note that the

travel distance and vehicle's load have a significant impact on different objective functions of the model as will be discussed in the next sections and chapters of this thesis.

Table 2

Transportation stage results (Echelon II)

Waste type w	Vehicle type s no.	Transfer stations Route	Waste facility (destination)	Travelled distance (Km)
1	2	T.S 5 → T.S 3 → T.S 8	1 M	230
	9	T.S 2 → T.S 6 → T.S 7	2 M	286
	6	T.S 1 → T.S 4 → T.S 9	3 M	231
2	3	T.S 5 → T.S 3 → T.S 8	3 H	204
	5	T.S 2 → T.S 6 → T.S 7	1 H	260
	1	T.S 1 → T.S 4 → T.S 9	2 H	255
3	4	T.S 5 → T.S 3 → T.S 8	3 L	256
	8	T.S 2 → T.S 6 → T.S 7	2 L	309
	7	T.S 1 → T.S 4 → T.S 9	1 L	221

Table 3

Transportation stage results (Echelon III)

Waste type f	Vehicle type u no.	Transfer stations Route	Waste facility (destination)	Travelled distance (Km)
1	1	T.S 5	2 M → 2 H → 3 L	187
2	2	T.S 2	1 H → 3 M → 2 L	234
3	3	T.S 1	3 H → 1 M → 1 L	212

3.6 Penalty Costs and Health Condition of Drivers

This section highlights the results related to the second objective function, which aims at minimizing the costs resulting from being late in collecting or transporting different types of waste from and to transfer stations and different waste facilities. The costs are incurred due to the change in the health state of drivers due to suffering from a work-related injury that causes pain and discomfort in driving, and thus arriving late to different nodes. As

discussed in previous chapters, the model assumes two health conditions of drivers: health state – where drivers are healthy and not suffering from any injuries or discomfort- and pain state – where work-related injuries affect drivers and cause a degradation in performance and productivity of drivers. Note that the performance and productivity of drivers are often measured by the total travel distance and the time needed to cover a certain distance. In our approach, the productivity of drivers is measured based on the time needed to collect and transport waste to different nodes in the network, and any late delivery will result in penalty costs incurred by the waste management company. In our developed model, the variables $time_{hs}^{Dq}$ and $time_p^{Dq}$ are used to measure the performance of drivers. Specifically, the model assumes a municipal route with a speed of 50 - 60 km/hr, for healthy drivers, and a relative decline in speed for drivers under pain state based on the severity of the injury. In addition, the penalty cost is a parameter set to \$100, changing according to the late time of expected delivery. Moreover, the health state of drivers at the beginning of the route is assumed to be perfectly healthy, and as the route goes. Drivers travel between nodes, and a probability of transiting from a healthy state to a painful state arises due to injuries that include but are not limited to back pain, fatigue, overexertion, muscle strains, etc. (Pickard et al., 2022), these injuries will degrade the health of drivers and thereby more time is needed to reach destination and thus incurred penalty. Table 4 shows this section's results, including the waste type, the number of waste vehicles, the selected route, the health condition of drivers after each node, and the incurred penalty after the end of the route. In this table, the routing stage is analyzed to show the health condition of drivers. Note that a driver starts with a high health state, and the health state keeps dropping after each node due to the possibility of suffering from different work-related injuries. In addition, on the routes with high travel distances the probability of transiting to a pain state becomes higher due to more driving time, which is the main cause of fatigue and muscle pain, as shown in routes (T.S 2→G12→G4→G6→G8→T.S 2) and (T.S 9→G4→G9→G2→G5→T.S 9) which have the highest travel distance referring to Table 8 in Appendix D that shows a detailed description of the travel distance. Moreover, higher penalty costs are incurred in routes with higher distances and in case of a sudden drop in health state due to a series injury. In addition, routes (T.S 5→G8→G10→G7→G6→T.S 5) and (T.S 1→G11→G7→G3→G8→T.S 1) show drivers with some health problems, whereas route (T.S 3→G2→G11→G4→G5→T.S 3) shows unhealthy driver which reflects on the

health state value and the penalty costs. Moreover, Figure 7 shows a graphical presentation of the change in the health state of the driver operating vehicle number 5 on the route (T.S 8→G12→G9→G1→G3→T.S 8). Finally, it should be mentioned that in many cases, drivers can collect and transport waste in the network and finish their duty without suffering from injuries or entering pain states; however, in our approach, it is assumed that work-related injuries are present in each route to highlight the effect of drivers' health condition on the waste management network.

Figure 7
Driver's health state along the route

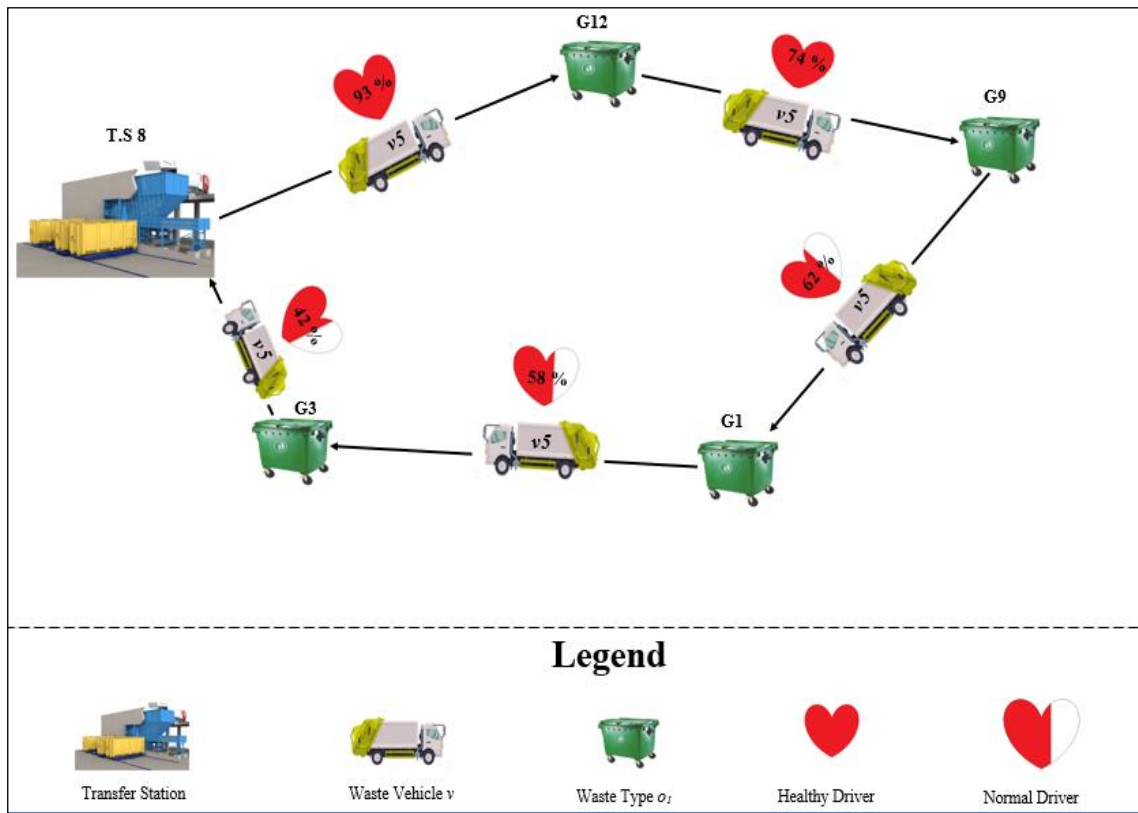


Table 4*Penalty costs and drivers' health condition results*

Waste type <i>o</i>	Vehicle type <i>v</i> no.	Route	Health condition (%)	Travelled distance (Km)	Penalty costs (USD)
1	7	T.S 5→G8→G10→G7→G6→T.S 5	65→61→55→53→50→48	272	254
	3	T.S 3→G2→G11→G4→G5→T.S 3	33→31→29→27→23→18	243	409
	5	T.S 8→G12→G9→G1→G3→T.S 8	98→93→74→62→58→42	268	312
2	4	T.S 2→G12→G4→G6→G8→T.S 2	99→89→85→74→68→54	363	390
	6	T.S 6→G1→G11→G10→G2→T.S 6	95→90→84→69→65→60	252	187
	2	T.S 7→G5→G9→G7→G3→T.S 7	97→88→82→73→66→56	323	381
3	9	T.S 1→G11→G7→G3→G8→T.S 1	66→55→51→49→48→46	234	315
	8	T.S 4→G1→G12→G6→G10→T.S 4	94→90→85→79→73→63	321	347
	1	T.S 9→G4→G9→G2→G5→T.S 9	98→87→79→70→63→57	381	408

3.7 Near-Optimal Solution for the Objective Functions

Table 5 shows the results of the five developed objective functions. Since VRP is considered as an NP-hard problem and solved by a heuristics method, the solution presents near-optimal results rather than optimal ones. Table 5 shows the near-optimal solutions for the total costs (fixed and transportation), penalty costs due to drivers' health condition, CO₂ and GHG emissions, the deviation from fair load allocation, and the risk of accidents, respectively. After reviewing the results in this table, we conclude that the fixed and transportation costs that are illustrated in Z_1 , vary between the 3 different vehicles. This is due to the difference in fuel consumption, type, and load capacity between those vehicles. Also, the same conclusion can be applied to the CO₂ emissions shown in Z_3 , due to the difference in vehicle type. Regarding Z_2 which shows the penalty costs due to the driver's health condition, the difference in vehicle type is not critical, since the drop/change in health state is caused by travel distance, amount of vehicle load, and the probability of suffering from work-related injuries. Furthermore, the workload balance shown in objective function Z_4 applies only to the waste collection level using waste vehicle type ν and their drivers and doesn't affect the other drivers in the other 2 levels, since the waste collection level includes many drivers and many waste nodes that must be visited in many locations, therefore, adequate workforce planning must be done. Finally, Z_5 shows the risk of accidents as a cost function, and since the risk of accidents is measured based on the travel distance and the amount of waste, different results were generated in the 3 levels. Again, vehicles type ν in the waste collection level possess the higher costs of accidents due to the high travel distance and the large amount of waste that must be collected as discussed previously.

Table 5
Near-optimal solution for the developed model

Vehicle type	Z_1	Z_2	Z_3	Z_4	Z_5
v_1	16732	180	11653	9.562	175350
v_2	22727	163	23302	8.045	186480
v_3	22174	312	108	10.613	179970
v_4	16745	390	19499	8.59	206850
v_5	22320	187	23401	9.685	193725
v_6	18506	381	21952	9.76	162540
v_7	24748	201	9021	10.32	168420
v_8	16623	347	30922	7.098	148260
v_9	18746	408	21333	7.98	193935
s_1	19660	174	16435	-	124075
s_2	17947	218	28968	-	95200
s_3	13210	366	9782	-	124810
s_4	14537	199	13040	-	99120
s_5	18397	254	13818	-	106575
s_6	14490	318	13980	-	119455
s_7	15379	166	4616	-	96040
s_8	22810	403	13903	-	103635
s_9	16732	208	7165	-	102340
u_1	12780	248	4649	-	104230
u_2	14955	225	5424	-	123760
u_3	11227	174	8694	-	108990

3.8 Sensitivity Analysis

A sensitivity analysis was conducted to investigate the strength and robustness of the developed SWMVRP model, and to understand how different parameters of the model interact with each other and their effect on objective functions. Our approach in the sensitivity analysis highlights the impact of the main parameters and variables of the model, which includes testing different problem sizes (test instances) to make sure that the model is applicable and practical to solve different scenarios in terms of problem size.

In addition, a sensitivity analysis section was devoted to investigating which objective function related to cost has the strongest effect on the total optimal solution. Moreover, the fixed cost, transportation costs, and amount of waste in generation nodes are varied to understand their effect on the different objective functions of the model, and results are compared to the ones presented in the work of Mojtahedi et al. (2021). Furthermore, the travel distance and vehicle load variables are varied to explore how they affect the health condition of drivers. Finally, a managerial insights section is discussed to spot light on the practical implications of the developed model.

3.8.1 Test instances

To test the effectiveness of the proposed model in offering satisfactory solutions for the waste management network under examination, it is necessary to test it with various problem sizes. When real-life instances are accessible, the model's validity can be confirmed by generating acceptable solutions. However, since such instances are lacking in the existing literature of SWMVRP, an alternative approach for model verification involves using instances of different sizes. The drawn results in the previous chapter assumed a medium size problem with twelve generation nodes, nine transfer stations, nine waste vehicles of type v , nine waste vehicles of type s , and three waste vehicles of type u . In addition, three waste processing facilities of each type (treatment, recycling, and disposal) were assumed, where three different possible types of waste can be found in generation nodes, transfer stations, and treatment/recycling facilities as explained and discussed in the developed model. Table 10 in Appendix E shows the scenarios where each scenario presents a different-sized test instance. Also, Table 11 in Appendix E shows the results of the five developed objective functions of the SWMVRP model in different instances. In the aforementioned table, the values of all objective functions arise as the problem size increases, which is a reasonable situation given the increase in different node types, as well as, the number of waste vehicles in the waste management network. For example, the value of the first objective function increases as the problem size increases, since it deals with the fixed and transportation costs of vehicles; thus, as the number of vehicles increases and the travel distance increases, more costs are incurred in the form of fuel, maintenance, and other costs. Also, in the second objective function, we notice an increase in the penalty costs due to the decrease in drivers' health conditions due to the increase in total travel distance and the total collected/transported waste. Note that as

the network expands (in terms of nodes and waste vehicles) in size, the total traveled distance and the total amount of collected, transported, and processed waste increases which is the reason why we notice an increase in the values of the objective functions. However, in some situations, as in instance S8 a decrease in values is observed, which is because although the network expands in size, the travel distance and the total amount of waste in the network can be less than smaller sized instances. Finally, the last column in Table 11 (Appendix E) shows the solving time of the instances; note that as the instance increases, the solving time increases.

3.8.2 The Effect of Altering Cost-Related Objective Functions Weights

In order to comprehend the impact of each objective function on the total near-optimal solution, we iteratively modify the weights of the objective functions. This involves assigning a higher weight to each function one at a time. However, in this section, our approach is to explore and understand the effect of cost-related objective functions on the total solution. Therefore, our main focus is Z_1 , Z_2 , and Z_5 . Thus, we define a new function, which is as shown in equation D:

$$Z_{cost} = Z_1 + Z_2 + Z_5 \quad (D)$$

Where Z_{cost} is the total cost function. The results of the total cost nearly optimal solution under different weight variations for the three objective functions are presented in Table 12 and Figure 4 in Appendix E. The table displays four scenarios, one of which is the equivalence status, where all functions are assigned the same weight. After examining the obtained results, it was found that the fifth objective function Z_5 , which aims at minimizing the travel risk, has the highest effect on the total cost function, where $Z_{cost} = 6,230,800$ \$, while the other objective functions have a moderate effect on the total cost function. Note that objective function Z_5 relies on the total travel distance and the amount of waste in the network. Therefore, close attention must be given to travel distance and the amount wasted by decision-makers to ensure that extra costs aren't incurred. Indeed, planning the route of different waste vehicles in the waste management network, as well as planning and forecasting the amounts of accumulated waste, have a significant effect on the total costs and must be planned adequately.

3.8.3 The Effect of Key Parameters on the Objective Functions

Conducting a sensitivity analysis allows us to evaluate the potential variability of the proposed model when the key parameters are varied. Therefore, key parameters are varied individually to examine their effect on objective functions. Specifically, the fixed costs of waste vehicles FC_q , the transportation costs between different nodes in the network TC_{ij}^q , the amount of waste accumulated at generation nodes BG_{og} , and the total number of waste vehicles Q . The effect of those parameters is tested on all objectives. In addition, the conducted sensitivity analysis is compared to the results found in the work of Mojtahedi et al. (2021). The sensitivity indicator is determined by calculating the average value of each objective function across all non-dominated solutions for a range of values in each parameter. Tables 6 – 7 and Tables 13-14 (Appendix E) show the results of the conducted sensitivity analysis. The first drawn result in this section is the effect of the vehicles' fixed costs on the objective functions under study, as shown in Table 13 in Appendix E. From the results, we conclude that as the fixed costs increase, the first objective function Z_1 , which aims at minimizing the total costs, changes broadly; the CO₂ emissions objective function Z_3 was slightly affected by the increase in the fixed costs and an odd relationship was noticed the value of Z_3 increased with the increase in fixed costs to a certain point until it falls and increase again. Concerning the social objective function Z_4 , a minor change was observed in its value as the value of the fixed costs changed. Moreover, the values of Z_2 and Z_5 were not affected by the change in the FC_q , which is expected since neither the penalty costs nor the cost of accidents are directly related to the fixed costs. However, an odd change in the value of Z_2 was noticed in the fourth scenario. In Table 13 (Appendix E), the value of FC_q was changed by multiplication of 2, 4, and 6 to investigate its effect on the model's objectives.

Furthermore, the second key parameter to explore its effect on the objective functions is the transportation (variable) costs TC_{ij}^q . An examination of Table 14 (Appendix E) reveals that the responses of the objective functions are steadier when it comes to changes in the value of TC_{ij}^q compared to variations in the value of FC_q . As the transport cost increases, both the total cost Z_1 and green emissions Z_3 reveal a consistent upward increase. However, the total deviation from fair load allocation Z_4 , the penalty costs due to the change in health state Z_2 , and the cost in the form of risks of accidents Z_5 show a minor change, and no clear correlation is observed between it and the increase in transportation

costs. In summary, as TC_{ij}^q rises, financial and environmental costs also increase, while the social impact exhibits minor insignificant change. Similarly, the value of TC_{ij}^q was changed by multiplication of 2, 4, and 6.

The sensitivity analysis on the effect of the amount of waste at generation nodes (BG_{og}) is illustrated in Table 6. Upon reviewing the results, it becomes evident that the objective functions reflect certain trends. The total cost Z_1 , green emissions Z_3 , penalty costs Z_2 , and the costs of accidents Z_5 consistently rise as the amount of waste at waste generation nodes increases. Conversely, the total deviation from fair load allocation Z_4 shows a steady decrease with increased waste at waste generation nodes. To put it simply, overall, as BG_{og} rises, there is a continuous increase in both the financial and environmental costs while the social impact experiences a steady reduction. Note that the relationship between the parameters is reasonable and can be predicated since the increase in the amount of accumulated waste needs extra trips and extra vehicles and, thus, additional costs and CO₂ emissions. In addition, as BG_{og} rises the total load of waste vehicles will be higher and will reach the maximum load of the vehicle, which increases the probability of accidents since heavier vehicles are harder to drive and operate compared to lighter ones. Note that the relationship between health state and vehicle load is discussed in the next section. In contrast, extra workload among drivers and workers will be incurred, which hinders fair load allocation, which can be observed in the developed mathematical model in previous chapters. As the previous parameters in this section, the value of BG_{og} was changed by a multiplication of 2, 4, and 6.

Table 6

Sensitivity analysis of the amount of waste at generation nodes

Scenario	BG_{og}	Z_1	Z_2	Z_3	Z_4	Z_5
S1	1	650,239	32,489	30,512	103.22	2,853,235
S2	2	668,051	39,986	31,986	99.28	3,154,985
S3	4	892,741	43,114	33,007	98.61	3,412,763
S4	6	1,103,685	45,862	35,710	95.88	3,974,588

Finally, the last key parameter to be examined is the total number of waste vehicles, which includes the three types proposed in the model (v,s,u). Analysis of Table 7 – which presents the relationship between the number of each vehicle type and their effect on the

objective functions - reveals that the responses of the objective functions are consistently aligned with variations in the value of Q . Specifically, as the total number of vehicles increases, the total cost Z_1 , penalty costs Z_2 , green emissions Z_3 , total deviation from fair load allocation Z_4 , and the risk of accidents Z_5 , all show a steady rise. The financial, environmental, and social impacts increase progressively as the total number of vehicles rises. After reviewing and analyzing the obtained results, the increase in all objective functions when increasing the number of different types of waste vehicles in the network is realistic and expected. The increase in fleet size yields extra fuel consumption, extra insurance and maintenance costs, more travel distance, and more workload. Moreover, the increase in fleet size increases the probability of suffering from work-related injuries which results in extra penalty costs, in addition to the higher probabilities of road accidents.

Table 7
Sensitivity analysis of the number of waste vehicles fleet

Scenario	v	S	u	Z_1	Z_2	Z_3	Z_4	Z_5
S1	12	12	4	965,580	69,125	77,965	153.16	7,027,986
S2	18	18	6	1,219,621	76,874	79,800	245.88	8,680,777
S3	24	24	8	1,907,962	151,063	128,017	599.56	13,930,845
S4	30	30	10	2,402,744	160,179	149,969	705.98	15,175,006

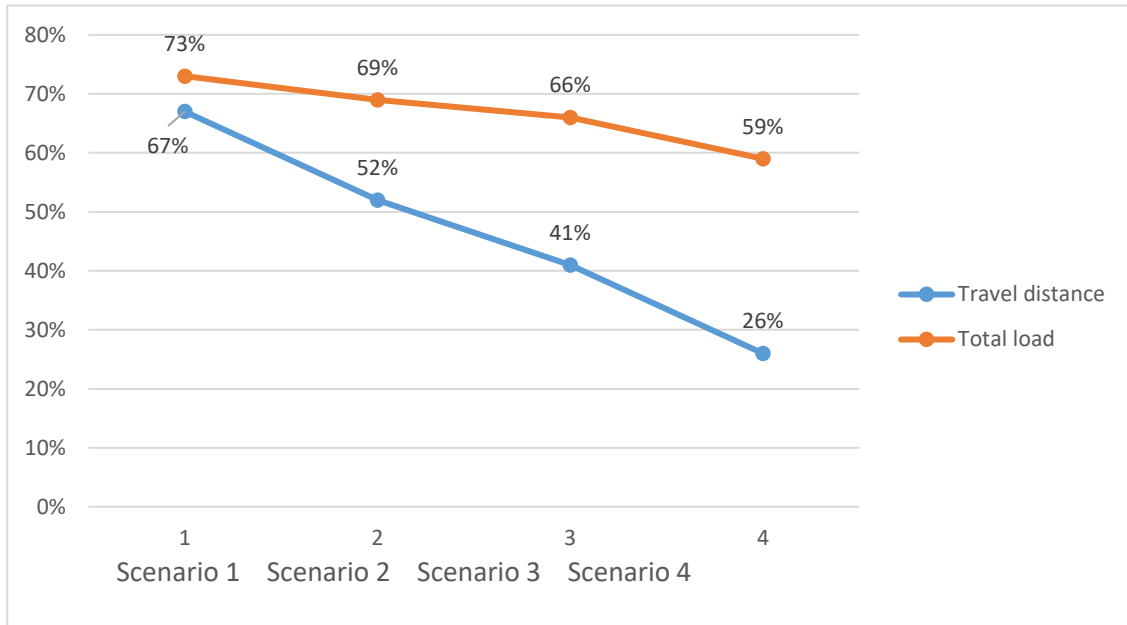
3.8.4 The Effect of Travel Distance and Vehicle's Load on Driver's Health Condition

The last relationship to be examined in this chapter is related to the health state of drivers, mainly how altering the travel distance and the amount of load in waste vehicles will affect the health state of drivers, which is shown in the second objective, functions as penalty costs. The results of altering the total traveled distance are shown in Table 8, while the effect of altering a total load of waste vehicles along the route is shown in Table 9. Moreover, the relationship between those variables is plotted in Figure 8. Tables 9 and 10 present four different scenarios in which the travel distance is increased and the total load is increased as well to explore the relationship. Also, five generation nodes were assumed, where the route starts and ends from the same transfer station. As shown in the results, the relationship between those variables can be described as follows: as the traveled distance and the total load increase, the health state decreases, thereby, penalty

costs are incurred. However, the distance traveled has a greater effect on health than the total load.

Figure 8

The relationship between health state traveled distance, and vehicles' total load of waste



3.8.5 The Effect of Altering the Health State of Drivers on the Penalty Costs.

This section aims to reveal and discuss the relationship between different drivers' health status and the model's objective functions, mainly the Z_2 . Altering the health state of drivers is expected to affect the developed model, however, we aim to highlight the effect on the second objective function due to the existing direct relationship. Table 8 shows the results of the conducted sensitivity analysis on three different health states of drivers based on the category shown in Chapter Five which is unhealthy, normal, and healthy drivers. Results showed an inverse relationship between drivers' health state and penalty costs, where a healthy driver yields a decrease in penalty costs (saving costs) compared to the unhealthy and normal drivers. This outcome is expected and reasonable since healthy drivers require lower driving time to collect and transport waste between nodes, and thus arriving and leaving on time without incurring any late collection/delivery costs. In addition, Figure 9 graphically presents the relationship between the three health states and the incurred penalty costs.

Table 8

The effect of driver's health state on penalty costs

Scenario	Health State	Z_2
S1	Unhealthy (Pain state)	52,255
S2	Normal	44,625
S3	Healthy	31,547

Figure 9

The relationship between drivers; health state and penalty costs

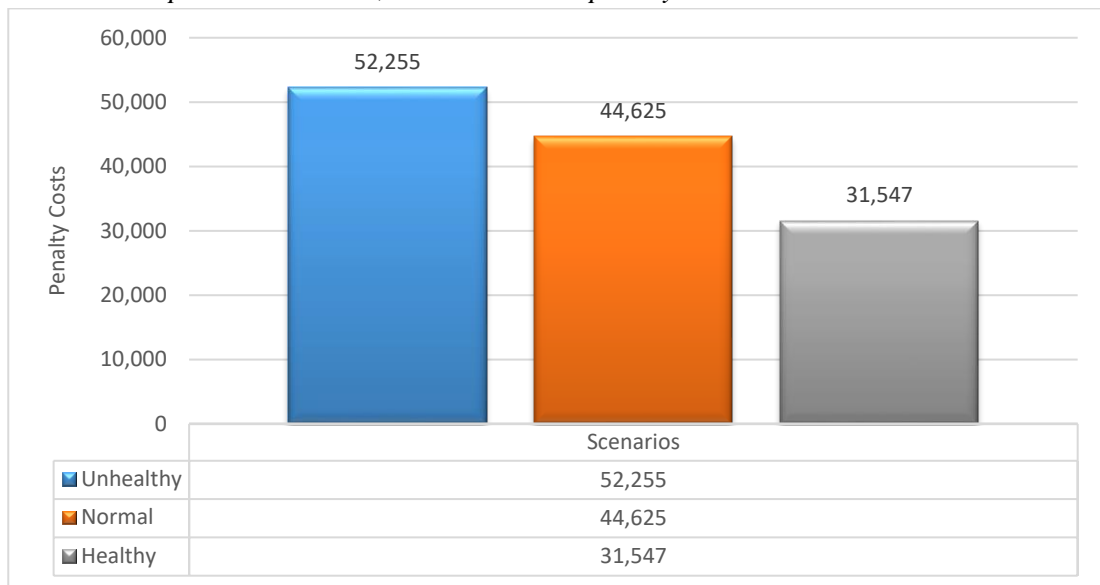


Table 9*The effect of travel distance on driver's health state*

Scenario	Route	Traveled distance (Km)					Total Travelled	Z ₂ (\$)
S1	T.S→G5→G3→G2→G1→G4→T.S	52	69	85	45	51	302	217
S2	T.S→G1→G5→G4→G2→G3→T.S	31	105	95	88	102	421	475
S3	T.S→G3→G1→G2→G4→G5→T.S	106	93	79	118	140	536	605
S4	T.S→G1→G4→G3→G5→G2→T.S	151	143	128	144	152	718	890

Table 10*The effect of vehicle's load on driver's health state*

Scenario	Route	Load of waste after visiting node <i>i</i> (kg)					Total load (kg)	Z ₂ (\$)
S1	T.S→G3→G1→G4→G5→G2→T.S	0	120	146	111	73	450	198
S2	T.S→G2→G5→G3→G1→G4→T.S	0	184	221	166	209	780	367
S3	T.S→G5→G4→G1→G3→G2→T.S	0	290	306	276	193	1,065	420
S4	T.S→G4→G2→G5→G1→G3→T.S	0	435	389	381	415	1,620	496

Chapter Four

Discussions and Conclusions

4.1 Discussion

In this research, an SWMVRP model was developed, presented, and discussed to achieve the three pillars of sustainability, which includes the consideration of economic, environmental, and social issues for the sake of all stakeholders, including the drivers, society, the environment, and waste management companies that seek profit. In addition, this research considers the health state of drivers operating the different types of waste vehicles. In other words, the model shows the health state of drivers after each visited node to check if the driver is healthy or facing a work-related injury while driving such as fatigue, muscle pain, back pain, or any other injuries. Moreover, the emphasis on the social element in the waste management network is supported by developing an objective function that aims at minimizing the risk of accidents through the total traveled distance by the driver and the total amount of waste collected or transported, along with taking into consideration a fair allocation of workload among drivers. Furthermore, our approach was to develop a comprehensive model that applies to real-world problems. Therefore, the total costs of the waste management network, including fixed and variable costs, were considered, along with the CO₂ emissions, in three different echelons rather than one. This offers a realistic scenario of how waste management companies conduct business. The model was solved using an NSGA-II due to its capability to resolve complex NP-hard problems specially SWMVRP and other waste management models, since NSGA-II provided good results with reasonable solving time, as shown in the work of Rabbani et al. (2018). The results of the model were presented in three main stages: the routing stage which includes the waste collection process from generation nodes; the transportation stage, which concerns the transportation of waste between transfer stations and waste processing facilities; and finally, results related to the drivers which include the health state of drivers, the penalties incurred due to the decrease in the driver's health condition, and the risk of accidents. Also, a sensitivity analysis was conducted that revealed the relationship between different model objectives and key parameters such as fixed costs, transportation costs, the amount of waste at generation nodes, and the number of waste vehicles in the network, as well as the effect of altering the travel distance and the amount of collected/transported waste on drivers' health state. The total near-optimal

solution was found to be affected significantly by the fifth objective function that aims at minimizing the risk of accidents and, therefore, must be considered seriously. The obtained results and the conducted sensitivity analysis can be a guideline for decision-makers in the field of SWM to make wise decisions regarding the well-being of drivers, society and the environment alongside the financial profit and economic success.

4.2 Research Contributions

Many efforts and contributions were made in the field of waste management VRP in general and SWMVRP in particular; however, a few of which focused on and highlighted the role and the well-being of the social factor, including the drivers and the society living near the routes. Therefore, the main contribution of this research is the deep consideration of the social pillar of sustainability in the field of SWM. This thesis's contributions can be stated as follows: the first contribution of this research is the development of a mathematical model that solves a SWMVRP while considering the financial, environmental, and social factors; also, the model is considered a waste management network that simulates real-world problems in this field. The second contribution is the consideration of the well-being and the health of waste vehicles drivers, mainly by assuming two different health states of drivers which include a healthy state and a pain state, which are determined by the probability of facing the work-related risk of injuries while driving, such injuries are many but the most common is fatigue due to driving long hours and distances, as well as, the injuries in muscles and lower back pain. Moreover, the model analyzes the risk of accidents that may affect the driver and the surrounding society due to the transportation of different types of waste that may contain hazardous materials. To the best of our knowledge, this approach was not considered before in the field of SWMVRP. Our research encourages the monitoring of drivers' health state while collecting or transporting waste due to the many significant gains that can be achieved, mainly in enhancing drivers' productivity, which leads to financial profits and meeting corporate social responsibility goals.

4.3 Managerial Insights

In all countries, mainly developed and developing ones, the number of waste facilities and waste generation nodes keeps increasing due to urbanization and industrial activities. In those countries, waste management is of great interest due to its effect on society and

all stakeholders living nearby. Therefore, waste management must be planned adequately in all sectors, including logistics and transportation. Thus, presenting simply waste management VRP models is not feasible. Our approach introduces a rich, comprehensive model that tackles real-world applications and is close to practical implementation. Practicality needs comprehensive models covering multiple objectives and constraints that mirror real-life situations. However, in under developed (least developed) countries and some of developing ones, applying the proposed SWM model in this research will be a challenge and perhaps not possible. Mainly due the absence of private SWM companies, as well as, the lack of resources (facilities) and poor SWM practices in municipalities.

Additionally, it must possess authenticity to offer managerial insights crucial for facilitating effective decision-making. Within this model, the outcomes and the sensitivity analysis carried out in our study can be utilized to support the decision-making process. First and foremost, the developed model illustrates the importance of monitoring the health state of drivers since it is connected to productivity in accomplishing the daily workload. For instance, Tables 9 and 10 in the conducted sensitivity analysis show the effect of the total travel distance and the total amount of collected/transported waste on the health state of drivers. Of course, a daily workload must be covered and a certain amount of waste must be processed without neglecting or postponing any of the scheduled activities. However, planning the workforce and the routes adequately ensures the carrying out of business perfectly and guarantees drivers' well-being. Note that results from the conducted sensitivity analysis suggest that if the health state of drivers drops, productivity drops, and thereby, the time needed to get the job done will increase significantly, thus, penalty costs will be incurred due to late delivery. Furthermore, Tables 6 – 7 and Tables 13-14 (Appendix E) demonstrate the effect of the main parameters, which are fixed costs, transportation costs, total amount of waste at generation nodes, and the total number of vehicles in the network. Results show the great effect of the number of used vehicles since it requires different types of costs for operation, produces more CO₂ emissions, and results in extra workload on drivers; therefore, before increasing the fleet of waste vehicles, careful consideration must be taken on the mentioned aspects.

4.4 Limitations

Although our efforts were directed towards developing a comprehensive model that answers to real-world problems, which include rich parameters, variables, and multi-objectives, some model limitations arise that hinder the efforts to develop practical models. The following are the main limitations of the proposed SWMVRP model:

- **Hypothetical data:** While some of the data employed in the developed model was drawn from existing literature, it should be noted that most of the data were suggested hypothetically. The integration of empirical real-world data and instances from existing literature, if accessible, has the potential to refine the model and amplify its practical relevance.
- **Deterministic models:** The proposed model was developed as a deterministic one that includes deterministic parameters, which, after solving the model, will generate deterministic results. On the other hand, considering fuzzy, stochastic values yields more practical and realistic models to solve real-world problems.

4.5 Future Work

The work in improving the existing mathematical models in the field of SWMVRP will continue since there is always room for enhancement. The following bullets include some recommendations for future work that will significantly improve the proposed model.

- **Smart SWMVRP:** Lately, the use of technology is embedded in all of our daily activities and sectors, including the logistics and transportation sectors. In the field of waste management, previous efforts were made to incorporate technology in waste management VRP in the form of volume sensors to provide continuous data about the level of waste in bins (Ramos et al., 2018). However, our recommendation is to incorporate body sensors that transmit real-time data about the health state (mainly fatigue) of drivers as shown in the work of Kaplan et al. (2015) to help plan the routes and the drivers' workload.
- **Drivers' differences:** considering different driver's behavior is a solid addition to the proposed model since it will result in a more realistic and practical model as driving behaviors differ from one driver to another. Such behaviors are discussed in Abu Al Hla et al. (2019) work, where drivers are assumed to be risk takers, risk-averse, or neutral risk takers. In addition, drivers may have different Green Driving Indexes,

which reflect the driver's knowledge of environmentally friendly driving techniques and behavior as shown in the work of Asrawi et al. (2017).

- Dynamic SWMVRP model: developing a dynamic version of our model will improve its applicability in the real world. In this model the dynamism, include the possibility of changing routes, workload, and possibility the drivers to overcome the issue of suffering from work-related injuries. Note that dynamic VRP models require different solution methodologies in terms of algorithms and programming.

List of Abbreviations

Abbreviation	Meaning
AC-VRP-SPDVCFP	Asymmetric and Clustered Vehicle Routing Problem with Simultaneous Pickup and Deliveries, Variable Costs and Forbidden Paths
AFVs	Alternative-Fuel powered Vehicles
AMO	Ability, Motivation, and Opportunity AMO theory
CVRP	Capacitated Vehicle Routing Problem
DFA	Discrete Firefly Algorithm
DVRP	Dynamic Vehicle Routing Problem
EVRP	Electric Vehicle Routing Problem
FMEA	Failure-Mode-and-Effects-Analysis
GA	Genetic Algorithm
GDI	Green Driving Index
GHG	Green House Gases
GOVRPTW	Green Open Vehicle Routing Problem with Time Windows
GVRP	Green Vehicle Routing Problem
HEVs	Hybrid Electric Vehicles
HVRP	Heterogeneous Vehicle Routing Problem
ICEVs	Internal Combustion Engine Vehicles
ICT	Information and Communication Technology
ILP	Integer Linear Programming
IoT	Internet Of Things
LP	Linear Programming
MCDM	Multi-Criteria Decision-Making
MDFSMVRP	Multi-Depot, Fleet Size, and Mix Vehicle Routing Problem
MDVRP	Multi Depot Vehicle Routing Problem
MOOP	Multi-objective Optimization Problem
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Nonlinear Programming
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
OVRP	Open Vehicle Routing Problem

PVRP	Periodic Vehicle Routing Problem
RVRP	Rich Vehicle Routing Problem
SPVRPTW	Stochastic Periodic Vehicle Routing Problem with Time Windows
SSWMVRP	Sustainable Solid Waste Management Vehicle Routing Problem
SW	Solid Waste
SWM	Solid Waste Management
SWMVRP	Solid Waste Management Vehicle Routing Problem
TBL	Triple Bottom Line
TPMA	Three Process Model of Alertness
VRP	Vehicle Routing Problem
VRPPDTW	Vehicle Routing Problem with Pickup and Delivery with Time Windows
VRPTW	Vehicle Routing Problem with Time Windows
VRPTWOV	Vehicle Routing Problem with Time Windows with Overtime and Outsourcing Vehicles

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Appendices

Appendix A

Problem Presentation Figures

Figure 1

Routing Stage (Echelon I) of the developed model

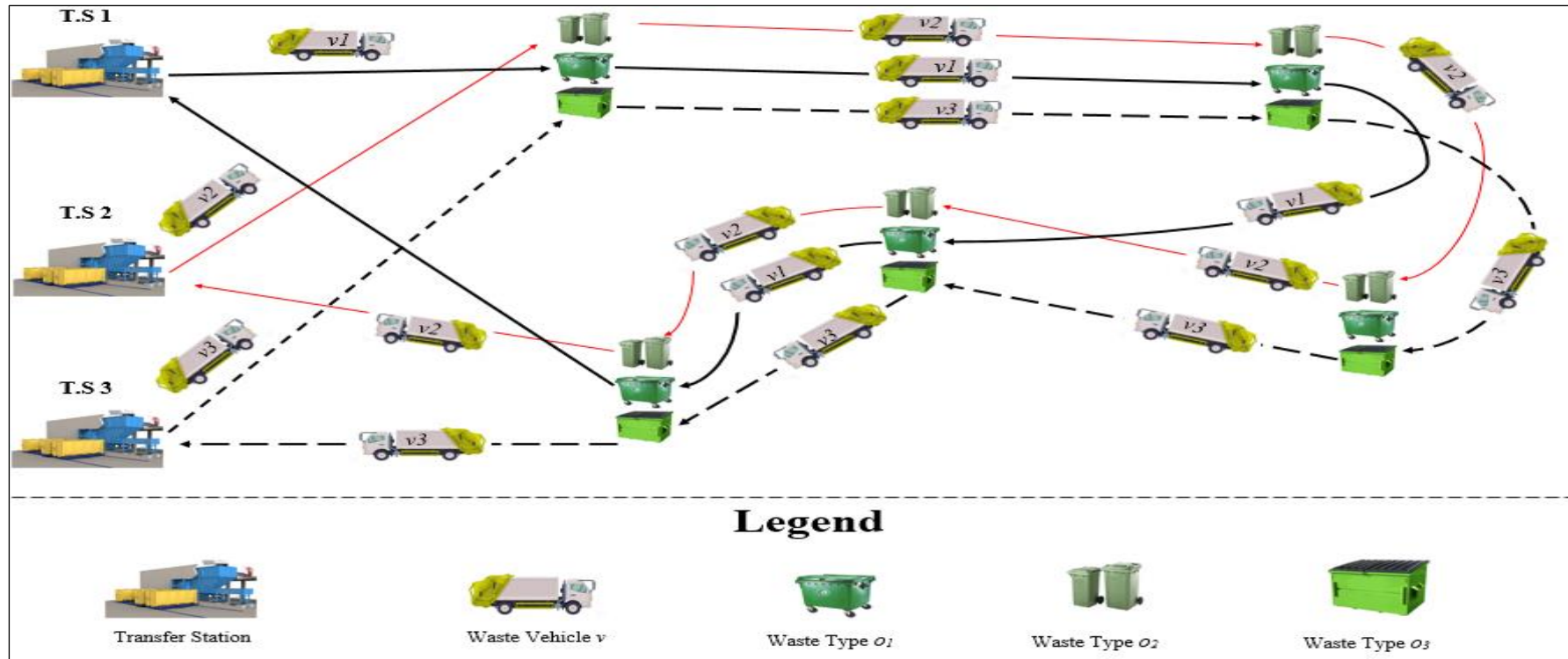


Figure 2

Transportation Stage 1 (Echelon II) of the developed model

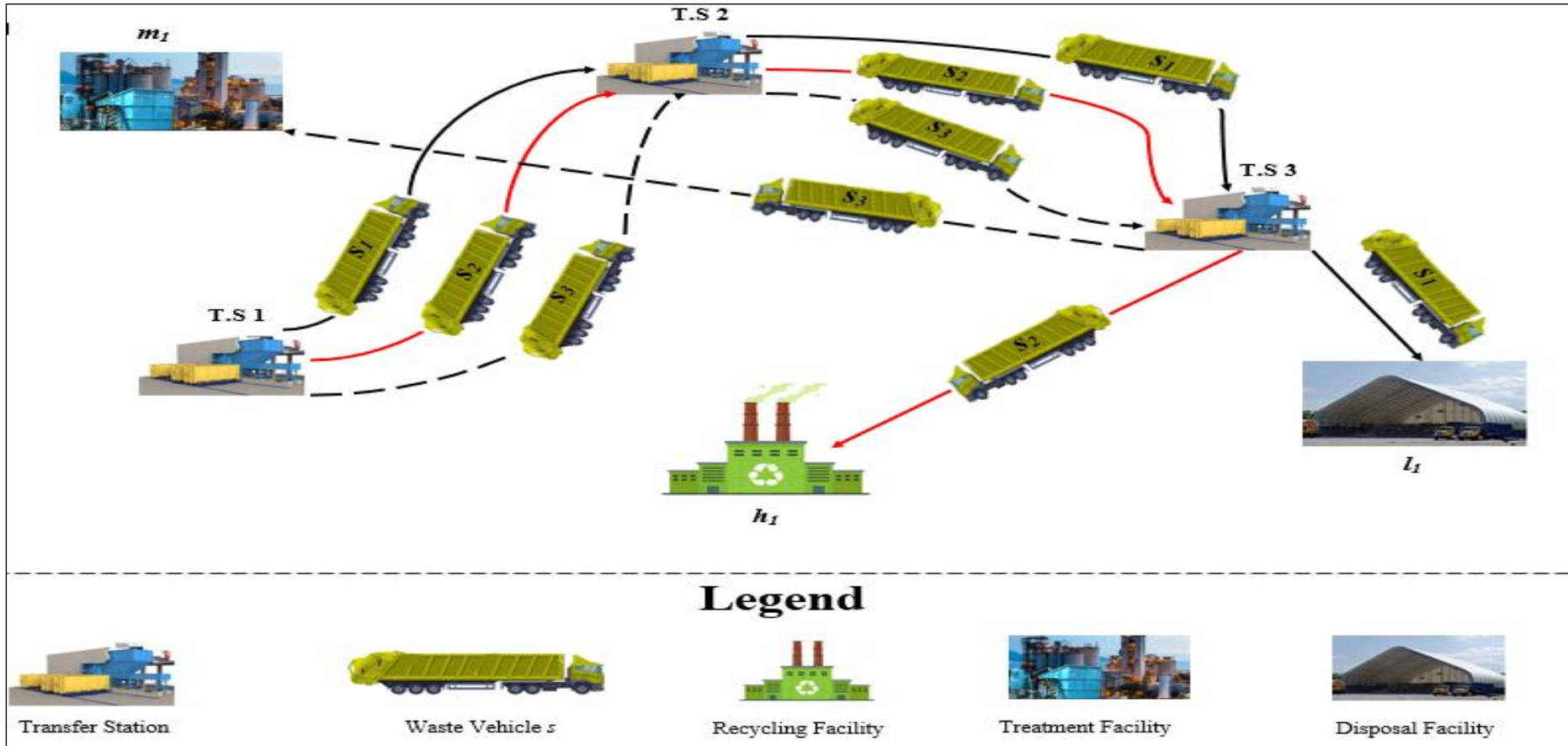
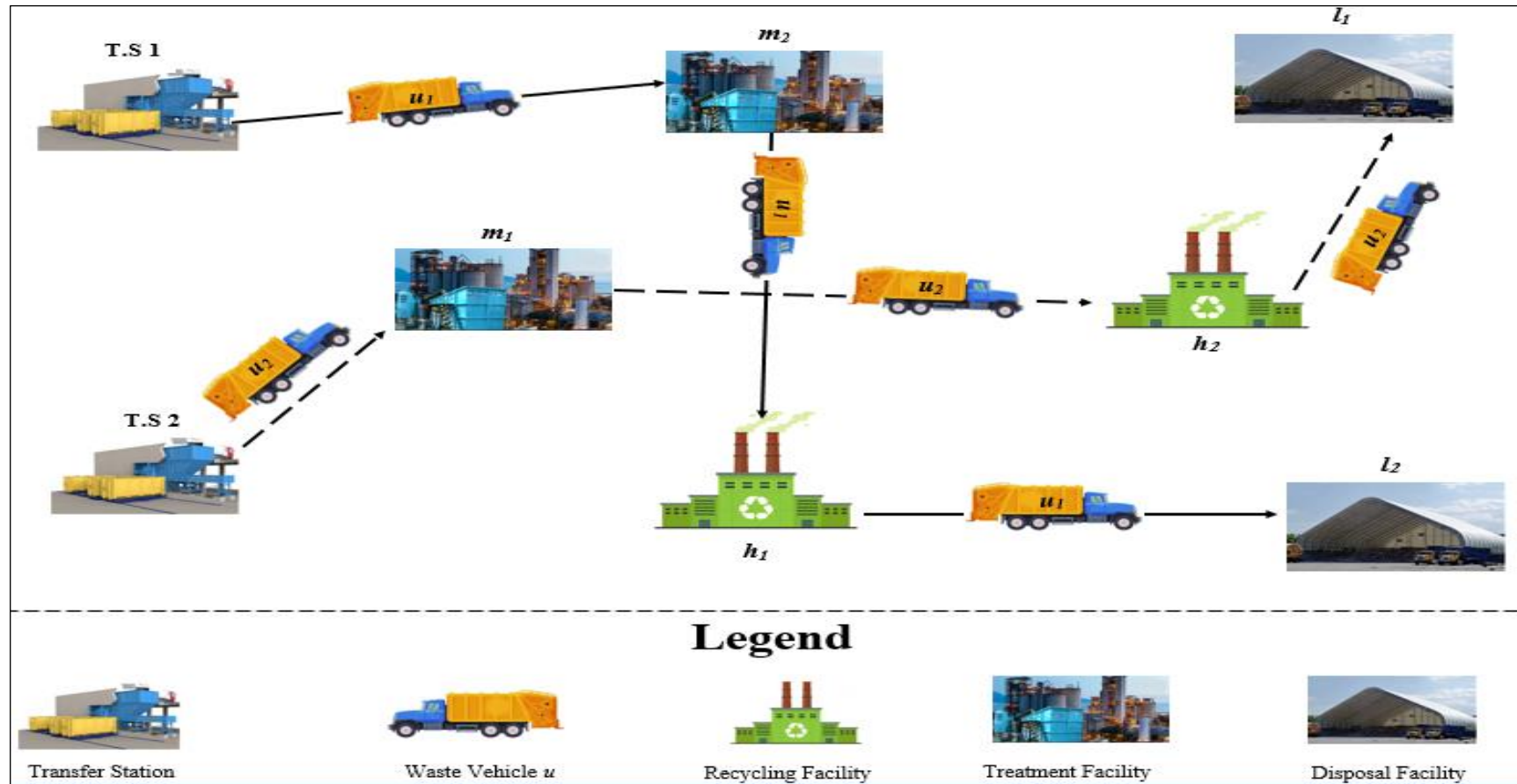


Figure 3

Transportation Stage 2 (Echelon III) of the developed model



Appendix B

Mathematical Model Sets, indices, parameters, variables, and constraints

Table 1

Sets & Indices

Sets & Indices	Description
i	Index of the source node, $i = 0, 1, \dots, N$.
j	Index of destination node, $j = 1, 2, \dots, N$.
g	Index of waste generation nodes, $g = 1, 2, \dots, G$.
k	Index of waste transfer stations, $k = 1, 2, \dots, K$.
m	Index of waste treatment facilities, $m = 1, 2, \dots, M$.
h	Index of waste recycling facilities, $h = 1, 2, \dots, H$.
l	Index of waste disposal facilities, $l = 1, 2, \dots, L$.
v	Index of waste collection vehicles, $v = 1, 2, \dots, V$.
s	Index of waste transportation semi-trailers vehicles, $s = 1, 2, \dots, S$.
u	Index of residue transferring semi-trailer vehicles, $u = 1, 2, \dots, U$.
q	Index of fleet of waste vehicles, $q = 1, 2, \dots, Q$, where $Q = V \cup S \cup U$.
D_q	Index of drivers for the fleet of waste vehicles, $D_q = 1, 2, \dots, D_Q$, where $D_q = D_v \cup D_s \cup D_u$.
D_v	Index of drivers of waste collection vehicles, where $D_v \in D_q$.
D_s	Index of drivers of waste transportation semi-trailer vehicles, where $D_s \in D_q$.
D_u	Index of drivers of residue transferring semi-trailer vehicles, where $D_u \in D_q$.
o	Index of different types of waste at generation nodes, $o = 1, 2, \dots, O$.
w	Index of different types of waste at transfer stations after sorting, $w = 1, 2, \dots, W$.

f	Index of different types of generated residue after treatment and recycling, $f = 1, 2, \dots, F.$
t	Index of waste treatment technologies, $t = 1, 2, \dots, T.$
r	Index of waste recycling technologies, $r = 1, 2, \dots, R.$
d	Index of waste disposal technologies, $d = 1, 2, \dots, D.$
hs	Index of a healthy state.
p	Index of pain state with productivity loss.

Table 2
Parameters

Parameter	Description
FC_q	Fixed costs of waste vehicle q .
BG_{og}	The amount of waste type o at waste generation node g .
TC^{qD}_{ij}	Transportation costs/unit distance of vehicle q between nodes i and j , including every node in the network (g, k, m, h, l, o, w).
TC^{qW}_{ij}	Transportation costs/unit load of vehicle q between nodes i and j , including every node in the network (g, k, m, h, l, o, w).
VO_{oq}	1, if waste type o is collected using vehicle q ($q \in V \in Q$); 0, otherwise.
VW_{wq}	1, if waste type w is transported using vehicle q ($q \in S \in Q$); 0, otherwise.
VF_{fq}	1, if residue type f is transported using vehicle q ($q \in U \in Q$); 0, otherwise.
AM_{tm}	1, if treatment technology t is available at treatment facility m ; 0, otherwise.
AH_{rh}	1, if recycling technology r is available at recycling facility h ; 0, otherwise.
AL_{dl}	1, if disposal technology d is available at disposal facility l ; 0, otherwise.
DIS_{ij}	Travel distance between node i and node j .

CER_q	The rate of CO ₂ emissions generated from vehicle q .
FCR_q	Fuel consumption rate of vehicle q .
$GE^{q,ij}$	CO ₂ emissions produced by vehicle q when traveling between nodes i and j .
LT_{wt}	1, if treatment technology t is suitable for waste type w ; 0, otherwise.
LR_{wr}	1, if recycling technology r is suitable for waste type w ; 0, otherwise.
LD_{wd}	1, if disposal technology d is suitable for waste type w ; 0, otherwise.
LF_{fd}	1, if disposal technology d is suitable for residue type f ; 0, otherwise.
MXO_{qo}	The maximum load capacity of vehicle q suitable for waste type o .
MXW_{qw}	The maximum load capacity of vehicle q suitable for waste type w .
MXF_{qf}	Maximum load capacity of vehicle q suitable for residue type f .
MXC_q	The maximum load capacity of vehicle q calculated from the average of the parameters: MXO_{qo} , MXW_{qw} , and MXF_{qf}
ROI_q	Fuel consumption amount of vehicle q with no load (empty).
ROF_q	Fuel consumption amount of vehicle q after full load.
MXK	Maximum number of waste transfer stations in the network.
AW_{wk}	The ratio at which transfer station k sort waste type w .
BW_{wr}	The ratio of total recycled waste type w at recycling facility r .
CW_{wt}	The ratio of waste type w amount reduction after treatment at treatment facility t .
MUM_f	The ratio of residue type f resulted after treatment at a treatment facility.
MUH_f	The ratio of residue type f resulted after recycling at a recycling facility.
CPK_k	The total capacity of a single transfer station k .
CPM_m	The total capacity of a single treatment facility m .

CPH_h	The total capacity of a single recycling facility h .
CPL_l	The total capacity of a single disposal facility l .
A	Coefficient for monetizing travel accidents (\$/kg-km).
π_{Dq}	Steady-state probability of the healthy state driver D_q
μ_{Dq}	Steady-state probability of the pain state of driver D_q
Pen^{Dq}	Penalty costs incurred if a driver (vehicle) is late from collecting or transporting waste (\$/hr.).

Table 3
Decision Variables

Variable	Description
X_{ij}^q	1, if vehicle q travels from node i to node j ; 0, otherwise
X_{ij}^{Dq}	1, if driver D_q travels from node i to node j ; 0, otherwise
P_{wk}	The amount of waste w sorted at transfer station k .
E_{fi}	The amount of residue f coming out from treatment/recycling facilities, $i \in M \cup H$.
Z_q	1, if vehicle q is used; 0, otherwise.
ZK_{kq}	1, if vehicle q is used and assigned to transfer station k ; 0, otherwise.
YK_{ok}	The amount of waste type o processed at transfer station k .
YM_{wm}	The amount of waste type w processed at treatment facility m .
YH_{wh}	The amount of waste type w recycled at recycling facility h .
YL_{wl}	The amount of waste type w disposed at disposal facility l .
YF_{fl}	The amount of residue type f disposed at disposal facility l .
XM_m	The total amount of residue generated at the treatment facility m .
XH_h	The total amount of residue generated at recycling facility h .

XML_{ml}	The amount of residue generated from treatment facility m to be transported to disposal facility l .
XHL_{hl}	The amount of residue generated from recycling facility h to be transported to disposal facility l .
W_{qi}	The load of waste vehicle q after visiting node i .
$time_{hs}^{Dq}$	The time needed to travel one km in a healthy state (hr. / km).
$time_p^{Dq}$	The time needed to travel one km in pain state (hr. / km).

Table 4
Constraints

No.	Constraint
12	$\sum_{k \in K} \sum_{g \in G} X_{kg}^q \leq 1 \quad \forall q \in V \in Q$
13	$\sum_{k \in K} \sum_{g \in G} X_{kg}^q = Z_q \quad \forall q \in V \in Q$
14	$X_{ij}^q - Z_q \leq 0 \quad \forall i, j \in G, q \in V \in Q$
15	$\sum_{i \in K} \sum_{j \in K \cup M \cup H \cup L} X_{ij}^q \leq MXK - 1 \quad \forall q \in S \in Q$
16	$\sum_{k \in K} \sum_{j \in M \cup H \cup L} X_{ij}^q = Z_q \quad \forall q \in S \in Q$
17	$\sum_{k \in K} \sum_{j \in M \cup H} X_{kg}^q \leq 1 \quad \forall q \in U \in Q$
18	$\sum_{i \in K} \sum_{j \in M \cup H} X_{ij}^q = Z_q \quad \forall q \in U \in Q$
19	$X_{ij}^q - Z_q \leq 0 \quad \forall i, j \in M \cup H, q \in U \in Q$

$$20 \quad \sum_{i \in K \cup G} X_{ij}^q - \sum_{i'' \in K \cup G} X_{ji''}^q \geq 0 \quad \forall j \in G; q \in V \in Q$$

$$21 \quad \sum_{i \in K} X_{ij}^q - \sum_{i'' \in K \cup M \cup H \cup L} X_{ji''}^q \geq 0 \quad \forall j \in K; q \in S \in Q$$

$$22 \quad \sum_{i \in K} X_{ij}^q - \sum_{i'' \in K \cup M \cup H \cup L} X_{ji''}^q \geq 0 \quad \forall j \in K; q \in S \in Q$$

$$23 \quad \sum_{i \in k \cup G} \sum_{q \in V \in Q} X_{ij}^q \times VO_{oq} = 1 \quad \forall j \in G; o \in O$$

$$24 \quad \sum_{i \in k \cup M \cup H \cup L} \sum_{q \in S \in Q} X_{ij}^q \times VW_{wq} = 1 \quad \forall j \in K; w \in W$$

$$25 \quad \sum_{i \in k \cup M \cup H} \sum_{q \in U \in Q} X_{ij}^q \times VF_{fq} = 1 \quad \forall j \in M \cup H; f \in F$$

$$26 \quad \sum_{j \in G} X_{kj}^q = ZK_{kq} = \sum_{j \in G} X_{jk}^q \quad \forall k \in K; q \in V \in Q$$

$$27 \quad \sum_{j \in k \cup M \cup H \cup L} X_{ji}^q - \sum_{i'' \in K} X_{i''j}^q = ZK_{kq} = \sum_{j \in M \cup H \cup L} X_{i''j}^q \quad \forall j \in K; q \in S \in Q$$

$$28 \quad X_{ij}^q \leq \sum_{i'' \in L} X_{i''j}^q \quad \forall i \in K; q \in U \in Q$$

$$29 \quad \sum_{j \in M \cup H} X_{ij}^q = ZK_{kq} = \sum_{i'' \in L} X_{i''j}^q \quad \forall i \in K; q \in U \in Q$$

$$30 \quad X_{ij}^q \leq \sum_{i'' \in M \cup H} X_{i''j}^q \quad \forall j \in L; j \in K; q \in U \in Q$$

$$31 \quad W_{qi} - W_{qj} + \sum_{o \in O} VO_{oq} \times MXO_{qo} \times X_{ij}^q \leq \sum_{o \in O} VO_{oq} (MXO_{qo} - BG_{oj}) \quad \forall i, j \in G; q \in V \in Q$$

$$32 \quad \sum_{o \in O} VO_{oq} \times BG_{og} \leq W_{qi} \leq \sum_{o \in O} VO_{oq} \times MXO_{qo} \quad \forall i \in G; q \in V \\ \in Q$$

$$33 \quad \sum_{k \in K} \sum_{o \in O} X_{kg}^q \times VO_{oq} \times BG_{og} \leq W_{qg} \quad \forall g \in G; q \in V \\ \in Q$$

$$34 \quad W_{qg} \leq \sum_{o \in O} VO_{oq} (MXO_{qo} + \sum_{k \in K} X_{kg}^q \times (BG_{og} - MXO_{qo})) \quad \forall g \in G; q \in V \\ \in Q$$

$$35 \quad W_{qi} - W_{qj} + \sum_{w \in W} VW_{wq} \times MXW_{qw} \times X_{ij}^q \\ \leq \sum_{w \in W} VW_{wq} (MXW_{qw} - P_{wj}) \quad \forall i, j \in K; q \\ \in S \in Q$$

$$36 \quad \sum_{w \in W} P_{wj} \times VW_{wq} \leq W_{qi} \leq \sum_{w \in W} VW_{wq} \times MXW_{qw} \quad \forall i \in K; q \in S \\ \in Q$$

$$37 \quad \sum_{k \in K} \sum_{o \in O} X_{kj}^q \times P_{wj} \times VW_{wq} \leq W_{qj} \quad \forall j \in G; q \in S \\ \in Q$$

$$38 \quad W_{qi} - W_{qj} + \sum_{f \in F} VF_{fq} \times MXF_{qf} \times X_{ij}^q \\ \leq \sum_{f \in F} VW_{fq} (MXW_{qf} - E_{fj}) \quad \forall i, j \\ \in M \cup H; q \\ \in U \in Q$$

$$39 \quad \sum_{w \in W} E_{fi} \times VF_{fq} \leq W_{qi} \leq \sum_{f \in F} VW_{fq} \times MXF_{qf} \quad \forall i \in M; q \in U \\ \in Q$$

$$40 \quad \sum_{k \in K} \sum_{f \in F} X_{ij}^q \times VF_{fq} \times E_{fi} \leq W_{qi} \quad \forall j \in M \cup H; q \\ \in U \in Q$$

$$41 \quad W_{qj} \leq \sum_{o \in O} VF_{fq} (MXF_{qf} + \sum_{k \in K} X_{ij}^q \times (E_{fi} - MXF_{qf})) \quad \forall g \in G; q \in V \\ \in Q$$

$$42 \quad X_{ij}^q \leq \sum_{w \in W} \sum_{i \in T} VW_{wq} \times LT_{wt} \times AM_{tj} \quad \forall i \in K; j \\ \in M; q \in S \\ \in Q$$

$$43 \quad X_{ij}^q \leq \sum_{w \in W} \sum_{r \in R} VW_{wq} \times LR_{wr} \times AM_{rj} \quad \begin{array}{l} \forall i \in K; j \\ \in H; q \in S \\ \in Q \end{array}$$

$$44 \quad X_{ij}^q \leq \sum_{w \in W} \sum_{d \in D} VW_{wq} \times LD_{wd} \times AM_{dj} \quad \begin{array}{l} \forall i \in K; j \\ \in L; q \in S \in Q \end{array}$$

$$45 \quad X_{ij}^q \leq \sum_{f \in F} \sum_{d \in D} VW_{fq} \times LF_{fd} \times AL_{dj} \quad \begin{array}{l} \forall i \in M \cup H; j \\ \in L; q \in U \\ \in Q \end{array}$$

$$46 \quad P_{wk} = AW_{wk} \sum_{o \in O} YK_{ok} \quad \begin{array}{l} \forall k \in K; w \\ \in W \end{array}$$

$$47 \quad XM_m = \sum_{w \in W} \sum_{t \in T} YM_{wm} \times AM_{tm} (1 - CW_{wt}) \quad \forall m \in M$$

$$48 \quad XH_h = \sum_{w \in W} \sum_{r \in R} YL_{wh} \times AM_{rh} (1 - BW_{wr}) \quad \forall h \in H$$

$$49 \quad \sum_{i \in MUH} E_{fi} = \sum_{t \in T} \sum_{r \in R} XM_m \times AM_{tm} \times MUM_f + \sum_{r \in R} \sum_{h \in H} XH_h \times AH_{rh} \times MUH_f \quad \forall f \in F$$

$$50 \quad YK_{ok} = \sum_{q \in V \in Q} \sum_{g \in G} X_{gk}^q \times W_{qg} \times VO_{oq} \quad \forall k \in K; o \in O$$

$$51 \quad YM_{wm} = \sum_{q \in S \in Q} \sum_{k \in K} X_{km}^q \times W_{qm} \times VW_{wq} \quad \begin{array}{l} \forall w \in W; m \\ \in M \end{array}$$

$$52 \quad YH_{wh} = \sum_{q \in S \in Q} \sum_{k \in K} X_{kh}^q \times W_{qh} \times VW_{wq} \quad \begin{array}{l} \forall w \in W; h \\ \in H \end{array}$$

$$53 \quad YL_{wl} = \sum_{q \in S \in Q} \sum_{k \in K} X_{kl}^q \times W_{ql} \times VW_{wq} \quad \forall w \in W; l \in L$$

$$54 \quad YF_{fl} = \sum_{q \in U \cup Q} \sum_{i \in M \cup H} X_{il}^q \times W_{qi} \times VF_{fq} \quad \forall f \in F; l \in L$$

$$55 \quad \sum_{o \in O} \sum_{g \in G} BG_{og} = \sum_{o \in O} \sum_{k \in K} YK_{ok}$$

$$56 \quad \sum_{w \in W} \sum_{k \in K} P_{wk} = \sum_{w \in W} \sum_{h \in H} YH_{wh} + \sum_{w \in W} \sum_{m \in M} YM_{wm} \\ + \sum_{w \in W} \sum_{l \in L} YL_{wl}$$

$$57 \quad \sum_{f \in F} \sum_{i \in M \cup H} E_{fi} = \sum_{f \in F} \sum_{l \in L} YF_{fl}$$

$$58 \quad \sum_{o \in O} YK_{ok} = CPK_k \quad \forall k \in K$$

$$59 \quad \sum_{w \in W} YM_{wm} = CPM_m \times \sum_{t \in T} AM_{tm} \quad \forall m \in M$$

$$60 \quad \sum_{w \in W} YH_{wh} = CPH_h \times \sum_{r \in R} AH_{rh} \quad \forall h \in H$$

$$61 \quad \sum_{m \in M} XML_{ml} + \sum_{h \in H} XHL_{hl} = CPL_l \times \sum_{d \in D} AL_{dl} \quad \forall l \in L$$

$$62 \quad P_{wk}, E_{fi}, YK_{ok}, YM_{wm}, YH_{wh}, YL_{wl}, YF_{wf}, XM_m, XH_h, XML_{ml}, XML_{hl}, W_{qi}, time_{hs}^{Dq}, \\ time_p^{Dq} \geq 0$$

$$63 \quad X_{ij}^q, Z_q, ZK_{kq} \in \{0,1\}$$

$$64 \quad X_{ij}^q = X_{ij}^{Dq}$$

Appendix C
Solution Methodology Tables

Table 5

An example of a chromosome in a waste management network.

1	2	3	4	5	6	<i>g</i>	Solution 1
2	1	3	5	6	4	<i>k</i>	
2	5	3	1	6	4	<i>m</i>	
6	5	2	3	1	4	<i>h</i>	
5	2	3	6	1	4	<i>l</i>	
1	7	2	3	6	5	<i>v</i>	
5	2	1	6	3	4	<i>s</i>	
4	1	2	3	6	5	<i>u</i>	
5	1	2	3	6	4	<i>o</i>	
1	2	5	3	6	4	<i>w</i>	
2	1	3	5	6	4	<i>f</i>	
2	1	3	4	6	5	<i>t</i>	
3	6	1	4	5	2	<i>r</i>	
1	6	4	3	5	2	<i>d</i>	

Table 6

Example of NSGA-II crossover.

1	2	3	4	5	6	<i>g</i>	Parents 1
2	1	3	5	6	4	<i>k</i>	
2	5	3	1	6	4	<i>m</i>	
6	5	2	3	1	4	<i>h</i>	
5	2	3	6	1	4	<i>l</i>	
1	7	2	3	6	5	<i>v</i>	
5	2	1	6	3	4	<i>s</i>	
4	1	2	3	6	5	<i>u</i>	
5	1	2	3	6	4	<i>o</i>	
1	2	5	3	6	4	<i>w</i>	
2	1	3	5	6	4	<i>f</i>	
2	1	3	4	6	5	<i>t</i>	

3	6	1	4	5	2	<i>r</i>	
1	6	4	3	5	2	<i>d</i>	

2	3	5	6	1	4	<i>g</i>	Parents 2
5	2	3	7	6	4	<i>k</i>	
5	3	2	1	6	4	<i>m</i>	
1	3	2	5	6	4	<i>h</i>	
5	1	4	2	3	6	<i>l</i>	
5	2	7	1	6	3	<i>v</i>	
2	3	1	6	7	5	<i>s</i>	
7	6	2	5	1	4	<i>u</i>	
5	6	1	3	2	4	<i>o</i>	
2	6	5	4	3	1	<i>w</i>	
1	6	3	5	4	2	<i>f</i>	
1	6	2	3	5	4	<i>t</i>	
3	4	6	5	1	2	<i>r</i>	
4	6	2	5	3	1	<i>d</i>	

6	1	4	0	1	2	<i>g</i>	offspring
7	6	4	1	2	1	<i>k</i>	
1	6	4	0	2	5	<i>m</i>	
5	6	4	0	6	5	<i>h</i>	
2	3	6	0	5	2	<i>l</i>	
1	6	3	4	1	7	<i>v</i>	
6	7	5	4	5	2	<i>s</i>	
5	1	4	3	4	1	<i>u</i>	
3	2	4	0	5	1	<i>o</i>	
4	3	1	0	1	2	<i>w</i>	
5	4	2	0	2	1	<i>f</i>	
3	5	4	0	2	1	<i>t</i>	
5	1	2	0	3	6	<i>r</i>	
5	3	1	0	1	6	<i>d</i>	

Table 7*NSGA-II mutation process.*

6	1	3	0	1	4	<i>g</i>	offspring
7	6	2	1	2	2	<i>k</i>	
1	6	5	0	2	6	<i>m</i>	
5	6	3	0	6	4	<i>h</i>	
2	3	6	0	5	2	<i>l</i>	
1	6	3	4	1	7	<i>v</i>	
6	7	5	4	5	2	<i>s</i>	
5	1	4	3	4	1	<i>u</i>	
3	2	4	0	5	1	<i>o</i>	
4	3	1	0	1	2	<i>w</i>	
5	4	2	0	2	1	<i>f</i>	
3	5	4	0	2	1	<i>t</i>	
5	1	2	0	3	6	<i>r</i>	
5	3	1	0	1	6	<i>d</i>	

Table 8*Example of the solution representation.*

2	3	6	11	10	8	9	5	4	7	12	1
Route of waste generation nodes for waste type 1											
5	9	2	4	12	8	10	1	3	6	7	11
Route of waste generation nodes for waste type 2											
1	6	7	10	2	12	5	3	11	9	8	4
Route of waste generation nodes for waste type 3											
4	1	3	5	2	6						
Order of waste treatment facilities											
4	3	1	2								
Order of waste recycling facilities											
2	1	5	4	3							

Order of waste disposal facilities											
1	4	3	6	8	10	12	11	9	2	7	5
Order of waste vehicle type 1 (waste collection vehicles)											
4	3	6	5	1	2						
Order of waste vehicle type 2 (transportation semi-trailers)											
2	5	3	1	4							
Order of waste vehicle type 3 (residue transferring trucks)											
1	2	3	6	8	10	12					
Driver's health state (healthy)											
4	5	7	9	11							
Driver's health state (pain)											

Appendix D

Research Results Tables

Table 9

Generated test instances

Level	Identifier	Problem size (G, K, M, H, L, V, S, U, O, W, F, T, R, D)
Small	P1	(2, 3, 2, 2, 2, 3, 3, 3, 2, 2, 2, 2, 2, 2)
	P2	(3, 6, 2, 2, 2, 5, 5, 5, 3, 3, 2, 2, 2, 2)
	P3	(4, 6, 3, 3, 3, 5, 5, 5, 4, 4, 3, 3, 3, 3)
	P4	(4, 6, 4, 4, 4, 7, 7, 7, 5, 5, 3, 3, 3, 3)
	P5	(6, 6, 5, 5, 5, 9, 9, 9, 7, 7, 4, 3, 3, 3)
	P6	(8, 6, 7, 7, 7, 9, 9, 9, 8, 8, 4, 3, 3, 3)
Medium	P7	(12, 8, 10, 10, 10, 10, 10, 10, 10, 10, 5, 4, 4, 4)
	P8	(14, 8, 12, 12, 12, 10, 10, 10, 12, 12, 5, 4, 4, 4)
	P9	(18, 10, 16, 14, 12, 12, 10, 11, 14, 12, 6, 5, 5, 5)
	P10	(20, 10, 17, 16, 14, 13, 11, 12, 16, 14, 6, 5, 5, 5)
	P11	(23, 12, 18, 18, 16, 14, 14, 12, 20, 16, 6, 5, 5, 5)
	P12	(28, 14, 20, 20, 18, 14, 14, 12, 22, 20, 7, 6, 6, 6)
Large	P13	(34, 14, 24, 24, 20, 14, 14, 14, 26, 24, 8, 6, 6, 6)
	P14	(38, 15, 28, 26, 24, 15, 14, 14, 30, 28, 8, 6, 6, 6)
	P15	(44, 15, 32, 30, 28, 15, 15, 14, 34, 32, 8, 6, 6, 6)
	P16	(48, 16, 34, 32, 28, 15, 15, 15, 34, 34, 8, 6, 6, 6)
	P17	(54, 18, 38, 36, 30, 16, 16, 16, 38, 36, 9, 7, 7, 7)
	P18	(56, 18, 40, 36, 32, 16, 16, 16, 40, 38, 9, 7, 7, 7)
	P19	(64, 21, 48, 44, 38, 18, 18, 16, 52, 46, 9, 8, 8, 8)
	P20	(72, 24, 54, 48, 48, 18, 18, 18, 58, 56, 10, 9, 9, 9)

Source: (Mojtahedi et al., 2021).

Table 10*Parameters of the developed model*

Parameter	Value
(x_i, y_i)	$1000 \times (U(0, 1), U(0, 1))$
(x_j, y_j)	$1000 \times (U(0, 1), U(0, 1))$
DIS_{ij}	$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$
FC_q	$\text{Rand}\{1, 2, \dots, 5\} \times 10^6$
$VO_{oq}, VW_{wq}, VF_{fq}, AM_{tm}, AH_{rh}, AL_{dl}$	$\text{Rand}\{0, 1\}$
TC_{ij}^q	$\text{Rand}\{1, 2, \dots, 5\} \times 10^3$
CER_q	2.61 (CO ₂ emission rate for diesel oil) 2.17 (CO ₂ emission rate for natural gas) 2.57 (CO ₂ emission rate for gasoline)
$MXO_{qo}, MXW_{qw}, MXF_{qf}$	$\text{Rand}\{1, 5, \dots, 20\} \times 10^2 \text{ m}^3$
BG_{og}	$\text{Rand}\{1, 2, \dots, 8\} \times \text{Kg}$
ROI_q	$U(0.1, 0.3)$
ROF_q	$U(0.2, 0.5)$
$LT_{wt}, LR_{wr}, LD_{wd}, LF_{fd}$	$\text{Rand}\{0, 1\}$
$CPK_k, CPM_m, CPL_l, CPH_h$	$\text{Rand}\{1, 2, \dots, 4\} \times 10^4 \text{ m}^3$
$AW_{wk}, BW_{wr}, CW_{wt}, MUM_f, MUH_f$	$U(0.1, 1)$

Table 11*Vehicles' load along the route*

Route	Load of waste vehicle v after visiting node i (kg)					Total load (kg)
T.S→G8→G10→G7→G6	0	101	228	332	443	443
T.S→G2→G11→G4→G5	0	61	197	298	393	393
T.S→G12→G9→G1→G3	0	86	184	300	450	450
T.S→G12→G4→G6→G8	0	134	252	369	430	430
T.S→G1→G11→G10→G2	0	115	221	370	471	471
T.S→G5→G9→G7→G3	0	134	221	308	425	425
T.S→G11→G7→G3→G8	0	105	213	292	364	364
T.S→G1→G12→G6→G10	0	78	162	251	316	316
T.S→G4→G9→G2→G5	0	122	216	354	484	484

Table 12*Travelled distance along the route*

Route	Travelled distance by vehicle v (Km)					Total Travelled distance (Km)
T.S→G8→G10→G7→G6	37	27	33	79	96	272
T.S→G2→G11→G4→G5	29	92	58	23	41	243
T.S→G12→G9→G1→G3	64	55	64	58	27	268
T.S→G12→G4→G6→G8	90	24	75	85	89	363
T.S→G1→G11→G10→G2	22	36	61	99	34	252
T.S→G5→G9→G7→G3	81	49	83	33	77	323
T.S→G11→G7→G3→G8	88	53	33	27	33	234
T.S→G1→G12→G6→G10	22	64	67	76	92	321
T.S→G4→G9→G2→G5	96	71	99	66	49	381

Table 13*Vehicles' load along the route (Echelon III)*

Waste type w	Route	Load of waste vehicle u after visiting node i (kg)			
1	T.S 5 → 2 M → 2 H → 3 L	147.67	278.67	428.67	0
2	T.S 2 → 1 H → 3 M → 2 L	143.33	300.33	442	0
3	T.S 1 → 3 H → 1 M → 1 L	121.33	227.67	389	0

Appendix E

Sensitivity Analysis Tables and Figures

Table 14

Test instances

Instance size	g	k	m	h	l	v	s	u	o	w	f
S1	12	9	3	3	3	9	9	3	3	3	3
S2	24	9	3	3	3	9	9	3	3	3	3
S3	36	12	4	4	4	12	12	4	3	3	3
S4	42	18	6	6	6	18	18	6	3	3	3
S5	48	18	6	6	6	18	18	6	3	3	3
S6	60	24	8	8	8	24	24	8	4	4	4
S7	72	24	8	8	8	24	24	8	4	4	4
S8	90	30	10	10	10	30	30	10	5	5	5
S9	100	30	10	10	10	30	30	10	5	5	5

Table 15

Objective functions values at different instances

Instance	Z_1	Z_2	Z_3	Z_4	Z_5	Solving time (minutes)
S1	469,063	58,708	28,249	81.48	2,997,365	12.33
S2	929,780	67,958	91,332	80.51	6,523,720	18.56
S3	1,179,677	72,874	244,800	145.3	7,027,335	41.78
S4	1,150,797	77,859	645,840	326.62	6,731,655	140.7
S5	1,368,167	74,549	712,800	327.77	8,556,030	168.89
S6	2,719,686	147,160	1,424,600	578.66	16,469,670	633.52
S7	2,816,888	165,770	1,585,900	1,735	15,036,550	989.94
S8	2,364,700	157,060	2,838,000	873.72	18,442,975	3212.42
S9	3,355,590	178,060	2,910,000	1,296.7	20,442,975	3453.34

Table 16

The effect of cost related objectives of the total cost function

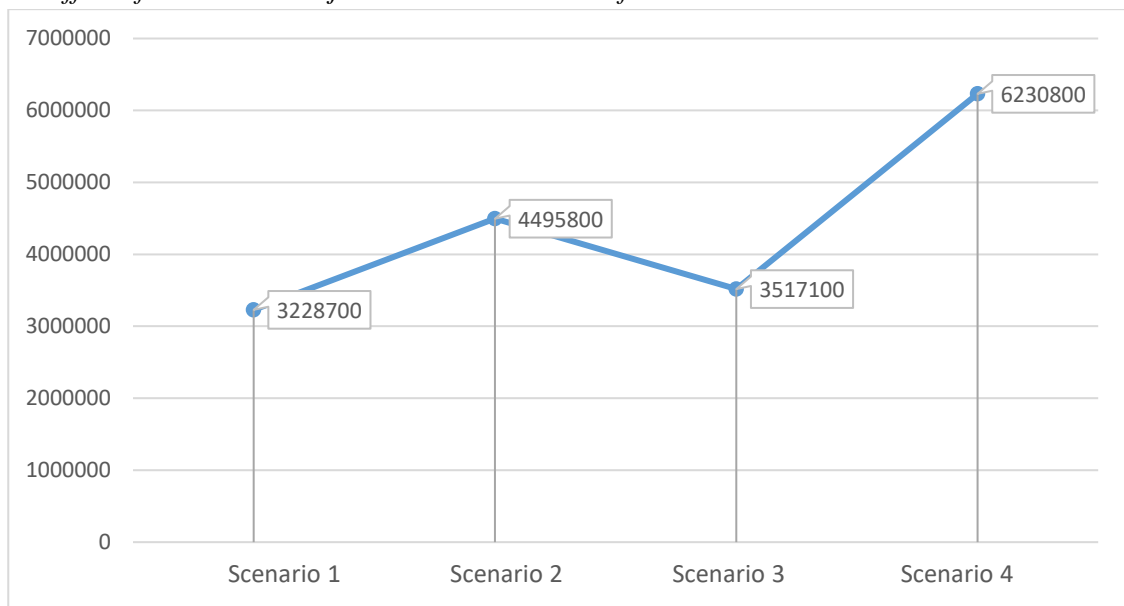
Scenario	WT_{Z_1}	WT_{Z_2}	WT_{Z_5}	Z_{cost} (\$)
Scenario 1	1	1	1	3,228,700
Scenario 2	2	1	1	4,495,800
Scenario 3	1	2	1	3,517,100
Scenario 4	1	1	2	6,230,800

Table 17*Sensitivity analysis of the fixed costs*

Scenario	FC_q	Z_1	Z_2	Z_3	Z_4	Z_5
S1	1	508,930	42,208	23,249	102.42	3,170,540
S2	2	850,145	42,903	26,557	114.50	3,201,882
S3	4	1,057,782	42,063	27,026	122.86	3,098,128
S4	6	1,199,694	50,177	26,982	123.37	3,196,155

Table 18*Sensitivity analysis of the transportation costs*

Scenario	$TC^{q_{ij}}$	Z_1	Z_2	Z_3	Z_4	Z_5
S1	1	434,891	38,255	25,265	96.22	3,530,400
S2	2	758,736	39,107	27,632	97.95	3,542,012
S3	4	1,206,127	39,684	28,199	95.19	3,612,256
S4	6	1,491,956	40,135	30,487	96.58	3,630,949

Figure 4*The effect of cost-related objectives on the total cost function*



جامعة النجاح الوطنية
كلية الدراسات العليا

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في الاعتبار الحالة الصحية للسائق ومخاطر الحوادث

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قدمت هذه الرسالة استكمالاً لمتطلبات الحصول على درجة الماجستير في الإدارة الهندسية، من كلية الدراسات
العليا، في جامعة النجاح الوطنية، نابلس - فلسطين.

2024

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الملخص

نظراً للنمو السريع لل عمران، فقد لفتت مسألة إدارة النفايات الصلبة اهتمام المجتمع وجميع الجهات المعنية، لما لها من ضرر سيلحق بالمواطن والبيئة إذا لم تتم إدارة النفايات بشكل صحيح. يهدف بحثنا إلى حل نموذج مشكلة توجيه مركبات إدارة النفايات الصلبة الذي يدمج الركائز الثلاث للاستدامة مع عاملين اجتماعيين، وهما الحالة الصحية للسائقين وخطر الحوادث. وبشكل أكثر تحديداً، يهدف منهجنا إلى دراسة تأثير الحالة الصحية المختلفة للسائق على المتغيرات المختلفة في شبكة إدارة النفايات الصلبة في النموذج المطروح، من خلال تقدير احتمالية المعاناة من إصابات العمل، باستخدام المنهجية الإحصائية من خلال نموذج Markov Chain. بالإضافة إلى ذلك، يعمل نهجنا على توسيع واقع النموذج من خلال النظر في المحددات والمتغيرات المختلفة التي من شأنها تحسين التطبيق العملي للنموذج، مثل أخذ بعين الاعتبار دالات تكلفة مختلفة و تضمينها في النموذج الرياضي. علاوة على ذلك، ولضمان ممارسات تجارية مستدامة، يهدف نموذجنا إلى تقليل انبعاثات ثاني أكسيد الكربون الناتجة عن أنواع مختلفة من نفايات المركبات. كما تمت دراسة العامل الاجتماعي من خلال مراعاة الحالة الصحية للسائقين، والتقليل من مخاطر الحوادث التي تواجه السائقين، وتقليل أي انحراف عن عبء العمل المتوازن بين السائقين. تم استخدام خوارزمية Non-Dominated Sorting Genetic Algorithm II لحل النموذج المطور، وذلك بسبب قدرتها على معالجة

مشاكل توجيه المركبات متعددة الأهداف بشكل عام، وبشكل رئيسي مشاكل توجيه مركبات إدارة النفايات الصلبة. وأوضحت تحليلات الحساسية كيفية تفاعل المتغيرات و المحددات المختلفة مع بعضها البعض، بالإضافة إلى تأثير مسافة السفر وحمولة السيارة على الحالة الصحية للسائقين. ويحقق تنفيذ هذا النموذج في قطاع إدارة النفايات العديد من المزايا لمقدمي الخدمات، وذلك بسبب القدرة على مراقبة الحالة الصحية للسائقين عند كل نقطة في الشبكة. مما يؤدي إلى ضمان وجود سائقين صحيين منتجين يقومون بالعمليات المطلوبة، ويمكنهم تحقيق النجاح المالي إلى جانب بيئة عمل صحية وآمنة.

كلمات مفتاحية: مشكلة توجيه المركبات، إدارة النفايات الصلبة، الحالة الصحية، الاستدامة، مخاطر الحوادث.