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Integrating Drivers Differences into Green Waste Collection Vehicle Routing Problem

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Dedication

رسالتي مهداة إليكم يا من تشرفتم بدعمكم ومساندتكم ودعائمكم
لخالتي محمود الحج محمد (أبو العبد) الإنسان الذي كان له الدور الكبير في
التشجيع والحث على هذه الخطوة وما يتبعها من مواصلة طريق العلم والتعليم
إلى والديّ العزيزين اللذان بدعائمكم وتشجيعكم وصبركم عليّ واصلت الطريق
إلى إخوتي وأخواتي بدعمهم ودعائمهم بالسر والعلن وتوفير جو أسري هادي
شكرا لكم فردا فردا يا من عمّرتهموني ودعّمتهموني

فجزاكم الله خير الجزاء

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إلى كل من دعم وساند، إلى أساتذتي الكرام الذين أشرفوا على الرسالة
وقدموا لي كل نصيحة ومساعدة لإتمام دراستي

لكم كل الشكر والحب

أنا الموقع أدناه، مقدم الرسالة التي تحمل العنوان:

Integrating Drivers Differences into Green Waste Collection Vehicle Routing Problem

أقر بأن ما اشتملت عليه هذه الرسالة إنما هي نتاج جهدي الخاص، باستثناء ما تمت الإشارة إليه حيثما ورد، وأن هذه الرسالة كاملة، أو أي جزء منها لم يقدم من قبل لنيل أي درجة علمية أو بحث علمي أو بحثي لدى أي مؤسسة تعليمية أو بحثية أخرى.

Declaration

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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Table of Contents

Dedication	III
Acknowledgment	IV
Declaration	V
List of Tables	VIII
List of Figures.....	IX
List of Abbreviations	X
Abstract.....	XI
Chapter one: Introduction	1
1.1 Overview.....	1
1.2 Problem statement	5
1.3 Research significance.....	7
1.4 Research questions	8
1.5 Research objectives.....	9
1.6 Research methodology.....	9
1.7 Thesis organization	10
Chapter two: Literature review.....	11
2.1 Overview	11
2.2 Vehicle routing problems.....	12
2.2.1 Green VRP	15
2.3 Hazardous waste management.....	16
2.3.1 Hazardous waste	17
2.3.2 HWM and VRP.....	18
2.4 Effect of driver's behavior on VRP.....	21
2.4.1 The effect of fatigue on VRP	22
2.4.2 Green Driving Index	25
Chapter three: Model formulation.....	29
3.1 Overview	29
3.2 Mixed Integer Nonlinear Programming.....	29
3.3 Model description	31
3.3.1 Assumptions.....	33
3.3.2 Sets	35
3.3.3 Parameters	35
3.3.4 Variables	37
3.3.5 Objective functions	29
3.3.6 Constraints	41
3.4 Methodology.....	48
3.4.1 Non-dominated sorting genetic algorithm II (NSGS-II)	49
Chapter four: Model results	56
4.1 Overview.....	56
4.2 Results and discussion.....	56

4.2.1 Routing stage results	58
4.2.2 Transportation stage results	59
4.2.3 Workforce planning for drivers	61
4.2.4 Driver's awakesness level	62
4.2.5 Test instances	65
Chapter five: Sensitivity analysis	67
5.1 Overview	67
5.2 Sensitivity analysis on the effect of driver's GDI	67
5.2.1 The effect of driver's GDI level on total costs	68
5.2.2 The effect of driver's GDI on transportation risk.....	70
5.2.3 The effect of driver's GDI on awakesness level	71
5.2.4 The effect of driver's awakesness levels on total costs.....	73
5.2.5 The effect of driver's awakesness levels on transportation risk	75
Chapter six: Conclusions and recommendations.....	77
6.1 Summary	77
6.2 Thesis contributions.....	79
6.3 Model limitations.....	80
6.4 Recommendations for future work.....	81
References	82
الملخص	ب

List of Tables

NO.	Table	Page
Table 3.1	Example of a chromosome that presents the proposed HWVRP	51
Table 3.2	NSGA-II crossover process	53
Table 3.3	NSGA-II mutation process	54
Table 4.1	Results of routing stage	59
Table 4.2	Results of transportation stage	60
Table 4.3	Workforce planning results	62
Table 4.4	Driver's awakeness level	64
Table 4.5	Comparison metrics for problem instances	65

List of Figures

NO.	Figure	Page
Figure 1.1	HWM system	3
Figure 2.1	Three process model of alertness (TPMA) model (Bownde and Ragsdale, 2018)	24
Figure 3.1	NSGA-II Flow chart	55
Figure 4.1	Comparison of computational time	66
Figure 5.1	The effect of driver's GDI level on total costs	69
Figure 5.2	The effect of driver's GDI on transportation risk	71
Figure 5.3	The relation between driver's GDI and awakens level	72
Figure 5.4	The effect of awakens on total costs	75
Figure 5.5	The effect of awakens on transportation risk	76

List of Abbreviations

HWVRP	Hazardous Waste Vehicle Routing Problem
GDI	Green Driving Index
NSGA - II	Non-Dominated Sorting Genetic Algorithm - II
HWM	Hazard Waste Management
VRP	Vehicle Routing Problem
GHG	Greenhouse Gases
MINLP	Mixed Integer Nonlinear Programming
MILP	Mixed Integer Linear Programming
LP	Linear Programming
IP	Integer Programming
CVRP	Capacitated VRP
TDVRP	Time-Dependent VRP
TDVRPTW	TDVRP with Time Window
MDVRP	Multi Depot VRP
SVRP	Stochastic VRP
LRP	Location Routing Problem
FLP	Facility Location Problem
PVRP	Periodic VRP
DVRP	Dynamic VPR
IRP	Inventory Routing Problem
FSMVRP	Fleet size, and Mixed Vehicle Routing Problem
GVRP	Green VRP
FCMIRP	Fuel Consumption, and Multi-inventory Routing Problem
FCR	Fuel Consumption Rate
EVRP	Electrical VRP
AFV	Alternating-fuel Vehicles
HWLRP	Hazardous Waste Location Routing Problem
TDSPFM	Truck Driver Scheduling Problem with Fatigue Monitoring
TPMA	Three Process Model of Alertness
MOOP	Multi-objective Optimization Problem
KSS	Karolinska Sleepiness Scale

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Abstract

Hazardous waste management is a crucial issue that needs adequate attention and planning. Many efforts were done by researchers on the Hazardous Waste Vehicle Routing Problem (HWVRP). However, a very few of these consider human aspects while solving the problem. In this research, two human related aspects were included in the developed HWVRP model, which are driver's Green Driving Index (GDI) and driver's awakesness levels. Therefore, three levels of drivers' GDI were assumed based on their awareness of environmentally friendly driving behavior, as well as, three levels of alertness which reflect the degree of sleepiness (awakesness) of drivers. The effect of the aforementioned levels on different functions such as cost function is investigated to reveal the influence of driver differences on HWVRP. The proposed multi-objective model was designed to tackle real world problems by dealing with multi-vehicles, multi-waste type, multi-waste nodes (generation, treatment, recycling and disposal) along with different driver's GDI and awakesness levels. This HWVRP model aims at: (1) minimizing total costs such as transportation, hiring, firing, training, and waste amount related costs, (2) minimizing transportation risks on the population located along the transportation route,

(3) minimizing site risks on the population living around waste processing facilities, and finally (4) maximizing driver's awakesness level. A Non-Dominated Sorting Genetic Algorithm - II (NSGA - II) was used to solve the developed model, due to its popularity in solving such problems in an effective and timely manner. Different size instances were used for the purpose of model validation; in addition, a sensitivity analysis was conducted on the effect of different parameters / variables on the model's objective functions to ensure that the model functions as it should. Results showed a direct relationship between driver's GDI levels and the total costs, where the increase in driver's level yields a reduction in costs up to certain point, but costs start to increase again due to training and salaries costs for high-level drivers. Moreover, an indirect link was found between awakesness levels and transportation risk, where increasing the level of driver's awakesness resulted in a reduction in transportation risks, although no mathematical relation is present between the two functions.

Chapter One

Introduction

1.1 Overview

Nowadays, many cities are placing a lot of efforts toward becoming cleaner and smarter for the sake of their stakeholders, including citizens, environment, and waste collection profitable companies. Lately, the idea of smart cities received a great attention by governments and researchers. Such cities aim at improving the way of carrying out business and every day practices in urban cities to create a comfortable life for citizens physically and mentally, in addition to preserving the environment. Among the seven known pillars that create and support smart cities is waste management, which holds a significant importance. Indeed, managing waste properly comes with many benefits, such as protecting the health of people and the environment from hazardous materials, as well as creating a civilized form of collecting and managing waste bins to provide an aesthetic view for citizens. Waste management is the process of collecting, transporting, processing, recycling, disposing, and monitoring waste materials. Environmental, technological, technical, social, economic, and political factors must be taken into consideration in the process of managing wastes. Important decisions have to be made to utilize the available resources and protect the environment.

Collecting waste is considered the most important process of waste management, since it is the process where bins are drained from waste in a

timely fashion to prevent any harm caused by gases and hazardous emissions. According to Or and Curi (1993), the process of waste collection accounts for nearly 80% of the costs associated with waste disposal, and is considered as the most-costly aspect of the cycle. These costs are due to the massive use of trucks and labor in addition to the time of planning and scheduling. The industrial facilities around the world produce huge quantities of wastes in the forms of solid, liquid, and gas. A huge amount of these wastes affects the environment, living organisms, and humans (Misra and Pandey, 2005). An ineffective hazard waste management system leads to a polluted environment and substantial harm to human health (Herva *et al.*, 2014). Therefore, it is important to plan the procedure of collecting such hazardous wastes for the sake of protecting the environment and the well-being of human lives (Misra and Pandey, 2005).

Hazard Waste Management (HWM) is ‘a complex system primarily consists of the following: collection, transportation, recycling, treatment, and disposal processes’ (Rabbani *et al.*, 2018). While hazardous waste has become an environmental issue, it continues to increase with the development of industries (Samanlioglu, 2013). Figure 1.1 shows a typical HWM process with waste source node and three waste management facilities. The process starts with a waste generation node that contains treatable, recyclable, or disposable wastes. After treatment some amount of waste is recycled, while the rest is disposed. Similarly, at recycling facilities waste is recycled and turned into useful products or materials, and the rest

of waste is disposed as residue at disposal locations. There is no doubt that if such wastes end up in land or

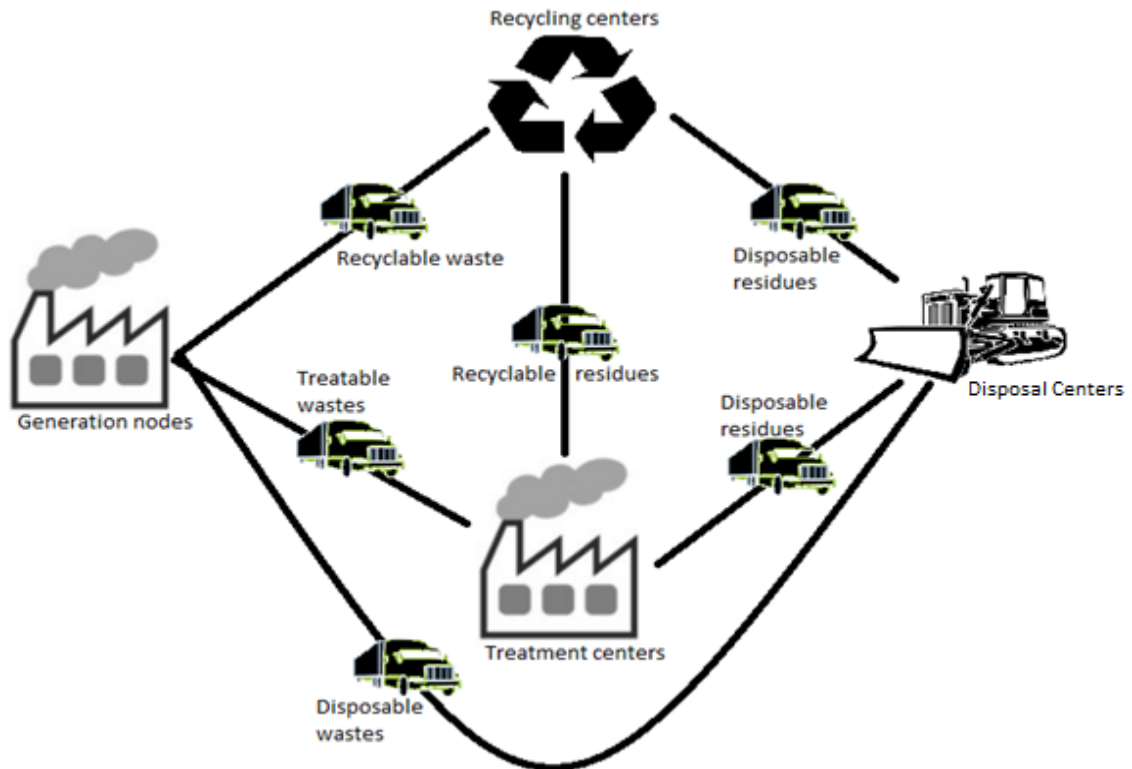


Figure 1.1: HWM system

water or even in exposed areas, an excessive harm will occur due to the absorption of toxic minerals and the emissions of hazardous gases. Therefore, the process of collecting such waste must be planned adequately. As mentioned earlier, the process of collecting and managing waste consumes a lot of resources including waste collection trucks and labor. Each aspect related to these resources such as fuel for trucks, working hours for labor, and safety of the population, must be considered and planned carefully. Moreover, a lot of attention must be present while selecting routes for the trucks to drain a geographically distributed waste bin. In many cases,

a great deal of complexity appears in route planning due to the large number of waste trucks, bins and labor. Therefore, many researchers treated waste collection as a Vehicle Routing Problem (VRP). The researchers considered VRP as one of the well-known applications in operations research field and the most challenging combinatorial optimization problems. It falls into the category of NP-Hard problems, which means that, in practice, the effort required for solving this problem exactly increases exponentially with the problem size. The basic VRP deals with a fleet of homogenous transportation trucks serving various sets of customers (Dantzig and Ramser, 1959). Recently, VRP-related studies have grown by about six percent annually in the literature researches (Eksioglu *et al.*, 2009). Computerized methods for real-world transportation applications often result in significant savings ranging from 5% to 20% in the total costs (Toth and Vigo, 2002). Moreover, different variants are considered in modeling the VRP within different stages of transportation. Some of the difficulties include demand uncertainty, travel times, pick-up and delivery time window, and input information. Additionally, the VRP has widely been studied due to its importance and effects on various industries (Lahyani *et al.*, 2017).

A green waste collection problem is considered in this study, where several vehicles are used for collecting waste from different places and sending them to a treatment facility to be shipped toward disposal or recycling facilities. Then, all the vehicles must return to the depot after disposing or recycling the waste to a disposal or recycling facilities. These services have

a high impact on the public concerns about the environment and population growth, especially in developing countries. Researchers aim at reducing the costs associated with distance traveled, finding the optimal location of disposal facilities, and minimizing the number of vehicles used.

Additionally, a significant part that considerably affects VRP results is human factors. Smart driver route-choices could lead to the reduction of pollution costs based on real-time information. The drivers, who control the transportation operation, should be considered critical while analyzing a VRP model. Integrating drivers' behavior in the VRP has a significant effect on the logistics performance of a specific company (Abu Hla, *et al.*, 2019; Srivatsa Srinivas and Gajanand, 2017). Alam and McNabola, (2014) found that green driver behavior could decrease fuel consumption by 45%. Moreover, Liimatainen (2011) showed that driver's behavior is correlated with individual differences where the fuel consumption could vary by up to 30%. Therefore, this research focuses on developing a multi-objective Waste Collection Green VRP model, which takes into consideration multiple products, multiple periods, the green policy, drivers' differences in terms of drivers' behaviors, and fatigue rates with the objective of minimizing traveling costs and fuel emissions.

1.2 Problem statement

The issue of waste management drew the attention of society lately, due to the possible impacts and harm that can happen if waste is not properly collected and treated. In addition, the operation of waste collection must be

managed appropriately to avoid any accumulation of waste in bins, which in return harm the environment because of the emissions of hazardous gases. In a typical waste collection system, specially designed trucks driven and operated by labor travels from one or more depots to collect waste from different waste bins in different locations. As the fleet of waste trucks, labor, and waste bins grow larger, the complexity of operations increases. This complexity follows from the presence of many routes that must be covered to collect waste from bins, as well as from the parameters that should be considered, such as travelled distance, fuel consumption, working hours, overtime, and safety concerns. This is why many researches study the issue of waste management as a VRP, which must be planned carefully. In addition to route planning, different driver behaviors strongly affect the execution of waste collection process; while many drivers are normal, some drivers are aggressive and reckless, and other drivers are overcautious. This difference in drivers' behavior affects the fuel consumption and the safety of society. Another drivers' behavior that is ignored by VRP studies is awakeness level. Such indicator is related to fatigue rates at different times of a day, and may cause many troubles if overlooked, especially when shipping hazardous waste that causes risk to people around routes and waste processing facilities. Given so, this research aims at integrating driver's differences into green waste collection, to be solved as VRP. Two types of behaviors are considered in this research. First, the awareness of driving attitude and its consequences toward the environment in terms of fuel consumption and Greenhouse Gases (GHG) emissions, which is referred to

as Green Driving Index (GDI). Secondly, driver's awakeness (sleepiness) levels at different periods of the day. The objectives of the proposed model are minimizing travel costs and fuel emissions while considering different drivers' personalities, alertness levels, green policies, multiple products and multiple periods.

1.3 Research significance

The significance of this research comes from the consideration of driver's awakeness levels at different periods of the day. Indeed, the level of awakeness and consequently fatigue rates of drivers possess a great importance in waste collection and transportation, especially when dealing with hazardous waste. According to Ani et al. (2020), physical and mental fatigue of drivers such as muscle power loss and reduction in efficiency, alertness and mental performance is a main cause of fatal accidents. Therefore, monitoring driver's fatigue / alertness levels significantly improve driver's and citizen's safety, by providing an early sign and warning that the driver needs to rest (May and Baldwin, 2009). Although studying driver's skills and environmental awareness is important in optimizing and saving costs and reducing GHG emissions (Asrawi et al., 2017), however, such goals are insignificant compared to the well-being of drivers and citizens. To the best of the researcher knowledge, green driving indices and awakeness levels of drivers have not been considered in any VRP models, therefore such contribution to the literature of VRP must be investigated. In addition, the inclusion of detailed and different variants of

VRP such as different routing costs, two types of risk caused by hazardous waste transportation and processing, drivers with different GDI levels, different types of waste, and four nodes for waste management (generation, treatment, recycling and disposal), creates a rich and realistic waste management VRP model that complies with real world situations.

1.4 Research questions

After solving the proposed model, the following questions are answered with the aim of providing a clear explanation of the problem under study, in addition to exploring the relationships between different aspects in this thesis.

1. How can drivers with different GDI affect routing costs and GHG emissions?
2. What is the effect of hiring, laying-off, and training of drivers on routing costs and GHG emissions?
3. How can drivers with different alertness levels affect the process of HWM?
4. What periods of the day results in the highest and lowest awakensness (fatigue) levels?

1.5 Research objectives

This research focuses on achieving the following objectives and goals:

- Determine the optimal routes of waste collection vehicles to follow from source nodes and distribute them to treatment, recycling, or disposal nodes considering the GDI level.
- Determine the drive, duty, awake, and duty times, which lead to maximizing the driver's awakesness while considering the green driver's index level.

1.6 Research methodology

The following steps show the intended methodology to conduct this research:

1. Defining the problem by identifying the gap between current HWM models and the real case.
2. Reviewing the related research on green waste collection, as well as on different drivers' behaviors in VRP, to define the research gaps and collect data.
3. Developing a mathematical model to present the problem using a Mixed Integer Nonlinear programming (MINLP) approach for optimization.
4. Using Non-Dominated Sorting Genetic algorithm II to solve the optimization problem, since exact methods are not suitable due to the

complexity of the problem, which includes multi objective functions and different variants of VRP.

5. Performing sensitivity analysis to explore the robustness of the model to different input variables.
6. Implementing the model: looking for some real cases to test the model.

1.7 Thesis organization

The other chapters included in this thesis are organized as follows. Chapter two presents the literature review, which examines previous studies related to waste collection VRP, green waste collection VRP, hazardous waste, and driver's behavior in VRP. Chapter three presents the developed mathematical model that considers the green waste collection VRP with different drivers. Chapter four presents the computational results with detailed discussion and explanations. In chapter five, sensitivity analysis is performed on the model and its objective functions. Finally, chapter six discusses the conclusions and proposes extensions for future research.

Chapter Two

Literature Review

2.1 Overview

In order to gain a better understanding of the problem at hand, a review and summery of previous studies in the literature of waste collection management must be done. Therefore, in this chapter, related studies in the field of green VRP, hazardous waste management VRP, and the effect of different drivers' behaviors on VRP is presented. Reviewing the literature is the first step to conduct this research since it summarizes research gaps, limitations, and unanswered open questions in waste collection VRP. This literature review aims at accomplishing the following objectives:

1. Gaining a strong base of knowledge regarding the issue of green waste collection VRP and the effect of different drivers' personalities and behaviors.
2. Defining research gaps and limitations in order to extend previous research to present a solid contribution to the literature and prevent any form of duplication.
3. Exploring methodologies used to carry on research including: mathematical model formulation, solving algorithms, model validation, and results presentation and analysis.

2.2 Vehicle routing problems

Due to the growing concern from decision making personnel in governments, in addition to the trend adopted by profitable companies in various sectors to fulfill their environmental responsibilities, the idea of sustainability and green practices to manage businesses grew and flourished. Reducing the carbon exhausts and the waste in all stages/activities of the supply chain (such as producing, distribution, recycling) is one of the most crucial goals that green of thinks (green logistics in companies) are working to achieve, as well as, managing waste collection, recycling, treatment, and all activities related. One of the essential activities of any supply chain is transportation. There are hundreds of tons of goods/wastes that must be transported from one point to another, loaded in vehicles that work by burning fuel and firing carbon in the air. This huge amount of emissions leads to polluting the environment; therefore, companies are taking into consideration the implementation on green logistics to reduce emissions as much as possible. As a matter of fact, the interest in transportation sector does not primarily aim at reducing emissions but rather reduce costs. Given so, building models that create routes with the purpose of reducing emissions and costs would be more realistic and applicable in profitable corporations.

Most VRP models are built to reduce the costs and find the best route while taking into consideration the logistic and physical capabilities as constraints. The first occurrence of VRP was in 1959 by Dantzig and Ramser; the

authors built a mathematical model to optimize a real life VRP about a central gas station that distributes gasoline to several gas services. The following equation shows the objective of their model:

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

Where D is the total distance, d_{ij} is the traveled distance from point i to point j , and x_{ij} is 1 if the model chooses a route from point i to point j , 0 otherwise. The objective of this model is to minimize the total traveled distance by all vehicles. In addition to the traveled distance parameter, they added a truck capacity parameter to their model to achieve more realistic solutions (considering the capacity of each truck), yielding what is known as capacitated VRP (CVRP). In the following years, researchers continued to improve this model and integrate more and more parameters to achieve more realistic solutions. Cooke and Halsey (1966) added the time parameter to the VRP, where they considered the travel time between source and destination nodes, with the aim of minimizing travel time between nodes. VRP models in which the time required to travel between different locations varies during the day are called Time-Dependent VRP (TDVRP). Solomon (1987) studied TDVRP with time window (TDVRPTW); the proposed model was designed with time window constraint to improve the efforts of solving VRPs and making it more realistic to address real life needs. On the other hand, Malandraki (1989) developed a TDVRP model, where the effect of different traffic periods on vehicle speeds was analyzed. Moreover, Ichoua et al. (2003) considered vehicle speed variations in a TDVRP

models. In addition, Malandraki and Daskin (1992) proposed a special case of TDVRP, where they formulate the variation of travel time as a step function within the periods of the day. In their article, Lin et al. (2013) proposed a review on VRP model types such as the multi depot VRP (MDVRP) where each vehicle must start and end at the same point and there is more than one depot point, a problem first introduced by Tillman (1969). On the other hand, Stochastic VRP (SVRP) is a variant of VRP which considers uncertainty and randomness in one of the following parameters: customer demands, new customers and travel times (Gendreau et al., 2014). Location routing problems (LRP) combine VRP and Facility Location Problems (FLP); LRP models aim at minimizing the costs of the routes used to service customers while considering the optimal location of depots. Variants of LRP such as multiple demands and stochastic customers are considered, for instance, in the work of Nagy and Salhi (2007) and Min *et al.* (1998). Another variant of the VRP is Periodic VRP (PVRP), which mainly has the objective of minimizing costs, fleet size and travel times over a planning horizon of several periods. Beltrami and Bodin (1974) introduced the first PVRP model by solving a VRP for municipal waste collection with time constraint. Other applications of the PVRP are found in the distribution of fuel to gas stations, the grocery industry, and the supply of raw materials from suppliers to many geographically spread locations (Alegre et al, 2007). In addition, many other variations of VRP, such as dynamic VRP (DVRP), inventory Routing Problem (IRP), fleet size, and mixed vehicle routing problem (FSMVRP), generalized VRP, multi-compartment VRP, fuzzy

VRP, and others are found in the VRP literature. Each of the discussed variations aims at improving VRPs models to solve more realistic problems.

2.2.1 Green VRP

Air pollution and CO₂ emissions threaten our lives and the nature around us as well. Many governments have put forward some policies to minimize emissions and reduce fuel consumption. In line with these efforts, many companies changed their own policies to reduce fuel consumption and CO₂ emissions. The focus and concern of the transportation sector was the huge quantities of CO₂ emissions generated by transportation means (Salimifard *et al.*, 2012). The continuous improvements by researchers in VRP by developing rich, comprehensive and realistic models, allied with the efforts of transportation sector and logistics companies to reduce the emissions of CO₂, led to the definition of Green VRP (GVRP), which is a routing problem that focuses on energy consumption and CO₂ emissions. While fuel costs are a significant part of VRP calculations and objectives (Hooshmand and MirHassani, 2018), GVRP balances the tradeoff between costs and CO₂ emissions.

Fuel consumption depends on many factors such as vehicle speed, route conditions, weather, and route traffic (Poonthalir and Nadarajan, 2018; Xiao *et al.*, 2012; Kuo, 2010; Maras, 2008). Kara *et al.* (2007) proposed a VRP model with the objective of minimizing fuel consumption by considering the effect of vehicle load and travel distance on fuel consumption. Moreover, Cheng *et al.* (2018) considered the load, distance, and fuel price to evaluate

the fuel consumption routing problem with multi-inventory period characteristics (FCMIRP). Xiao et al. (2012) proposed a CVRP model to minimize the fuel consumption rate (FCR). The authors considered traveled distance and the vehicle's load in this model. Other researchers build their models intending to minimize energy consumption when using electrical vehicles (Electrical vehicle routing problem - EVRP) (Xiao et al., 2019). This type of vehicles depends on the electrical energy; using this vehicles of this type reduces CO₂ emission, but on the other hand, this new technology costs more than the traditional one (conventional fuel vehicles). There is another type of vehicles used in GVRPs, such as alternative-fuel vehicles (AFV). This type of vehicles is used by some government and nonprofit organizations to contribute to the effort to reduce CO₂ emissions. Other researchers considered AFVs in GVRP, such as Erdoğan et al. (2012) and Taha et al. (2014). Erdoğan et al. (2012) introduced the first research to consider using AFVs with GVRP; their model aims to minimize total distance with minimum fuel consumption without considering the load or distance effect on fuel consumption.

2.3 Hazardous waste management

Hazardous waste (HW) is the waste that hurts human and nature; it always comes from the industrial sector where manufacturing processes produce enormous quantities of liquid, gas, or solid waste. This waste is toxic and has a high-risk rate on the environment and humans. Dealing with this type of waste needs special tools, knowledge, care, and safe methods to minimize

and limit its risks. Hazardous waste management (HWM) is the method of collecting, transporting, processing, recycling, disposal, and monitoring the waste materials.

2.3.1 Hazardous waste

The definitions of HW differ from one country to another. The US Resource Conservation and Recovery Act of 1976 (RCRA) defines HW as follows: ‘to cause or significantly contribute to an increase in mortality or an increase in serious irreversible, or incapacitating reversible illness, or pose a substantial present or potential hazard to human health or the environment when improperly treated, stored, transported, disposed of, or otherwise managed.’. In Europe, HW is defined as: ‘such wastes that could potentially increase the hazardous properties of municipal solid waste when landfilled incinerated or composted’ (Gendebien *et al.*, 2002). HW exists in liquid, solid, or gas state and it has different types such as chemical, physical, petrol, etc. The U.S. Environmental Protection Agency (2018) defines a list of characteristics to categorize HW.

Having an idea about HW's definition and characteristics helps to understand that waste needs different types of technologies to recycle, dispose, or treat it. As an example, using biological technology to process petroleum waste and using a chemical process to handle medical waste. This complexity needs exceptional operational and tactical actions to minimize or eliminate the HW risks as much as possible. HW management (HWM) is one of the most complex and well-known models that operate to handle total system costs and risks.

2.3.2 HWM and VRP

HWM includes all processes and plans that are set to manage all steps and stages related to HW. Therefore, HWM includes the collection and transportation stages where waste vehicles work to collect the waste from different generation nodes, such as factories, and distribute it to disposal, treatment, or recycling facilities as needed. Many researchers developed mathematical models to help enhancing the planning of the collection and transportation in HWM. The first model that integrates HW with VRP was introduced by Zografros and Samara (1989), who created a mathematical model of hazardous waste routing problem (HWRP). This model aims at minimizing routing risk, disposal risk, and travel time. As time passes, many HWRP models were developed to provide solutions for more complex and realistic scenarios. The work of Akgül (1994) presented a Hazardous Waste Location Routing Problem (HWLRP) model to maximize the minimum distance to set locations of the disposal facilities while considering environmental risk. Jacobs and Warmerdam (1994) set an HWLRP mathematical model that aims to find the optimal route and setting of transportation, disposal, and storage of HW while considering waste type; this model also calculates the cost of treatment/disposal operations, depending on cost per unit of waste processed. Depending on previous HWLRP models and other VRPs models, Nema and Gupta (1999) developed a new HWLRP model that aims at minimizing total costs (disposal, treatment, and transportation) and minimizing total risk, including treatment, disposal, and transportation risk. Researchers worked to improve

the HWLRP models to achieve, on one hand, risks and costs as low as possible, due to the strict laws and penalties issued by governments on air pollution, while, on the other hand, fulfilling the needed of profitable companies to maximize profit and minimize costs (Costa *et al.*, 2016).

Moreover, the researchers formulated HWRP models to locate the position of HW facilities as shown in the work of Alumur and Kara (2005). They developed a model to answer questions regarding where to build treatment, recycling, and disposal facilities and which technology should be used with treatment facilities. Evren and Bahar (2007) proposed an HWRP mathematical model that includes air pollution standards to calculate the pollution concentrations at population centers, in addition of being a cost-based model. The model of Zhang and Zhao (2011) considered the diversity of waste type and technology type; this model was developed to minimize total costs and maximize the quality. A similar approach was adopted by Boyer *et al.* (2013), who formulated a model that contains two main objective functions: the first was to minimize the total costs (transportation, new facilities, and operational costs), and the second aims at minimizing the risk of transportation. Minimization of risk on population living around treatment and disposal nodes is considered by Samanlioglu (2013), who suggested in his model that, if the waste is non-recyclable, there should be a direct route from recycling center to disposal center. On the other hand, Ghezavati and Morakabatchian (2015) used the fuzzy stratification concept and human feeling in their model. Moreover, environmental risks are considered by Yilmaz *et al.* (2016), who built a two-objective functions

model. The first objective is to minimize total transportation costs and the second is to minimize the risk of HW on population and the environment. They also proposed a new definition for environmental impact considering some of the environmentally sensitive elements. Multi-type waste was considered in HWLRP in the work of Rabbani *et al.* (2018), who also considered waste compatibility as a requirement in their model. Most of the previously mentioned models did not use real life data; hypothetical data was used to solve models due to the lack of real-life instances. To address real life problems, Hidaya and Benhachmi (2018) considered an existing model in HWLRP and matched it to Moroccan regulations while considering new risk aspects. On the other hand, Aydemir-Karadag (2018) developed a rich HWLRP model which is applicable in real-life applications; in addition, the model included net present value function with the aim of calculating HWLRP profitability. Rabbani *et al.* (2019) proposed a multi-period HWLRP model that deals with a stochastic environment. In addition, Utku and Erol (2020) developed a HWLRP model that considers the treatment site, recycling, and disposal facilities. Also, they considered transporting HW between the facilities.

After reviewing the literature of HWVRP, the focus was on achieving one or more of the following objectives:

- Cost minimization of HW operations, including transportation costs, opening new (disposal, treatment, or recycling) facilities costs, or waste processing cost per unit waste.

- Risk minimization of HW on the population around the routes or the environment; on both the deterministic and the stochastic cases, this risk is known as the transportation risk.
- Risk minimization of HW on the population around treatment and disposal facilities (site risk).
- Some of the researches use the concepts of fuzzy stratification.
- Few efforts applied HWLRP on real cases to ensure its efficiency.

2.4 Effect of driver's behavior on VRP

Given what has been discussed in this chapter, it is noticeable that VRP and HWRP models included many objectives and variations of the routing problem. Objectives such as minimizing costs, CO₂ emissions, travelled distance, and transportation risk are always present and investigated by authors. However, one of the most critical factors in any routing problem, which is neglected by researchers, especially in HWLRP is the drivers' personality and their behavior. Both environmental issues (CO₂ emissions) and economic issues are affected by the drivers' behavior. Therefore, it is essential to integrate it into VRP and HWLRP models. The driver's behavior is the way the driver is handling and driving the vehicle; it is the actions that he/she takes in different circumstances. This behavior includes speeding habits, braking habits, following regulations, and fatigue driving. Due to its importance, this research focuses on fatigue driving.

2.4.1 The effect of fatigue on VRP

The level of driver's fatigue (tiredness) is an important indicator in transportation that must be considered. Likewise, decision makers in vehicle routing planning and scheduling should pay great attention to this indicator. The importance of fatigue rates is due to the fatal results that could happen if the driver is extremely tired and lacks concentration and alertness. In fact, in commercial trucks logistics, driver fatigue is believed to be the major cause of deadly accidents, as suggested by Chen and Xie (2014). In addition, Maclean *et al.* (2003) stated that driver sleepiness caused by fatigue is responsible for 20% of accidents yearly. Fatigued driver behavior is a result of lack of sleep, medical conditions, long driving times, monotonous tasks, and other factors. Many studies in the literature shed light on the effect of fatigue on driver's behavior. Zhang *et al.* (2016) investigated the effect of driver fatigue on car following (which is the measure of time and space gap between two successive vehicles). Different scales and indicators were used to measure fatigue levels including subjective sleepiness and time headway. Results showed the significant effect of fatigue on car following behavior, in a way that, at high fatigue levels, drivers tend to leave unsafe time headway with the leading vehicle. In addition, Ting *et al.* (2008) introduced a simulated approach study, which provides quantitative measures of fatigue levels. These measures provide significant data about the development of fatigue level to prevent accidents, as well as deciding the optimal safe highway driving durations. Similarly, Gastaldi *et al.* (2014) investigated the relationship between fatigue levels and performance, while considering

passive tasks. The authors used a driving simulator to obtain data from ten candidates. Results showed that long driving periods leads to higher fatigue levels and thereby increasing the likelihood of accidents. On the other hand, Bowden and Ragsdale (2018) presented a novel Truck Driver Scheduling Problem with Fatigue Monitoring (TDSPFM). This fatigue-related model aims at maximizing driver's alertness by finding the best schedule for drivers while considering working hours regulations and time window of each location with start, end and duration of service. The authors provided a starting point to study the tradeoff between the schedule and level of alertness of drivers to minimizing the probability of accidents and ensuring safe routing.

To assess the level of fatigue/alertness, the Three Process Model of Alertness (TPMA) model was used. TPMA is a bio-mathematical model to measure the level of alertness, performance, sleepiness, and sleep latency at different times of a day as shown in Figure 2.1.

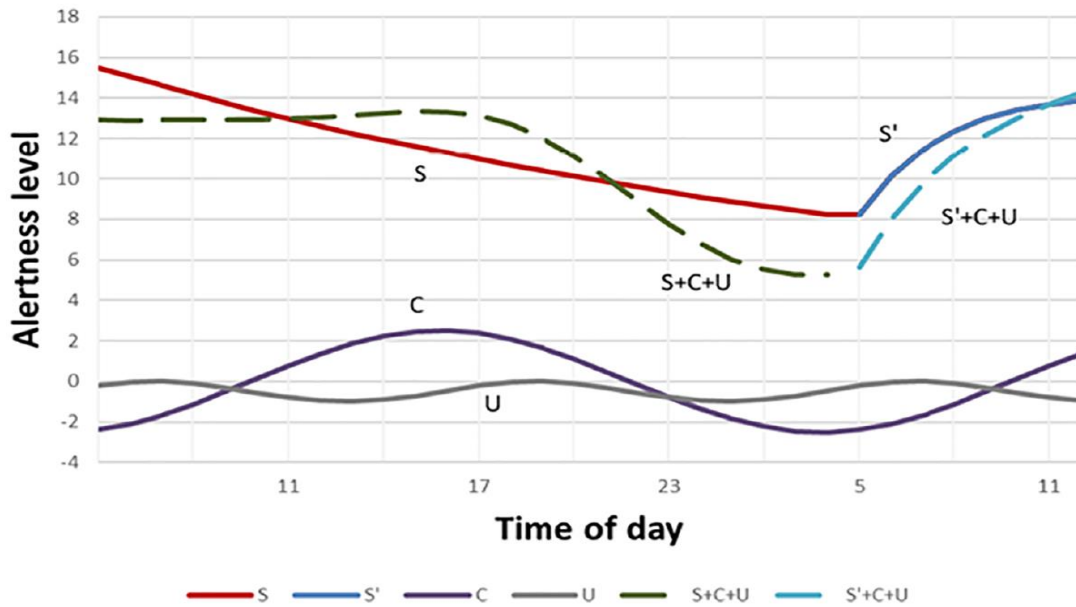


Figure 2.1: Three Process Model of Alertness (TPMA) (Bowden and Ragsdale, 2018)

TPMA model consists of three primary processes which are: process C, which shows the circadian rhythm and sleep-awake-cycle, this process shows the effect of time of day on alertness level as shown in Figure 2.1 where it starts with an incline in alertness followed by a decline at later hours of the day. Moreover, process S shows an exponential decline in alertness as time passes in a day due to fatigue, then a recovery time when sleeping is shown in process S'. Finally, process U illustrates the ultradian rhythm in form of awake-rest-cycle that causes the afternoon descent in alertness (Åkerstedt et al., 2007). To the best of the researcher knowledge, the issue of driver's fatigue levels was not considered in any HWVRP, and optimizing this fatigue levels yields many benefits, especially ones related to the well-being of drivers and the population. Indeed, when dealing with the transportation of hazardous waste, extreme actions on preventing and lowering the possibility of accidents must be taken, due to the horrific

consequences that may happen in case of crashing a HW truck. Therefore, integrating fatigue levels with HWVRP is a significant contribution to the literature which is worthy to be investigated.

2.4.2 Green Driving Index

Green driving is actions taken by drivers to protect and sustain the environment. Such actions include acceleration, braking, idling, and using air conditioning and consolidated trips. Such practices preserve the environment mainly in terms of reducing fuel consumption and Greenhouse Gases (GHG) emissions. These practices depend on the personality and behavior of the driver. Driving patterns are classified into three patterns, which are aggressive, calm, and eco-driving (Asrawi *et al.*, 2017). Each pattern leads to different fuel consumption and GHG emissions. Therefore, the Green Driving Index (GDI) can be defined as the awareness of drivers about the effect of driving styles on the environment and their willingness to preserve the environment by adopting an eco-friendly driving style. Sivak and Schoettle (2012) investigated the effect of the three levels of decision making (strategic, tactical and operational) on fuel consumption. In their study, the authors proposed that strategic decisions include selection of vehicle class, model and its maintenance, while tactical decisions deal with route type selection and traffic congestion; on the other hand, the operational level includes speeding, idling, and using air conditioning decisions. Among the three levels, the operational one directly relates to drivers' GDI and their driving behavior. Alessandrini *et al.* (2009) studied the relationship between

driving style and GHG emission (mainly CO₂ and NO_x); they linked the driving patterns with throttle standard deviations. Their results confirmed that up-normal pressing on the fuel throttle (aggressive driving style) results in more emissions. Using a different approach, Hiraoka *et al.* (2011) developed a driver assistance system with the aim of aiding and encouraging drivers to follow an eco-driving style. Moreover, Asrawi *et al.* (2017) presented a novel model that studies the effect of drivers' behavior on green supply chain management. The first objective of the proposed bi-objective model was minimizing total costs of the green supply chain, while the second took advantage of the reverse proportion relationship between GDI and GHG releasing to reduce the effect on the environment (by minimizing GHG emissions).

Given what had been discussed in this chapter, HWM and HWVRP are important topics that draw the interest of many researchers recently. However, a research gap was found in the literature of HWVRP, which is neglecting drivers' behavior, mainly fatigue levels and GDI. Therefore, the main focus in this research is to spotlight on effect of different drivers' behaviors on the routing plan, and other functions of the model such as cost function.

2.5 Non-dominated sorting genetic algorithm II (NSGS-II)

The article of Srinivas and Deb (1994), was the first article to introduce the NSGA, but because of its computational complexity and other disadvantages, (Deb *et al.*, 2002) introduced the second edition of the

algorithm (NSGA-II). The fast non-dominated sorting, fast, crowded distance estimation procedure, binary tournament selection operator, and simple crowded comparison operator are the main features of this algorithm (Tavakkoli-Moghaddam *et al.*, 2012). The use of NSGA-II in optimization problems was noted in recent published researches. According to Subashini and Bhuvaneswari (2012), the reason why NSGA-II is recommended for different optimization problems is due its ability to provide various Pareto-optimal solutions in a single model run, as well as, its efficiency in solving multi-objective problems. The authors summarized the advantages of NSGA-II which makes this solution methodology superior over other optimization algorithms, which are:

- ✓ The use of sorting techniques which creates solution as close as possible to the Pareto-optimal solution.
- ✓ The advantage of diversity in solutions, which is done by using the crowd distancing technique.
- ✓ The principle of elitism, in a sense that only the best solutions among the population is preserved and inherited to the next generation of solutions.

In HWVRP, the work of Rabbani *et al.* (2018) and Rabbani *et al.* (2019) supports and approves the advantages of solving complex multi-objective optimization problems using NSGA-II. Rabbani *et al.* (2018) solved a HWLRP model, considering multiple waste type and waste facilities. The authors solved the optimization problem using two algorithms which are NSGA-II and Multi-Objective Particle Swarm Optimization (MOPSO).

When comparing the obtained results from the two solution methodologies, NSGA-II shows an advantage over MOPSO in exploring more Pareto-optimal solutions and more uniformity in solution space. On the other hand, Rabbani *et al.* (2019) mentioned that the main advantages of NSGA-II are its low time complexity and the diversity in solutions with non-convex and non-smooth solution spaces. Such advantages promote the use of NSGA-II in optimization problems, specifically in HWVRP modeling where a great deal of complexity must be handled.

Chapter Three

Model Formulation

3.1 Overview

This chapter presents the process of developing the desired green waste collection model. The problem is expressed as a mathematical problem, and then a mathematical model is developed in the form of a Mixed Integer Nonlinear Programming (MINLP) model. This chapter includes an overview on MINLP models in terms of their importance and why they are used. In addition, this chapter shows a detailed presentation and description about the developed model including: sets, parameters, decision variables, objective functions, and constraints. Moreover, explicit choices and specification on this model in form of assumptions are introduced in this chapter. Assumptions are crucial links between mathematical modeling and real-world problems in addition to its essential role in providing appropriate solutions.

3.2 Mixed Integer Nonlinear Programming

MINLP is an optimization technique which is widely used in VRP models and many other models related to scheduling, staffing and supply chain management. In general, Linear Programming (LP) is an optimization methodology that consists of maximizing or minimizing a linear function. LP requires linear parameters, variables, constraints and non-negative

decision variables to perform the optimization process. The following example provides a better understanding on LP.

Objective function:

$$\max \text{ or } \min \sum_{i=1}^N \sum_{j=1}^N d_{ij} x_{ij}$$

Subject to

$$\sum_{i=1}^N \sum_{j=1}^N a x_{ij} \geq 1 \quad i, j \in N$$

$$x_{ij} \geq 0 \quad i, j \in N$$

This example illustrates a LP model with linear parameters, decisions variables and constraints. In addition to linearity, the decision variables can have continuous fractional values i.e., real number; therefore, the optimal solution produce fractional values. Such fractional values may be undesired for some problems or unreasonable in other models, to solve this issue Integer Programming (IP) is used, where decision variables are integers, some special cases come binary numbers, as shown by the following constraint:

$$x_{ij} \in \{0,1\}$$

When targeting real world problems, many parameters, variables and constraints are present in a single model, which results in a higher level of complexity. In many cases, optimized functions may include a product of two different decision variables, which leads to a non-linear problem that must be linearized.

The green waste collection model is an example of rich VRP models that tackle a real-world application. Many sets, parameter, decision variables, objective functions and constraints are included in this model due to its complexity. Moreover, integer variables such as the decision to travel from node to another or not, as well as, non-integer variables such as vehicle load and amount of waste are assumed in this model. Therefore, a Mixed Integer Non-Linear Programming (MINLP) approach must be used to find suitable solutions.

3.3 Model description

Due to the importance of hazardous waste collection and management with regard to different dimensions, especially economic, environmental and social dimensions, this field of research attracted many researchers to study, improve and consider real life problems and situations while studying and modeling hazardous waste collection systems. HWM systems are treated as complex systems due to the large numbers of facilities, manpower, vehicles and critical decisions that must be made regarding the risk on population and pollution that are linked with these systems (Rabbani *et al.*, 2018).

A multi-depot, multi-waste generation nodes, multi-disposal nodes, multi-treatment nodes, and multi-recycling nodes was proposed in the developed green hazardous waste collection model. The problem of optimizing the green waste collection system, was formulated as a location-routing problem, and was described as follows: a fleet of heterogeneous waste collection vehicles with different load capacities depart from different

locations to empty geographically spread waste generation containers. Different types of waste are considered based on whether waste is recyclable or not and on the technology used to treat non-recyclable waste. Therefore heterogeneous vehicles are used to segregate waste and avoid any hazardous interaction between different waste types (Rabbani *et al.*, 2018). After visiting waste generation nodes, waste vehicles can have three different destination nodes: disposal, recycling or treatment nodes. At treatment nodes, the accumulated waste is treated using three types of technology depending on its compatibility with waste type. After treatment, recyclable and non-recyclable residues are generated from this treatment facility. Next, recyclable residues will be transported to recycling facilities, whereas non-recyclable residues will be shipped to disposal locations. At recycling nodes, the process of waste recycling generates waste residues, which are shipped to disposal locations. Waste recycling plays a major role in minimizing environmental pollution by reducing the amount of waste for disposal, as well as minimizing the costs associated with the treatment process (Ren *et al.*, 2017). Moreover, the issue of risk is considered in this model. Two forms of risk due to hazardous waste are considered: transportation risk and site risk (Rabbani *et al.*, 2018). Transportation risk involves the harmful effect on the population and the environment due to moving loaded waste vehicles along the routes between two different nodes such as a generation node and a treatment node. The load of waste vehicles is taken into consideration in this type of risk. On the other hand, site risk deals with the risks caused by treatment and disposal facilities on the populations who are

living around them. Population density, in addition to the amount of waste existing in disposal and treatment plants, is considered with the aim of minimizing such risks.

Furthermore, the proposed model investigates the behavior of drivers and their effect on the green waste collection model under study. In terms of behavior, this model considers the GDI of drivers to explore how the awareness of drivers of environmentally friendly behaviors affects the process of HWVRP. Having drivers with different GDI results in different fuel consumptions and GHG emissions and thereby different routing costs (Asrawi *et al.*, 2017). Additionally, the model considers training (and training costs) of drivers to enhance green driving behaviors. Studies show that adequate training, supported with incentives, may lead to 10% reduction of fuel consumption (Young *et al.*, 2011). In addition to training cost, hiring and laying off costs in different periods are investigated. Finally, the presented model pursues a novel approach by considering driver's fatigue rate and the level of alertness, which is adopted by the work of Bowden and Ragsdale (2018), on the truck driver scheduling problem.

3.3.1 Assumptions

Assumptions (1-8) are adapted from the work of Rabbani *et al.* (2018). On the other hand, assumptions (9-11) are based on the work of Bowden and Ragsdale (2018).

1. This model assumes two types of waste:
 - a. Recyclable waste, which is transported to recycling locations.

- b. Non-recyclable waste, which is transported to treatment locations.
2. The two types of waste can be generated at each waste generation node.
3. The amount of waste at each generation node should not exceed the load capacity of waste vehicle.
4. Each generation node is visited by only one waste vehicle, for each type of waste.
5. For each waste type, a fleet of homogeneous waste vehicles is assumed.
6. All facilities have a limited capacity.
7. The number of future potential facilities to be established are assumed to be limited.
8. The model assumes deterministic parameters rather than probabilistic ones.
9. The drivers are assumed to be rested and with high levels of alertness when starting their jobs.
10. Alertness boosters, such as drugs and caffeine, are not considered.
11. While resting, drivers should have high quality of sleep with no interruptions.
12. A planning horizon of one week is considered.

3.3.2 Sets

Set	Index	Description
G	$= \{1 \dots g\}$	waste generation (source) nodes
T	$= \{1 \dots t\}$	Pool of existing operationalized treatment nodes
R	$= \{1 \dots r\}$	Pool of existing recycling nodes
F	$= \{1 \dots f\}$	Pool of existing disposal nodes
Q	$= \{1 \dots q\}$	Treatment technologies
D	$= \{1 \dots d\}$	Depots
W	$= \{1 \dots w\}$	Waste types
K	$= \{1 \dots k\}$	Fleet of collection vehicles
M	$= \{1 \dots m\}$	Green Driving Index (GDI) levels of drivers
P	$= \{1 \dots p\}$	Periods

3.3.3 Parameters

Parameter	Description
C_{ijk}	variable transportation cost of vehicle type k of one unit of waste from node i to node j
CF_k	fixed cost of using vehicle type k
dis_{ij}	travel distance from node i to node j
pop_{ij}	number of people affected by transportation risk along route $i-j$
PA_i	number of people affected by risk of facility at location $i \in (TUF)$
d_{wi}	amount of waste type w accumulated at generation node $i \in G$
b_{wq}	proportion of recycling for waste type w treated with technology $q \in Q$
r_{wq}	proportion of mass reduction for waste type $w \in W$ treated with technology $q \in Q$
W_i	proportion of total waste recycled at node $i \in R$
tc_i	capacity of treatment facility at node $i \in T$
rc_i	capacity of recycling facility at node $i \in R$
fc_i	capacity of disposal facility at node $i \in F$
com_{wq}	1 if waste type $w \in W$ is compatible with treatment technology $q \in Q$; 0 otherwise

v_{wk}	1 if waste type w is compatible with vehicle $k \in K$; 0 otherwise
α_{qi}	1 if treatment technology $q \in Q$ is available at operationalized treatment facility $i \in T$
δ_w	maximum capacity of a vehicle that is compatible with waste type $w \in W$
γ_w	maximum allowable traveling distance of a vehicle that is compatible with waste type $w \in W$
dc_m^p	regular driver cost of an m -level driver in period p
otc_m^p	overtime driver cost of an m -level driver in period p
hc_m^p	hiring cost for an m -level driver in period p
lc_m^p	layoff cost for an m -level driver in period p
tc_{mm}^p	training cost for an m -level driver trained to reach level m' in period p
TP_{mmi}	1 if training from skill level m to level m' at depot node $i \in D$ is possible, 0 otherwise
GI_m	the green driving index for an m -level driver
t^{rest}	minimum rest time to be considered a long rest in period p
$T^{elapsed \setminus R}$	maximum time since last long rest in period p
$T^{elapsed \setminus B}$	maximum time since last break in period p
T^{break}	minimum break in period p
$T^{max rest}$	maximum rest period allowed
$T^{max sleep}$	maximum amount of sleep allowed
$T^{sleepdelay}$	the delay after rest begins before falling asleep
$T^{awakedelay}$	the delay after waking before driving can begin
$T^{horizon}$	planning horizon
cp	default circadian phase
cm_m	midline estimating statistic of rhythm (MESOR) of process CP for m -level driver
ca_m	amplitude of process CP for m -level driver
dec	decay in alertness
la	lower asymptote of the internal alertness scale
gr	recovery multiplier
ha	higher asymptote of the internal alertness scale
bl	break level of recovery function SB'_{im}
Um_m	Midline estimating statistic of rhythm (MESOR) of process U for m -level driver
Ua_m	amplitude of process U for m -level driver

3.3.4 Variables

Variable	Description
x_{ijmk}^p	1 if an m -driver travels from node i to node j by vehicle $k \in K$ in period p ; 0 otherwise
XD_{ijkm}^p	1 if vehicle type k is assigned to an m -level driver to transport wastes from node i to node j in period p ; 0 otherwise
l_{ik}^p	load of vehicle $k \in K$ after visiting node i period p
xt_{wi}^p	amount of waste type $w \in W$ treated at node $i \in T$ in period p
xr_i^p	amount of waste recycled at node $i \in R$ in period p
xf_i^p	amount of waste disposed at node $i \in F$ in period p
xtr_{ij}^p	amount of recyclable waste residue transported from node $i \in T$ to node $j \in R$ in period p
xtf_{ij}^p	amount of waste residue transported from node $i \in T$ to node $j \in F$ in period p
xf_{ij}^p	amount of waste residue transported from node $i \in R$ to node $j \in F$ in period p
nd_{im}^p	number of m - levels drivers required at depot node $i \in D$ in period p
hd_{im}^p	number of m -level drivers hired at depot node $i \in D$ in period p
ld_{im}^p	number of m -level drivers laid-off at depot node $i \in D$ in period p
td_{imm}^p	number of m -level drivers trained to reach level m' at depot node $i \in D$ in period p
otd_{im}^p	number of hours m -level drivers worked overtime at depot node $i \in D$ in period p
XG_{ijk}^p	number of k -type vehicle needed for shipping wastes from depot node $i \in D$ to node $j \in (TUF)$ in period p
K_{jkm}^{driveP}	the time a driver with level m and vehicle k has been driving upon arriving at location j in period p
K_{jkm}^{dutyP}	the time a driver with level m and vehicle k has been on duty upon arriving at location j in period p
K_{jkm}^{breakP}	the time a driver with level m and vehicle k has been taking a break at location j in period p
K_{jkm}^{awakeP}	the time a driver with level m and vehicle k has been awake upon arriving at location j in period p

K_{jkm}^{dayP}	the time of day upon arrival of a driver with level m and vehicle k at location j in period p
RP_{imk}	rest period for m -level drivers with vehicle k at node $i \in (D \cup TUF)$ in period p
WD_{imk}	work duration for m -level drivers with vehicle k at node $i \in (G \cup TUF)$ in period p
$TI_{i,i+1,mk}$	the amount of time it takes a vehicle k with an m -level driver to drive between node i , where $i \in (G \cup D \cup T \cup F)$, and the next node $i+$, in period p
SI_{jkm}^P	the process S at location j for an m -level driver and vehicle k in period p
SB_{jkm}^P	the sub-process SB at location j an m -level driver and vehicle k in period p
C_{jkm}^P	the process C at location j for an m -level driver and vehicle k in period p
U_{jkm}^P	the process U at location j for an m -level driver and vehicle k in period p
Si_{jkm}^P	the process S' at location j for an m -level driver and vehicle k in period p

3.3.5 Objective functions

Min F1=

$\sum_{p \in P} \sum_{m \in M} \sum_{k \in K} \sum_{i \in G} \sum_{j \in GUTUR} c_{ij} x_{ijmk}^p l_{ik}^p$	(1a)
$+ \sum_{p \in P} \sum_{i \in T} \sum_{j \in R} c_{ij} x_{trij}^p$	(1b)
$+ \sum_{p \in P} \sum_{i \in T} \sum_{j \in F} c_{ij} x_{tfij}^p$	(1c)
$+ \sum_{p \in P} \sum_{i \in R} \sum_{j \in F} c_{ij} x_{rfij}^p$	(1d)
$+ \sum_{p \in P} \sum_{k \in K} \sum_{i \in D} \sum_{j \in FUT} CF_k XG_{ijk}^p$	(1e)
$+ \sum_{p \in P} \sum_{m \in M} \sum_{k \in K} \sum_{i \in DUGUTUR} \sum_{j \in GUTURUF} c_{ij} dis_{ij} \frac{1}{GI_m} XD_{ijmk}^p$	(1f)

$+ \sum_{p \in P} \sum_{d \in D} \sum_{m \in M} (dc_{md}^p nd_{md}^p + hc_{md}^p hd_{md}^p + lc_{md}^p ld_{md}^p + tc_{mm'd}^p td_{mm'd}^p + otc_{md}^p otd_{md}^p)$	(1g)
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Description of objective function one: it is a minimization of cost of multiple functions including, the cost associated with vehicle load (1a), the cost of transporting residue from treatment node to recycling node (1b), transporting from treatment node to disposal node (1c), transporting from recycle node to disposal node (1d), the fixed cost of vehicles shipping waste from depot to treatment and disposal nodes (1e), the costs associated with travel distance and GDI level of driver m (1f), the costs of regular drivers, overtime drivers, hiring, laying-off and training of drivers (1g).

Min F2=

$\sum_{p \in P} \sum_{i \in T} \sum_{w \in W} PA_i xt_{wi}^p$	(2a)
$+ \sum_{p \in P} \sum_{i \in F} PA_i xf_i^p$	(2b)

Description of objective function two: minimization of risk on people located around treatment nodes (2a) and disposal nodes (2b), while considering the number of people and the amount of treated and disposed wastes.

Min F3 =

$\sum_{p \in P} \sum_{i \in T} \sum_{j \in GUT} \sum_{m \in M} \sum_{k \in K} pop_{ij} x_{ijmk}^p l_{ik}^p$	(3a)
$+ \sum_{p \in P} \sum_{i \in T} \sum_{j \in F} pop_{ij} xt_{ij}^p$	(3b)

Description of objective function three: minimize the risk on population positioned along the transportation route between treatment planets and disposal locations (3b), in addition to risks caused by the amount of waste load carried by waste vehicles (3b).

MAX F4 =

$$\sum_{p \in P} \sum_{k \in K} \sum_{m \in M} \sum_{j \in DUGUTURUF} SI_{jkm}^p + C_{jkm}^p + U_{jkm}^p \quad (4a)$$

Where

$$SI_{jkm}^p = \sum_{p \in P} \sum_{k \in K} \sum_{m \in M} \sum_{j \in DUGUTURUF} l_a + \left(Si_{(j-1)km}^p - l_a \right) \times e^{dec \times K_{jkm}^{awakeP}} \quad (4b)$$

$$C_{jkm}^p = \sum_{p \in P} \sum_{k \in K} \sum_{m \in M} \sum_{j \in DUGUTURUF} C_m + C_a \times \cos\left(2 \frac{\pi}{24}\right) \times (K_{jkm}^{dayP} - cp) \quad (4c)$$

$$U_{jkm}^p = \sum_{p \in P} \sum_{k \in K} \sum_{m \in M} \sum_{j \in DUGUTURUF} U_m + U_a \times \cos\left(2 \frac{\pi}{12}\right) \times (K_{jkm}^{dayP} - cp - 3) \quad (4d)$$

Description of objective function four: the final objective function that aims at maximizing the driver's alertness by calculating the summation of the three processes of TPMA model at location j in a time period of the day p (4a). Equations (4b), (4c) and (4d) present defining equations on the calculations of S, C and U processes respectively.

3.3.6 Constraints

$\sum_{i \in D} \sum_{j \in G} x_{ijmk}^p$	$\forall m \in M, k \in K, p \in P$	(5)
$\sum_{i \in DUG} x_{ijmk}^p - \sum_{i \in GURUT} x_{jimk}^p = 0$	$\forall j \in G, m \in M, k \in K, p \in P$	(6)
$\sum_{i \in G} \sum_{j \in GURUT} x_{ijmk}^p v_m = 1$	$\forall m \in M, k \in K, p \in P$	(7)
$\sum_{i \in G} x_{ijmk}^p - \sum_{i' \in D} x_{ji'mk}^p = 0$	$\forall j \in R \cup T, m \in M, k \in K, p \in P$	(8)
$x_{ijmk}^p \leq \sum_{w \in W} \sum_{q \in Q} v_{kw} com_{wq}$	$\forall i \in G, j \in T, m \in M, k \in K, p \in P$	(9)
$x_{ijmk}^p \leq \sum_{w \in W} v_{kw} \left(\frac{(Z - \sum_{q \in Q} com_{wq})}{ Z } \right)$	$\forall i \in G, j \in T, m \in M, k \in K, p \in P$	(10)
$e_{ik}^p - e_{jk}^p + \sum_{w \in W} v_{wk} \left((\gamma_w + dis_{ij}) x_{ijmk}^p + (\gamma_w - dis_{ij}) x_{ijmk}^p \right) \leq \sum_{w \in W} v_{wk} \gamma_w$	$\forall i \in G, j \in G \cup R \cup T, m \in M, k \in K, p \in P$	(11)

$\sum_{i \in D} dis_{ijk} \leq e_{jk}^p \leq \sum_{w \in W} v_{wk} \left(\gamma_w + \sum_{i \in D} (dis_{ij} - \gamma_w) x_{ijmk}^p \right)$	$\forall j \in G, m \in M, k \in K, p \in P$	(12)
$e_{ik}^p \leq \sum_{w \in W} v_{kw} \gamma_w - \sum_{j \in D} dis_{ij} x_{ijmk}^p$	$\forall i \in R \cup T, m \in M, k \in K, p \in P$	(13)
$l_{ik}^p - l_{jk}^p + \sum_{w \in W} v_{wk} \delta_w x_{ijmk}^p \leq \sum_{w \in W} v_{wk} (\delta_w - d_{jw})$	$\forall i \in G, j \in G, m \in M, k \in K, p \in P$	(14)
$\sum_{w \in D} d_{wi} v_{wk} \leq l_{ik}^p \leq \sum_{w \in W} v_{wk} \delta_w$	$\forall i \in G, k \in K, p \in P$	(15)
$x_{ijmk}^p \left(\sum_{w \in W} d_{jw} v_{kw} \right) \leq l_{jk}^p$	$\forall i \in G, j \in G, m \in M, k \in K, p \in P$	(16)
$l_{jk}^p \leq \sum_{w \in W} v_{kw} \left(\delta_w + \left(\sum_{i \in D} d_{jw} - \delta_w \right) x_{ijmk}^p \right)$	$\forall j \in G, m \in M, k \in K, p \in P$	(17)
$xt_{wj}^p = \sum_{k \in K} \sum_{i \in G} x_{ijmk}^p l_{ik}^p v_{kw}$	$\forall j \in G, m \in M, p \in P$	(18)
$\sum_{w \in W} \sum_{q \in Q} xt_{wj}^p (1 - r_{wq}) b_{wq} = \sum_{j \in R} xtr_{ij}^p$	$\forall i \in T, p \in P$	(19)
$xr_j^p = \sum_{w \in W} \sum_{k \in K} \sum_{i \in G} x_{ijmk}^p l_{ik}^p v_{wk} + \sum_{i' \in K} xtr_{i'j}^p$	$\forall j \in R, k \in K, m \in M, p \in P$	(20)

$\sum_{w \in W} \sum_{q \in Q} xt_{wj}^p (1 - r_{wq}) (1 - b_{wq}) = \sum_{j \in R} xtf_{ij}^p$	$\forall i \in T, p \in P$	(21)
$xr_i^p (1 - w_i) = \sum_{j \in F} xrf_{ij}^p$	$\forall i \in R, p \in P$	(22)
$xf_i^p = \sum_{j \in T} xtf_{ji}^p + \sum_{j' \in R} xrf_{j'i}^p$	$\forall i \in F, p \in P$	(23)
$\sum_{w \in W} \sum_{i \in G} d_{wi} = \sum_{w \in W} \sum_{j \in T} xt_{wj} + \sum_{j \in R} xr_i^p$	$\forall i \in F, p \in P$	(24)
$nd_{im}^{p-1} + hd_{im}^p - ld_{im}^p + \sum_{m'} td_{im'm}^p - \sum_{m'} td_{imm'm'}^p = nd_m^p$	$\forall i \in D, m \in M, p \in P$	(25)
$\sum_{m \in M} nd_{im}^p \geq \sum_{j \in GUTUR} \sum_{k \in K} XG_{ijk}^p$	$\forall i \in D, p \in P$	(26)
$\sum_{m \in M} XD_{ijmk}^p = XG_{ijk}^p$	$\forall i \in D, j \in T \cup R, k \in K, p \in P$	(27)
$\sum_{m \in M} XD_{ijmk}^p = nd_{im}^p$	$\forall i \in D, j \in T \cup R, k \in K, p \in P$	(28)
$ld_{im}^p + \sum_{m'} td_{imm'm'}^p \leq nd_m^{p-1}$	$\forall i \in D, m \in M, p \in P$	(29)
$td_{imm'm'}^p \leq M * TP_{m'mi}$	$\forall i \in D, m \in M, p \in P$	(30)

$\left(\sum_{m' \in M} td_{imm'}^p \right) * ld_{im}^p = 0$	$\forall i \in D, m \in M, p \in P$	(31)
$0 \leq RP_{im}^p \leq T^{\max rest}$	$\forall i$	(32-49)
$minalertness_{im} \geq TPMA^{\min}$	$\in D U G U T$	
$k_{jmk}^{driveP} = \begin{cases} k_{i-1,mk}^{drivep} + TI_{i-1,i,m}^p x_{jimk}^p & RP_{(i-1)m}^p < t^{rest} \\ TI_{i-1,i,m}^p x_{jimk}^p & RP_{(i-1)m}^p \geq t^{rest} \end{cases}$	$\in T U R, m \in M, p \in P$	
$k_{jmk}^{dutyP} = \begin{cases} k_{i-1,mk}^{dutyP} + (TI_{i-1,i,m}^p + RP_{(i-1)m}^p + WD_{im}) x_{jimk}^p & RP_{(i-1)m}^p < t^{rest} \\ (TI_{i-1,i,m}^p + WD_{im}) x_{jimk}^p & RP_{(i-1)m}^p \geq t^{rest} \end{cases}$		
$k_{jmk}^{breakP} = \begin{cases} k_{i-1,mk}^{breakp} + (TI_{i-1,i,m}^p + RP_{(i-1)m}^p + WD_{im}) x_{jimk}^p & , RP_{(i-1)m}^p < t^{break} \\ (TI_{i-1,i,m}^p + WD_{im}) x_{jimk}^p & , RP_{(i-1)m}^p \geq t^{break} \end{cases}$		
$k_{jmk}^{awakeP} = \begin{cases} k_{i-1,mk}^{awakep} + (TI_{i-1,i,m}^p + RP_{(i-1)m}^p + WD_{im}) x_{jimk}^p & , RP_{(i-1)m}^p < t^{rest} \\ TI_{i-1,i,m}^p + (RP_{(i-1)m}^p x_{jimk}^p - t^{\max sleep}) + t^{awakedelay} + WD_{im} x_{jimk}^p & , RP_{(i-1)m}^p \geq t^{rest} \end{cases}$		
$k_{imk}^{day} = Al_{im} \text{ mod } 24$		
$SB_{imk}^P = ha - (ha - ss_{imk}^P) * e^{gr(t^{\max sleep} - t^{\text{sleepdelay}})}$		
$ss_{imk}^P = la + (Si_{i-1mk}^{ip} - la) * e^{decr(k_{jmk}^{awakeP} + t^{\text{sleepdelay}})}$		

$Si'_{imk} = \begin{cases} ha - (ha - bl) * e^{gr(t^{maxsleep} - t^{sleepdelay} - bt_i)} & RP_{(i-1)m}^p \geq t^{rest} \text{ AND } SB_{imk}^p < bl \\ Si_{imk}^p + gr(t^{maxsleep} - t^{sleepdelay}) & RP_{(i-1)m}^p \geq t^{rest} \text{ AND } SB_{imk}^p < bl \\ Si'_{i-1mk} & RP_{(i-1)m}^p < t^{rest} \end{cases}$		
$AI_{im} + RP_{im}^p + WD_{im} = DI_{im}$		
$DI_{im} + TI_{i,i+1,m}^p = AI_{i+1m}$		
$k_{jmk}^{driveP} \leq t^{drive}$		
$k_{jmk}^{dutyP} \leq t^{elapsed \setminus R}$		
$k_{jmk}^{breakP} \leq t^{elapsed \setminus B}$		
$AI_{im} + WD_{im} \leq t^{horizon}$		
$0 \leq RP_{im}^p \leq t^{max_rest}$		
$AI_{im} \leq L_i$		
$xtf_{ij}^p \geq 0, xfi_i^p \geq 0$	$\forall i \in T, j \in F, p \in P$	(50-60)
$xri_i^p \geq 0, xrf_{ij}^p \geq 0$	$\forall i \in R, j \in F, p \in P$	
$xtr_{ij}^p \geq 0, xt_j^p \geq 0, xt_{wi}^p \geq 0$	$\forall i \in T, j \in R, w \in W, p \in P$	
$l_{ik}^p \geq 0$	$\forall i \in G, k \in K, p \in P$	
$nd_{im}^p \geq 0, hd_{im}^p \geq 0, ld_{im}^p \geq 0$	$\forall i \in D, m \in M, p \in P$	

$td_{mm'}^p \geq 0, otd_m^p \geq 0$	$\forall m \in M, p \in P$
$XG_{ijk}^p \geq 0$	$\forall i \in D, j \in T \cup R, k \in K, p \in P$
$RP_{im} \geq 0$	$\forall i \in D \cup T \cup R, m \in M,$
$x_{ijmk}^p \in \{0,1\}$	$\forall i, j \in (D \cup G \cup R \cup T), m \in M, k \in K$
$XD_{onijmk}^p \in \{0,1\}$	$\forall o \in O, n \in N, i \in D, j \in T \cup R, m \in M, k \in K, p \in P$
$t_{qi} \in \{0,1\}$	$\forall i \in T, q \in Q$

Description of constraints: equation (5) ensures that the depot point is the starting point. On the other hand, equation (6) ensures the continuity of each path of the routing problem in terms of leaving each node after visiting it. Equation (7) states that each source (generation) node and each waste type must be collected only once. Equation (8) ensures that the path ends at depot center after unloading at different locations. Moreover, equation (9) ensures that each vehicle loaded with non-recyclable waste must head to treatment facility with adequate treatment technology to empty its load. Likewise, equation (10) states that each vehicle loaded with recyclable waste must empty its load at recycling facilities before heading to depot. Equations (11-13) deal with the travelled distance by ensuring that each vehicle does not exceed the allowable travelling distance. Furthermore, equations (14-17) state that the load of vehicles doesn't exceed its given capacity. Equation (18) calculates the total quantity of hazardous waste treated at each treatment node. Equation (19) models the route from treatment nodes to recycling facilities. Equation (20) is formulated to find the total amount of recyclable waste that had been processed at each recycling center. Equations (21), (22), and (23) determine the flow from recycling and treatment facilities to the disposal centers and define the amount of waste residue disposed at each disposal center, respectively. Equation (24) ensures that the total amounts of treated and recycled waste are covering all amount of demands at all nodes. Equation (25) calculates the number of drivers available at depot node at the starting point. Equation (26) ensures that the number of vehicles assigned to drivers is equal to the number of available vehicles assigned to ship waste

from depot to different locations. Equation (27) ensures that all vehicles at depots nodes are assignments to transport the waste. Equation (28) ensures that the number of drivers at depots nodes are equal to the number of assigned waste vehicles. Equation (29) ensures that the numbers of firing and training of drivers do not exceed total number of available drivers. Equations (30) and (31) ensure that the training driver to upgrade to the next level is impossible else if this training session is available and not fire them in the same period. Equations from (32) to (49) calculate and constraint all parameters and variables related the *alertnes* calculations, where equations (34-37) calculate the duration of driving, duty, awake, and break for each driver. Equations (38-40) calculate sub-process and process S' at each location and for each driver, which use to calculate process S. Equations (41-42) calculate the arriving and departure time of each location. Equations (43-49) are constraints related to the hours of service of drivers. Equations from (50) to (60) are constraints of decision variables, where constraints (50-57) ensure non-negative decision variables, whereas, constraints (58-60) restrict the related decision variables to be integers.

3.4 Methodology

Concerning the number of objective functions to be solved, there are two types of optimization, single-objective and multi-objective functions. In the first type, the algorithms work to find the optimal solution; which means that there is a single optimal solution whether it is a maximization or minimization problem. On the other hand, if the problem involves multi-

objective function depending on each other, more complicity will be encountered to find a single optimal solution because of the effect of the objectives on each other; if one function is improved, the other will be worsen. Therefore, a non-dominance criterion is used to solve the multi-objective model, to avoid the situation where some solutions dominate others. The non-dominate and globally optimal solutions are in a feasible space called Pareto optimal solution. All Pareto-optimal solutions are called Pareto optimal set. Whereas, The Pareto-optimal frontier is the corresponding graphically presentation of Pareto-optimal sit used in many algorithms for optimizing the multi-objective optimization problem (MOOP). In this research the MOOP is solved by heuristic methodology based on the non-dominated sorting genetic algorithm II (NSGS-II). The NSGS-II algorithm was coded using MATLAB 2014 software. Moreover, the code is executed on a personal computer with Windows 10 enterprise operating system, 2.00 GHz CPU, A6-7310 APU AMD processor, and 8.00 GB of RAM.

3.4.1 Non-dominated sorting genetic algorithm II (NSGS-II)

The NSGS-II algorithm is widely used to solve two or more objective functions models; it is an additional characteristic in the genetic algorithm selection phase. The following sub-sections explain NSGA-II components:

3.4.1.1 Population initialization

The first step is to generate a random initial parent population P_0 with the size number of (N_{pop}); this population is generated depending on the problem

range and constraints. The number of genes in a chromosome is equal to the number of decision variables in the model. In this model, chromosomes with $G \times M \times P$ matrix dimensions were used, where G is the number of generation nodes, M is sum of numbers of (waste types, facilities types, +2 rows green driver's index level), facilities types include recycling, disposal, and treatment facilities. P is different time periods. Table 3.1 shows an example of a chromosome. In the next step, the program calculates all variables values depend on the chromosome if all variables' values adapting with constraints equations, the program calculates objective function values.

3.4.1.2 Non-dominated sorting

After the initialization of random population, the fitness function of the objective functions for each chromosome was evaluated. Then, in the sorting procedure of non-domination function, every chromosome is ranked; the result of this process is Pareto front. Before ranking the chromosomes, every non-domination function is evaluated to obtain its non-domination level, where level 1 is the best, level 2 is the next, and so on. Then the individuals/solutions are divided into two fronts, the first one consists of all non-domination individuals and has fewer rank numbers. The second front consists of individuals that just dominated from individuals in the first front. In case of multi-objective function, the model has N number of objective functions. The process of comparison between solutions is done as follows: X and Y are placed in the same front if they do not dominate each other, but

X dominates Y if; X is not worse from Y for all objective function, and X is strictly better than Y for at least one objective function.

Table 3.1: Example of a chromosome that presents the proposed HWVRP

Period 1							Period 2						
1	3	4	5	6	2		4	1	2	5	6	3	Waste 1
2	4	1	3	5	6		5	2	3	1	4	6	Waste 2
4	1	2	5	6	3		6	5	3	2	4	1	Waste 3
2	4	5	6	1	3		2	4	1	3	5	6	Waste 4
1	2	3	0	0	0		1	3	2	0	0	0	Treatment facilities
2	1	0	0	0	0		1	2	0	0	0	0	Recycling facilities
1	0	0	0	0	0		1	0	0	0	0	0	Disposal facilities
1	3	2	1	2	3		0	0	0	0	0	0	Green driver index from driver 1-K/2
3	3	1	1	2	2		0	0	0	0	0	0	Green driver index from driver K/2-K
1	3	4	5	6	2		4	1	2	5	6	3	
2	4	1	3	5	6		5	2	3	1	4	6	
4	1	2	5	6	3		6	5	3	2	4	1	
2	4	5	6	1	3		2	4	1	3	5	6	
1	2	3	0	0	0		1	3	2	0	0	0	
2	1	0	0	0	0		1	2	0	0	0	0	
1	0	0	0	0	0		1	0	0	0	0	0	
1	3	2	1	2	3		0	0	0	0	0	0	
3	3	1	1	2	2		0	0	0	0	0	0	

3.4.1.3 Crowding distance

In case two or more solutions have the same rank, the crowding distance is used to choose the solutions, where the larger crowding distance is selected. Crowding distance is an estimate of the density of solutions surrounding a particular solution, which can be calculated using the following equation:

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

Where f_j^{max} is the minimum values of the objective function j , f_j^{min} is the maximum values of the objective function j , f_j^{i+1} is the value of objective function j of $(i + 1)$ solution, and f_j^{i-1} is the value of objective function j of $(i - 1)$ solution.

3.4.1.4 Crossover

Crossover is a NSGA-II operator which used to combine the information of chromosomes (solutions) for the purpose of keeping the generation of finest solutions for complex problems such as VRP, where a large population of solutions is generated. The crossover process generates new chromosomes from parent chromosomes called offspring or children. This process is based on using parts of the parent chromosomes to create offspring, and this offspring might be better than both of the parents if they took the best genes from parent chromosomes. In this model, a single-point crossover technique is used and it functions as follows: a couple of Pareto front solutions are selected randomly to be used as parents, a random point is selected as a cross over point, the first part of offspring chromosome comes from the beginning of the chromosome to the crossover point from the first parent (parent 1), whereas the second part of the offspring comes from another parent (parent 2), which is from the crossover point to the end of the chromosome. This process is shown in Table. 3.2.

Table 3.2: NSGA-II crossover process

Period 1						Period 2						parents 1	
1	3	4	5	6	2		4	1	2	5	6	3	
2	4	1	3	5	6		5	2	3	1	4	6	
4	1	2	5	6	3		6	5	3	2	4	1	
2	4	5	6	1	3		2	4	1	3	5	6	
1	2	3	0	0	0		1	3	2	0	0	0	
2	1	0	0	0	0		1	2	0	0	0	0	
1	0	0	0	0	0		1	0	0	0	0	0	
1	3	2	1	2	3		0	0	0	0	0	0	
3	3	1	1	2	2		0	0	0	0	0	0	
Period 1						Period 2						parents 2	
2	1	4	6	3	5		5	6	3	4	2	1	
6	5	3	4	2	1		4	1	3	6	5	2	
6	1	5	2	4	3		4	5	2	3	6	1	
5	2	3	4	1	6		1	5	2	3	4	6	
3	2	1	0	0	0		2	1	3	0	0	0	
1	1	0	0	0	0		1	2	0	0	0	0	
1	0	0	0	0	0		1	0	0	0	0	0	
1	2	2	1	1	3		0	0	0	0	0	0	
1	2	1	1	1	2		0	0	0	0	0	0	
Period 1						Period 2						offspring	
1	3	4	6	3	5		4	1	2	4	2	1	
2	4	1	4	2	1		5	2	3	6	5	2	
4	1	2	2	4	3		6	5	3	3	6	1	
2	4	5	4	1	6		2	4	1	3	4	6	
1	2	3	0	0	0		1	3	2	0	0	0	
2	1	0	0	0	0		1	2	0	0	0	0	
1	0	0	0	0	0		1	0	0	0	0	0	
1	3	2	1	1	3		0	0	0	0	0	0	
3	3	1	1	1	2		0	0	0	0	0	0	

3.4.1.5 Mutation

Mutation process works to enhance the diversity of the population after the crossover process. A few randomly selected genes to change their values based on predetermined mutation as shown in table 3.3. In this paper, the

mutation process is as follows, select two random columns and exchange them, to produce new offspring. Figure 3.1 presents a flow chart that explains the process of generating solutions using NSGA-II, which was adopted from the research of (Rabbani *et al.*, 2018).

Table 3.3: NSGA-II mutation process

Period 1							Period 2						parents
1	3	4	6	3	5		4	1	2	4	2	1	
2	4	1	4	2	1		5	2	3	6	5	2	
4	1	2	2	4	3		6	5	3	3	6	1	
2	4	5	4	1	6		2	4	1	3	4	6	
1	2	3	0	0	0		1	3	2	0	0	0	
2	1	0	0	0	0		1	2	0	0	0	0	
1	0	0	0	0	0		1	0	0	0	0	0	
1	3	2	1	1	3		0	0	0	0	0	0	
3	3	1	1	1	2		0	0	0	0	0	0	
Period 1							Period 2						offspring
1	3	5	6	3	4		4	1	1	4	2	2	
2	4	1	4	2	1		5	2	2	6	5	3	
4	1	3	2	4	2		6	5	1	3	6	3	
2	4	6	4	1	5		2	4	6	3	4	1	
1	2	3	0	0	0		1	3	2	0	0	0	
2	1	0	0	0	0		1	2	0	0	0	0	
1	0	0	0	0	0		1	0	0	0	0	0	
1	3	2	1	1	3		0	0	0	0	0	0	
3	3	1	1	1	2		0	0	0	0	0	0	

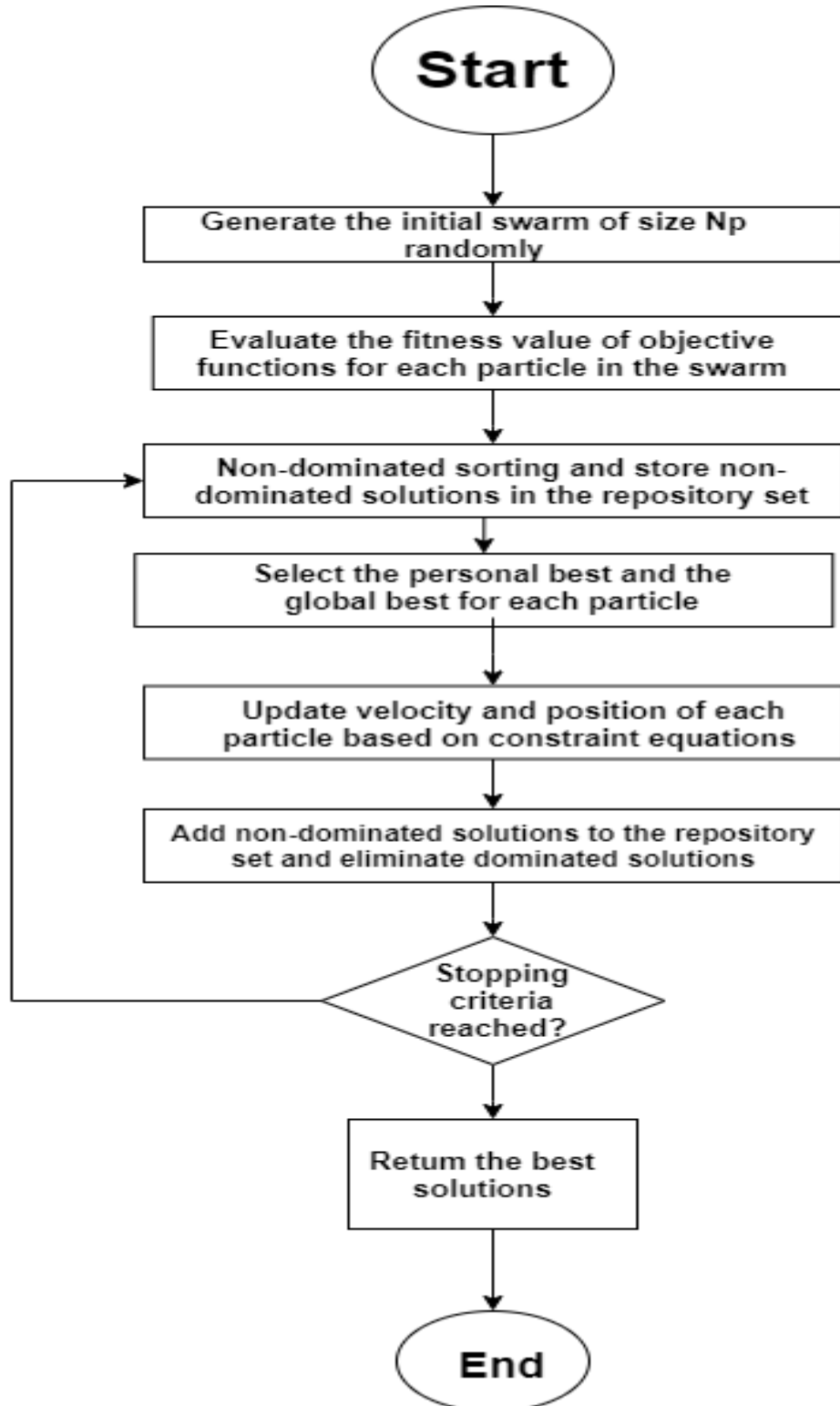


Figure 3.1: NSGA-II Flow Chart

Chapter Four

Model Results

4.1 Overview

This chapter presents and discusses the numerical results obtained from solving the proposed HWVRP model. In addition, the methodology used to solve the model is included in this chapter, a detailed explanation of the solution method and the used algorithm are discussed. Finally, a presentation of the results is shown including the validation of the model and its solvability, with a brief analysis and interpretation of the findings.

4.2 Results and discussion

This section shows and discusses the obtained results from the proposed HWVRP model. Foremost, model validation must be done to prove that the performance and accuracy of the model in optimizing the desired objective functions is as expected. Small, medium and large problem sizes and instances were conducted in this research to investigate how the proposed model handles large amount of inputs. However, for the purpose of validation, small size instances are investigated at the beginning and larger instances are presented in the following sections. Due to the lack of benchmark instances in the literature of hazardous waste VRP that considers social aspects such as risk on people and driver's awakesness levels, hypothetical data are assumed to solve the model using the random function generator in MATLAB. Even so, it's necessary to state that hypothetical

data may differ from real life problems with real data; therefore, many instances are applied to provide different solutions in each problem size to validate the applicability of the model. The obtained results are presented in four stages. The first two stages are concerned with waste collection routing and transportation respectively, in the first stage the waste vehicle routing is shown in form of (G, T, R, F) vector which shows the routing of waste vehicles that starts from a depot to generation nodes and then treatment or recycling facilities depending of the type of collected waste, and then to disposal locations before returning to depot. The second stage is the transportation stage where results concerning the shipment of waste from different facilities are shown. Three directions of shipment are considered in this model and presented in results, from treatment to recycling facilities, from treatment to disposal facilities and from recycling to disposal facilities. Moreover, the third and fourth stages of results present the social aspect of the model in terms of presenting the costs of hiring, firing and training of drivers (third stage) at different periods of the model. In addition to showing the awareness / fatigue levels of drivers (fourth stage) at different periods.

Twelve waste collection vehicles were considered in this model to collection waste from six waste generation nodes (G^1 to G^6). In addition, four types of waste can be generated at each generation node, where each vehicle is assigned specifically to collect only one waste type. Moreover, two periods of time for planning are assumed to investigate and compare results at each period. Finally, three levels of drivers are included depending on their GDI

where the first level (1) is the lowest in terms of awareness of green driving practices and the third level (3) is the highest.

4.2.1 Routing stage results

Table 4.1 shows results for the routing plan of waste collection vehicles, column one shows periods 1 and 2, whereas, the second column presents the four types of waste (1→ 4). Column three is vehicle number, note that the first three vehicles (1→ 3) is assigned to collect waste type 1 and vehicles (4→ 6) to collect waste type 2 and so on as shown in the table. GDI level of the vehicle driver is shown in column four, note that due to the training practices of drivers, period 2 shows higher level drivers compared to period 1 in terms of GDI levels. Respectively, column five presents the route that is taken by each vehicle, for example vehicle 1 at period 1 starts from depot to visit generation nodes G^2 and G^1 correspondingly and then to treatment facility T^3 before returning to depot ($D-G^2-G^1-T^3-D$). Finally, columns six and seven shows the total amount of waste collected by each vehicle and the total covered distance by each vehicle respectively.

Table 4.1: Results of routing stage

Period	Waste type	Vehicle no.	Driver level	Collection route	Amount of load(100kg)	Length of route (Km)
1	1	1	3	D-G2-G1-T3-D	86	122
		2	1	D-G5-G4-T3-D	30	117
		3	1	D-G6-G3-T3-D	84	127
	2	4	1	D-G6-G5-T1-D	54	92
		5	2	D-G2-G1-T1-D	82	87
		6	2	D-G4-G3-T1-D	55	120
	3	7	1	D-G2-G4-T3-D	59	119
		8	1	D-G3-G1-T3-D	67	155
		9	3	D-G6-G5-T3-D	68	109
	4	10	1	D-G6-G2-R1-D	73	97
		11	3	D-G3-G5-R1-D	73	112
		12	3	D-G1-G4-R1-D	55	121
	Waste type	Vehicle no.	Driver level	Collection route	Amount of load(100kg)	Length of route (Km)
2	1	1	2	D-G4-G6-T3-D	56	134
		2	3	D-G2-G3-T3-D	86	105
		3	3	D-G5-G1-T3-D	30	135
	2	4	3	D-G2-G4-T1-D	82	102
		5	2	D-G3-G6-T1-D	80	116
		6	2	D-G5-G1-T1-D	32	100
	3	7	1	D-G6-G4-T2-D	68	127
		8	2	D-G1-G3-T2-D	25	137
		9	2	D-G5-G2-T2-D	41	105
	4	10	3	D-G6-G3-R2-D	73	114
		11	3	D-G5-G1-R2-D	59	130
		12	3	D-G4-G2-R2-D	41	108

4.2.2 Transportation stage results

Table 4.2 shows the result of the transportation process between treatment, recycling and disposal facilities. Waste vehicles follow one of three possible routes either treatment – recycling route where after treatment some wastes could be recyclable, or treatment – disposal route in case the collected waste is non-recyclable after treatment and must be disposed, or recycle – disposal route where waste residue is transported for disposal after recycling. The first column in table 4.2 shows the period of time, whereas columns two and

three illustrates the shipment of waste residues in terms of the route between facilities and the amount of transported waste. On the other hand, columns four and five show the near optimal decisions regarding the amount of processed waste at each facility in different periods. Finally, the provided solution for the routing and transportation of waste resulted in a total cost of 782740 Dollars, a total site risk of 11428041 * people, and 8978516 km * people of transportation risk.

Table 4.2: Results of Transportation Stage

Period	Shipment of waste residues		Processing of wastes	
	Transfer route	Amount of load (100 kg)	Facility	Amount of waste processed at each facility (100 kg)
1	T1-R1	123.6802	T1	191
	T2-R1	255.13	T2	--
	T3-R1	--	T3	394
	T1-F1	5.77	F1	72.6
	T2-F1	57.77	F2	222.8
	T3-F1	--	R1	539
	T1-F2	11.9109	R2	-
	T2-F2	119.027		
	T3-F2	--		
	R1-F1	9.113		
	R1-F2	91.87		
2	T1-R2	125.619	T1	194
	T2-R2	86.68	T2	134
	T3-R2	111.373	T3	172
	T1-F1	28.8	F1	131.07
	T2-F1	19.96	F2	161.35
	T3-F1	25.62	R1	-
	T1-F2	35.57	R2	496
	T2-F2	24.57		
	T3-F2	31.5		
	R2-F1	56.594		
	R2-F2	69.66		

4.2.3 Workforce planning for drivers

With respect to man power planning, table 4.3 presents results regarding the number of needed drivers at each level, in addition to the hiring, firing and training practices and needs between the three levels of drivers. Note that the numbers of level 3 drivers increased gradually in periods 2, 3 and 4, in the contrary levels 1 and 2 drivers are decreased due to training practices from one level to another. Although training of drivers comes with a cost, but drivers with high GDI significantly reduce the total costs of collecting and shipping waste between generation nodes and other facilities. As mentioned in previous sections, higher awareness of green driving practices results in a reduction of fuel consumptions (and thereby GHG emissions) since eco-friendly driving style is adopted by those drivers rather than aggressive driving, in addition the costs of hazardous waste transportation risks are reduced due to the high sensibility of higher-level drivers in noticing dangers while driving. Therefore, the training of drivers to higher GDI levels is justified by the intentions to reduce the total costs of process of waste collection, reduce the transportation risks and finally to enhance the awakens levels of drivers. The number of needed drivers at each level in each period is calculated using the constraint shown in equation (25).

Table 4.3: Workforce planning results

Period	Driver level	Needed Drivers number	Hiring no.	Firing no.	Training from	Training to
1	1	2	1	-	4	-
	2	7	2	-	2	2
	3	3	-	-	-	4
2	1	1	-	1	-	-
	2	6	1	-	2	-
	3	5	-	-	-	2
3	1	1	1	1	-	-
	2	5	1	1	1	-
	3	6	-	-	-	1
4	1	1	-	-	-	-
	2	2	-	-	3	-
	3	9	-	-	-	3

4.2.4 Driver's awakesness level

This section presents and discusses results related to the novelty approach in this research, which integrates the driver's awakesness / fatigue levels in waste collection VRP. Assessing the awakesness levels of drivers indeed deliver a great contribution to VRP specially in anticipating the risks and dangers results in fatigue drivers with inadequate rest times and driving distances. Table 4.4 shows the results of driver's awakesness levels, specifically columns four and five which shows the level of awakesness at each visited node in the route and the awakesness graph respectively at different periods of the day. At each node the TPMA model is used to measure awakesness, by adding the results of the three processes of the model which are S process, C process and U process. It is necessary to point out that awakesness levels are affected by rest times, driving times and the time of day at which the driver is working. Tables A1 and A2 in appendix A













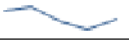











shows the arrival (A), working (W), rest (R), departure (D) and driving times (DR) of each driver at different periods. In order to assess the awakesness levels, a baseline was adapted from the work of (Bowden and Ragsdale, 2018) to show the minimum awakesness levels which is based on Karolinska Sleepiness Scale (KSS). The proposed minimum awakesness levels are as follows:

- Tired: 7.07 awakesness level.
- Semi-tired: 8.15 awakesness level.
- Not tired: 9.24 awakesness level.

In other words, a driver must have at least 7.07 awakesness level to not be considered tired, at least 8.15 awakesness level to not be considered semi-tired and finally 9.24 and above score to be alerted and not tired. Let's consider the situation of period 2 and vehicle 7 to verify the obtained results. A driver starts his job with high awake level of 9, after driving for 1.9 hours, working for 0.9 (0.2 + 0.7) hours and having an adequate rest time of 1.5 hours (as shown in table A2) the awakesness level arises to 9.5. But at the third node G⁴ the driver had a trip of 1.55 hours and 0 hours rest time which resulted in dropping the awakesness levels to 6.2. Its worthy to point out that driving hours and rest times directly affects the awakesness levels of drivers, where driving for long periods of time without resting for a decent amount of time results in decreasing the levels of awakesness and vice versa. In addition, the calculations of driver's awakesness levels is a cumulative process, which means as time of day passes, the awakesness levels will drop

regardless of the rest time between nodes and the driving hours. Moreover, as shown in table 4.4 higher level drivers have higher awakesness levels compared to lower-level ones, the effect of driver's GDI on awakesness levels is discussed in the sensitivity analysis chapter.

Table 4.4: Driver's Awakesness level

Period	Vehicle no.	Driver level	SI+CI+Ui (awake level)	Awake level graph
1	1	3	12-11.2-9.9-8.9-10.1	
	2	1	9-8.14-6.68-5.56-7.80	
	3	1	9-8.44-7.43-7.08-8.07	
	4	1	9-6.68-5.84-5.41-5.68	
	5	2	10-9.63-8.47-8.28-9.99	
	6	2	10-9.11-8.17-8.31-9.07	
	7	1	9-7.57-6.57-6.17-6.88	
	8	1	9-8.02-6.95-6.21-7.12	
	9	3	12-9.87-9.03-8.52-10.0	
	10	1	9-7.19-5.94-5.74-5.99	
	11	3	12-10.2-9.51-8.83-9.29	
	12	3	12-10.2-9.51-8.83-9.30	
2	1	2	10-10.3-9.4-8.8-9.5	
	2	3	12-12.2-9.6-8.5-9.9	
	3	3	12-12.0-11.-11.-13.	
	4	3	12-12.5-10.-8.9-10.	
	5	2	10-10.8-9.6-8.9-9.7	
	6	2	10-10.0-9.8-8.8-9.7	
	7	1	9-9.5-6.2-6.4-7.6	
	8	2	10-10.7-9.0-9.1-10.	
	9	2	10-10.2-8.2-9.0-10.	
	10	3	12-12.7-10.-9.7-10.	
	11	3	12-12.2-11.-9.1-9.6	
	12	3	12-12.4-9.5-9.9-11.	

4.2.5 Test instances

To prove the validity of the proposed model in providing adequate solutions for the waste collection VRP under study, different problem sizes must be tested. If real life instances are available, the validity of the model is verified if acceptable solutions are generated; however, due to the absence of such instance on the literature different size instances are the alternative approach for model verification. In the previous sections, small instances of six generation nodes, twelve waste collection trucks (with twelve drivers), three treatment facilities, two recycling facilities and two disposal facility. Therefore, different solutions are generated independently with 6 size and 10 iterations respectively, and the average of the generated solutions are presented in table 4.5.

Table 4.5: Comparison metrics for problem instances

Problem number	Problem dimension		Total costs(dollars)	Total site risk (people)	Transportation risk (people)	Total awakness level	CPU Time (s)
	G	K					
1	6	12	197223	6985264	2296868	640	76
2	8	16	1490918	9525006	21515295	853.99	137
3	10	20	1702807	12208824	53496828	1038.041	257
4	12	24	1984996	9864814	30517605	1112.7	390
5	14	28	2146804	9793906	51776537	1241.19	557
6	16	32	2162602	6952101	35871608	1324.01	801
Avarage	11	22	1614225	9221652.5	32579123.5	1034.99	369.67

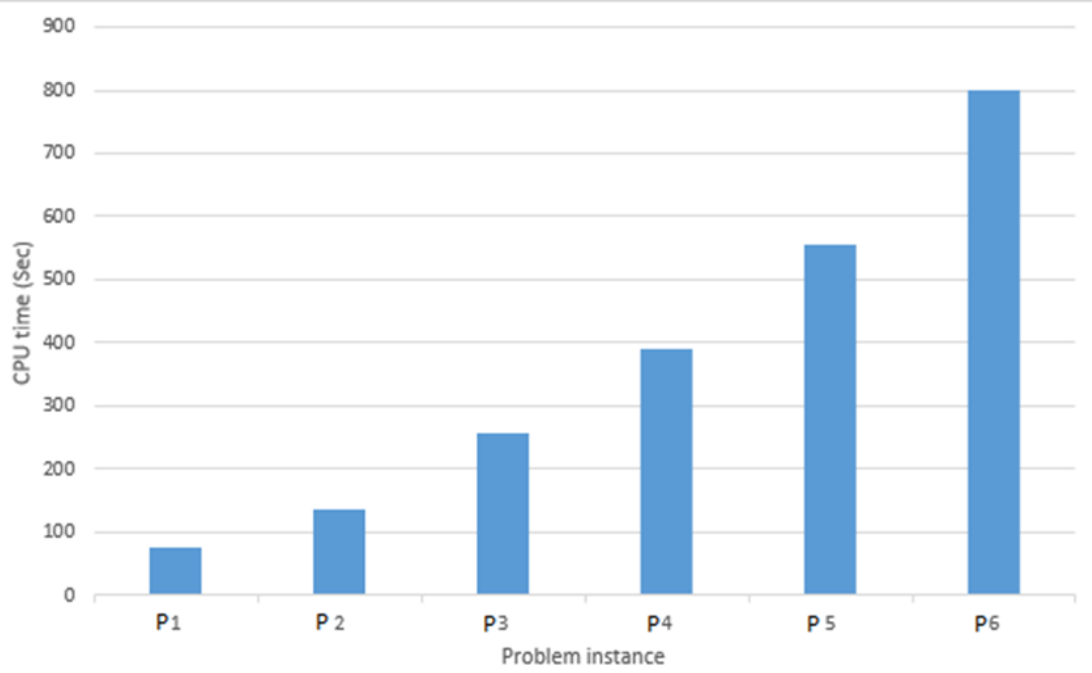


Figure 4.1: Comparison of computational time

Chapter Five

Sensitivity Analysis

5.1 Overview

In this chapter, the robustness of the developed model is tested by conducting sensitivity analysis on some of the parameters in the model. In this research, the main focus of the sensitivity analysis is on the parameters related to the contribution of this research to the literature of HWVRP. Therefore, this chapter spots light on the effect of driver's GDI and awakesness levels on the results of the objective functions in the model, in addition to investigating the effect of different driver's GDI on awakesness levels. Precisely, the sensitivity analysis is conducted to show:

- The effect of driver's GDI on awakesness levels.
- The effect of driver's GDI on total costs of the model.
- The effect of driver's GDI on transportation risk.
- The effect of driver's awakesness levels on total costs of the model.
- The effect of driver's awakesness levels on transportation risk.

5.2 Sensitivity analysis on the effect of driver's GDI

In this section, a sensitivity analysis is conducted on the effect of different drivers GDI levels on mainly three crucial functions in the model, total costs, hazardous waste transportation risk and driver's awakesness levels.

5.2.1 The effect of driver's GDI level on total costs

In order to investigate the effect of different driver's level on the total costs of the model, the three levels of driver's GDI are altered and the corresponding total costs are calculated and analyzed. Three combinations of different driver's levels are tested for five iterations and the average total cost is presented. At first, in scenario 1 a combination of 12 drivers was assumed, where the first four drivers are classified as level 1, the next four are level 2 and the last four are level 3 (4, 4, 4) in terms of GDI levels to test the relationship between driver's GDI and costs. This combination was tested for five iteration and resulted in an average cost of 1,042,068.2 \$ as shown in Figure 5.1. Next, in scenario 2 the previous combination of drivers was altered to (2, 4, 6) which indicated that the first two drivers are level 1, the next four are level 2 and the last six are level 3 in terms on GDI criterion. Similar to the previous combination, the average costs of the five iterations were 982405.2 \$. The 6.1% decrease in costs after increasing the level 3 drivers is justified by the high awareness of those drivers in eco-friendly driving techniques which results in saving fuel and thereby costs, in addition to their stability at work and reducing the need to fire or hire drivers. In scenario 3, the third and final combination, which follows the same classification in the first two scenarios, (2, 2, 8) where the level 3 drivers increased to 8 drivers. The resulted average costs were 1010845.6 \$ with an increase of 2.8% compared to the second combination. The variation in routing total costs is notable when increasing the number of level 3 GDI drivers with respect to the total number of drivers as shown in figure 5.1. To

justify such variation and interpret the relation between GDI level and total costs, the results should be divided into two stages. The first stage shows the significant decrease in total costs between scenario 1 and scenario 2, which is due to the positive impact of level 3 drivers. Such impact could be translated into saving fuel because of the eco-friendly driving behavior of level 3 drivers, as well as, less training is needed to promote drivers to higher GDI levels. Whereas for the second stage, an increase in costs was present due to the accumulated increase in salary costs of higher GDI levels, in addition to the continuous efforts to upgrade drivers to higher GDI levels through training. Thus, the results of this sensitivity analysis suggest that a trade-off must be planned wisely between GDI levels and the total costs in the developed HWVRP model.

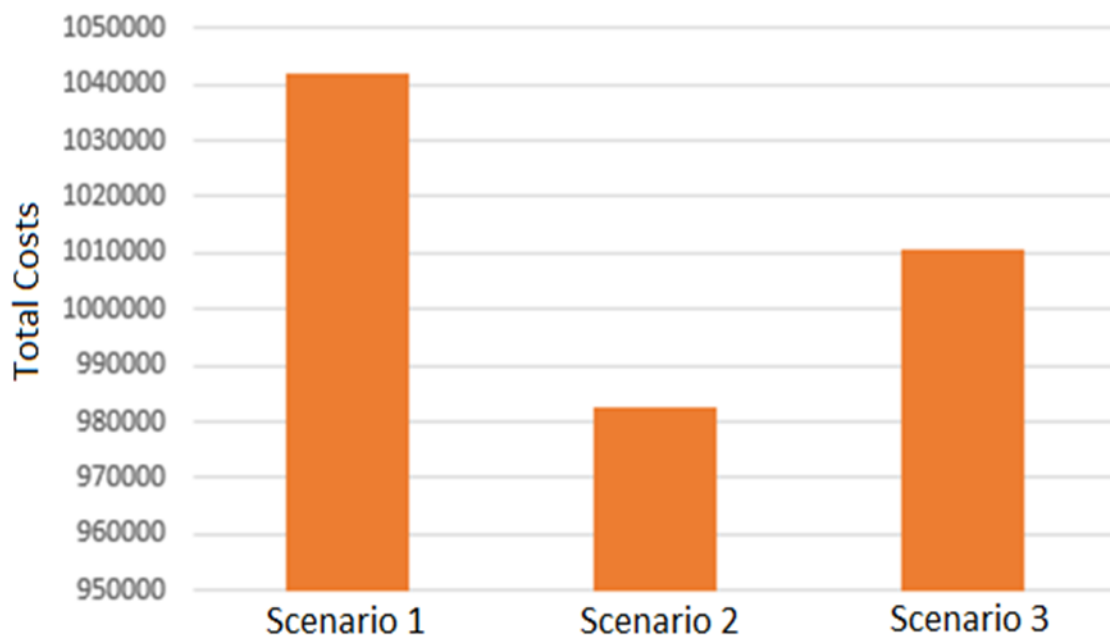


Figure 5.1: The effect of driver's GDI level on total costs

5.2.2 The effect of driver's GDI on transportation risk

In this section, the effect of driver's GDI on the transportation process between treatment and recycling facilities to disposal facilities is investigated, specifically the effect of different driver's level on the third objective function, which deals with the transportation risk. The same combinations of drivers and the number of iterations in the previous section are used, which are (4,4,4), (2,4,6) and (2,2,8). For the first combination in scenario 1 the average transportation risk was calculated and resulted in a 6261368.34 km * people. However, when increasing the number of level 3 drivers in the second scenario, a decrease of 11.45% in the transportation risk was noticed and the result was 5618299.58 km * people. Moreover, in scenario 3 a significant decrease in the transportation risk was observed when increasing the number of level 3 drivers to 8. The results showed a 4016208.7 km * people with a 39.89% difference compared to the previous combination. The inverse relationship between transportation risk and driver's GDI level is expected, since higher awareness levels of green driving actions and the great responsibility of level 3 drivers toward the society and the environment will eventually result in safer and lower transportation risk. It must be noted that this relationship considers the two mentioned aspects without considering the presence of other parameters and variables such as costs. Therefore, a trade-off between different objectives is done including a trade-off between transportation risk and total costs, where an optimization on the risks is conducted to certain point where it

won't be feasible any more in cost wise. Figure 5.2 shows the results of the sensitivity.

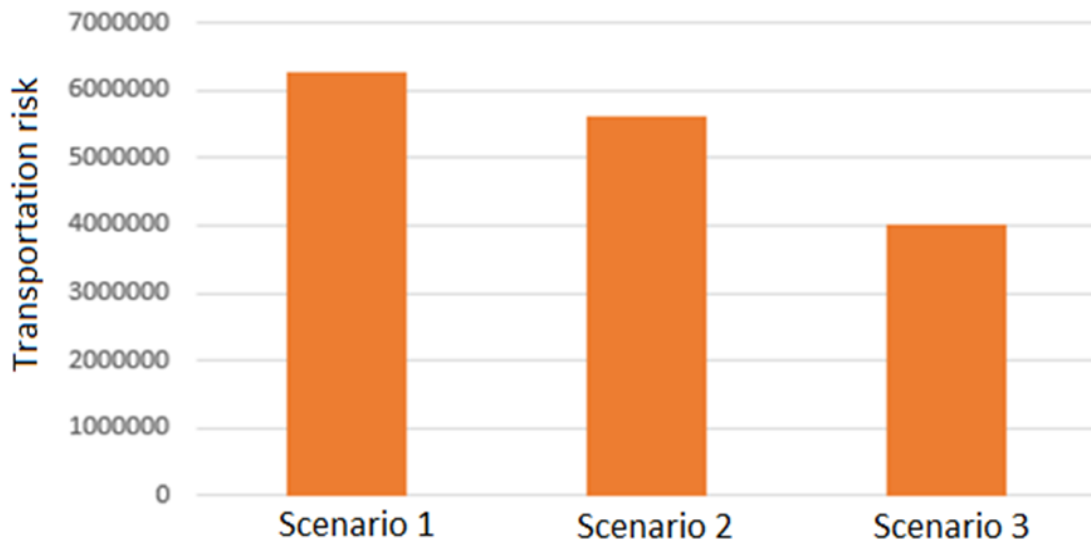


Figure 5.2: The effect of driver's GDI on transportation risk

5.2.3 The effect of driver's GDI on awakesness level

Figure 5.3 shows the results of a sensitivity analysis on the effect of driver's level on awakesness levels. From figure 5.3 it's clear that the relationship is proportional between the driver's GDI and awakesness. Such relationship is expected to be in that manner, since the personality and driving style of high GDI drivers allows them to maintain their awakesness levels and stay focus, which is opposite to aggressive and reckless drivers whom personality and nature tend to deplete their energy and focus. Actions such as speeding, aggressive braking, inadequate use of air conditioning system and continuous changing in lanes to overrun other vehicles while routing results in increasing fatigue levels and a lake of awakesness. For the first combination (4, 4, 4) in scenario 1 the average awakesness level after 5

iterations was 9.567. For the second (2, 4, 6) and third (2, 2, 8) combination (scenarios 2 and 3) the awakesness levels were 9.84 and 10.08 respectively. Sensitivity analysis on the effect of driver's Awakesness levels.

The next element of the model to be tested is the driver's awakesness levels, the sensitivity analysis is conducted of the effect of driver's awakesness on the other functions of the model. The following sub-sections present the results of the effect of awakesness on total costs of the model, in addition to the transportation risk. However, the effect of awakesness on the second objective function which is site risk is investigated since there is no relation or link between the two functions. Note that site risk is related to the amount of waste processed (treated or recycled) at different facilities, and it's not affected by the process of collecting waste from generation nodes or shipping waste between generation nodes and other facilities.

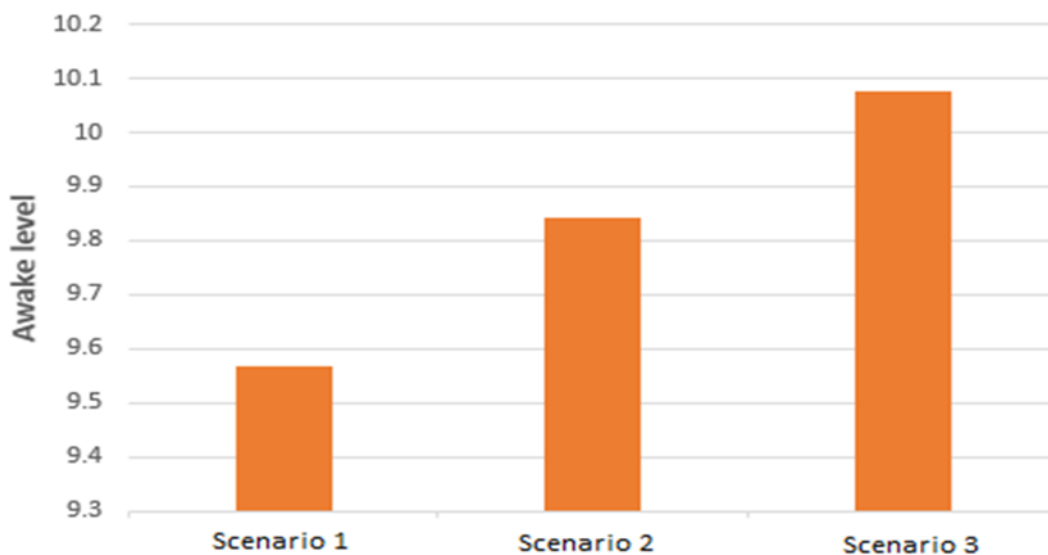


Figure 5.3: the relation between driver's GDI and awakesness levels

5.2.4 The effect of driver's awakesness levels on total costs

To conduct this sensitivity analysis, three scenarios were tested. For all scenarios a combination of (4, 4, 4), which is as previous sections indicates that the first four drivers are level 1, the next four are level 2 and the last four are level 3, are assumed and fixed without any actions of hiring, firing or training of drivers. Moreover, at each stage five iterations were performed to generate five different solutions and the average was calculated and shown in figure 5.4. Note that the results were presented using box plot graph to show the variations in total costs in every iteration, each plot shows the minimum and maximum costs in addition to the median, lower quartile and upper quartile. At scenario1 the awakesness levels was set between 8 and 9 to allow a difference between different driver's levels, where higher level drivers must have higher awakesness levels. The average of the five generated solutions was 1015500 \$ of costs. In the second scenario the awakesness level range was increased from 8 to 10 and results showed a total cost of 949916.8 \$ with a reduction of 6.9% compared to the previous test phase. However, in scenario 3 with awakesness level ranging from 8 to 12 the total costs arise 7.9% to mark an average total cost of 1019253.4 \$. Although there is no direct mathematical relation between costs and awakesness, but awakesness levels are strongly related to driver's GDI levels, which explains the behavior of the model in the first and second scenarios where an increase in awakesness levels resulted in saving costs. However, the increase in the average of total costs in the third phase is due to the presence of different type of costs in the model such as hiring, firing,

training, transportation and waste load related costs. Nevertheless, the increase in the average total costs is associated with a noticeable variation in the costs between the five iterations as shown in the bar plot graph in figure 5.4. Note that the variation in costs (at each scenario) increases as the driver's awakesness levels increases, which is due to expanding the ranges of awakesness levels i.e., at scenario 1 driver's awakesness levels are assumed to be in range from 8 to 9, however at scenario 2 the range was expanded to be from 8 to 10. Similarly, that is why scenario 3 has the highest variation since awakesness levels are assumed to be ranging from 8 to 12, a situation which will result in having highly alerted drivers with high awakesness levels, as well as, moderate and low alerted drivers in the same scenario.

costs in the third phase are due to the presence of different type of costs in the model such as hiring, firing, training, transportation and waste load related costs. Nevertheless, the increase in the average total costs is associated with a noticeable variation in the costs between the five iterations as shown in the bar plot graph in figure 5.4.

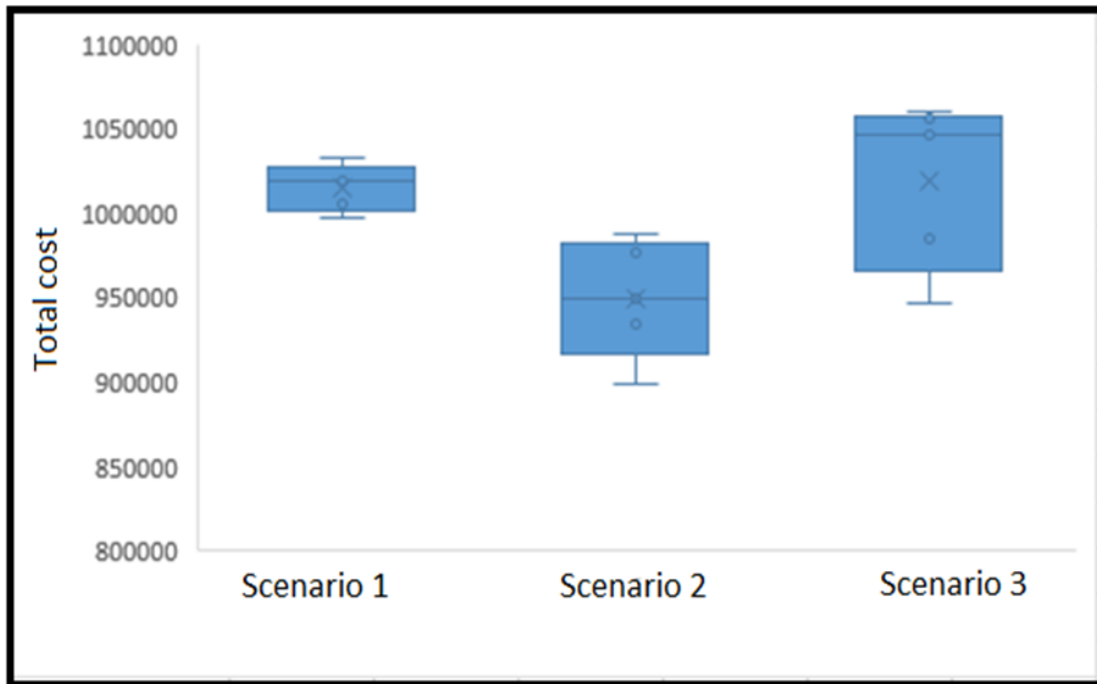


Figure 5.4: The effect of awakesness on total costs

5.2.5 The effect of driver's awakesness levels on transportation risk

Figure 5.5 shows the results of the conducted sensitivity analysis related to this sub-section. A (4, 4, 4) combination of driver's GDI levels is used with three test phases similar to the previous sub-section. The first test phase shows a 5815497.8 km * people average transportation risk at 8-9 awakesness levels of drivers. At the second test phase with awakesness levels ranging from 8 to 10, the average transportation risk was 4567027.1 km * people. The 27.34% decrease of transportation risk is expected due to the clear relationship between driver's level, awakesness and transportation risk, where a direct positive relation exists between driver's level and awareness, whereas, an inverse relation is found between them and transportation risk. In the third and final phase the average result was 4189471.2 km * people with 9.01% reduction in transportation risk.

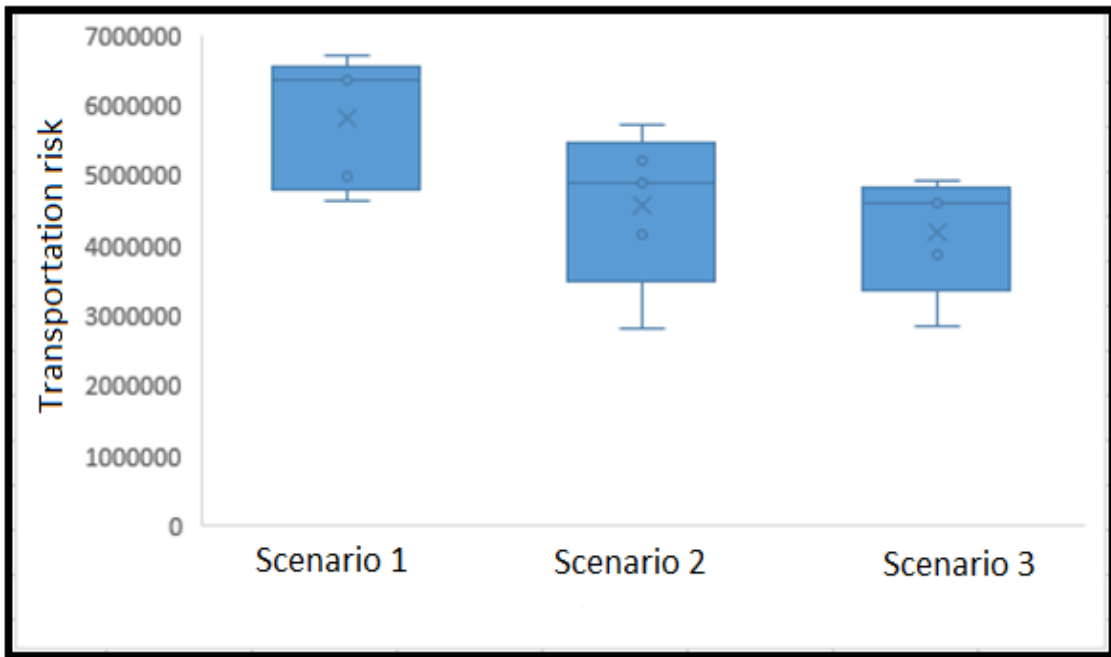


Figure 5.5: The effect of awakesness on transportation risk

Chapter Six

Conclusions and Recommendations

6.1 Summary

In this research, a HWVRP model was developed and presented that integrates and considers the GDI levels of drivers, in addition to the awakesness levels of drivers at different periods of time. The novelty of this approach revolves around the consideration of different driver's GDI and awakesness levels in HW collection and processing system. The proposed model is characterized as following: (1) the inclusion of four types of waste, where all types can be generated at any waste generated nodes, in addition to generation nodes this research considers treatment, recycling and disposal facilities; (2) two types of risks is considers which are site and transportation risks caused by shipping and processing waste; (3) considering green driving practices (GDI) which classifies drivers into three levels depending on their awareness of green and eco-friendly driving habits; (4) including hiring, firing and training of drivers at different periods to fulfill the needed number and level of drivers; (5) considering different awakesness levels of drivers at different times of a day, this levels are affected and related to driver's GDI levels.

A mathematical model was developed as a MINLP model to present the decision variables, parameters, sets and objective functions, in addition a set of assumptions needed to carry on the proposed model. Four objective

functions were developed to be optimized in this model, including the minimization of total costs (load, transportation, shipment and workforce planning costs), site risks and transportation risks, in addition to maximizing driver's awakesness levels. To solve the developed model MATLAB 2014 was used to translate the mathematical model into codes and then generate numerical data for presentation and discussion. Moreover, NSGA-II algorithm was used to solve the model due to its ability to handle complex NP-hard problems such as the proposed HWVRP (Rabbani et al., 2018). Hypothetical data was used due to the lack of real-life instances which includes all of the aspects of the model. The results of the model was divided into four stages depending on their type and relation to the model, the four stages are: (1) routing stage, which shows the results of routes taken by waste vehicles including depot, generation nodes and treatment nodes; (2) transportation nodes, that presents results related to the shipment of waste between treatment, recycling and disposal facilities, in addition to the amount of waste processed at each facility; (3) workforce planning, which shows the results of the number of needed drivers from each level as well as, the hiring, firing and training needs at each period; (4) driver's awakesness levels, to show how awake a driver is at each visited node, which is measured using TPMA model of sleepiness. After that a sensitivity analysis was conducted to understand how altering some variables and parameters affect the objective functions of the model. Mainly, the sensitivity analysis targeted five relations which are the effect of driver's GDI level on total costs, transportation risk and awakesness levels, as well

as, the effect of driver's awakesness levels on total costs and transportation risks. Studying the effect of driver's GDI and awakesness levels on other functions of the model is done to verify and validate the positive impact of the contribution in HWVRP. The importance of this results lays on providing different solutions with different driver combination (in term of GDI level), where each combination results in different awakesness levels at each node in addition to different costs and risks, which allows decision makers to make more wise judgments related for the well-being of employees and society besides the economic success of waste collection companies.

6.2 Thesis contributions

Many studies were conducted on waste management VRP, however a few considered and studied social aspects related and affected by the process of collecting waste. The proposed model in this research contributed to literature of HWVRP as follows: the first contribution is the consideration of driver's GDI levels in the waste collection process, as proven in previous chapters, the awareness of green driving activities and eco-friendly driving styles, resulted in reducing costs and risk on society. The second contribution of this model is the novel approach of considering the awakesness / fatigue levels of drivers at different nodes and times of a day. The consideration of driver's GDI and awakesness in HWVRP enables waste collection companies to meet its sustainable development needs, since the adequate selection and route planning of drivers in terms of GDI and

awakeness level results in total costs reduction, lower fuel consumption and GHG emissions, preserving the environment by reducing pollution caused by HW toxic emissions and finally reducing the risk on the society located around waste processing facilities and along the transportation route between those facilities. Moreover, the planning of rest times for drivers to recover from fatigue trips fulfills the corporate social responsibility of the waste companies toward their drivers. The third and final contribution is the introduction of a complex model that consists of many parameters and variables that could be applied in real world problems.

6.3 Model limitations

Despite of the complexity of the model in terms of incorporating of many variables, which on the other hand strengthen the model and support its realism. However, there are some limitations which should be mentioned that may hinder the realistic of the presented results. The limitations of the model are summarized in the following points.

- Hypothetical data: even though the results of the model seemed reasonable and are aligned with the purpose of the model, as well as, the validation of the model through testing different size instances, the lack of real-world instances to test the model hinders the reality of the results.
- Deterministic values: all of the proposed parameters in the HWVRP model were assumed to be deterministic, such as different costs in the model and the amount of waste at generation nodes. Likewise, the needed time for resting and recovering from fatigue is assumed to be fixed and

the same between different drivers, without considering factors that prevent drivers from resting that may occur due to internal or external causes such as sleeping disorders and outside disturbances. Adding stochastic parameters to the model is more realistic and applicable to solve real world problems.

6.4 Recommendations for future work

The following points present recommendations for future improvements in the proposed HWVRP in this research.

- **Smart HWVRP:** nowadays the use of technology enabled the enhancement of operations in many industries. In logistics and transportation sector and mainly waste management VRP the use of volume sensors introduced impressive results as shown in the work of (Ramos et al., 2018). Therefore, it is worthy to investigate the addition of such sensors in waste generation nodes to transmit continuous real time data about the amount of accumulated waste.
- **Uncertainty:** solving the model with stochastic parameters such as the amount of waste and prioritizing the selection of generation nodes for waste collection, will improve the applicability of the model.
- **Using hybrid metaheuristic algorithms:** the use of such solving approach using a combination of two or more algorithms (hybrid) will reduce the time needed to solve the problem.

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جامعة النجاح الوطنية

كلية الدراسات العليا

دمج اختلافات السائقين في مشكلة توجيه مركبة جمع النفايات الخضراء

إعداد

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قدمت هذه الأطروحة استكمالاً لمتطلبات الحصول على درجة الماجستير في الإدارة الهندسية بكلية الدراسات العليا في جامعة النجاح الوطنية في نابلس، فلسطين.

2021م

ب

دمج اختلافات السائقين في مشكلة توجيه مركبة جمع النفايات الخضراء

إعداد

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الملخص

تعتبر إدارة النفايات الخطرة مشكلة معقدة وتتطلب اهتماماً وتخطيطاً كافيين لإنجازها. الكثير من الباحثين بذلوا جهوداً في مشكلة توجيه مركبات جمع النفايات الخطرة، لكن القليل من هذه الأبحاث أخذ بعين الاعتبار الجوانب البشرية أثناء حل المشكلة. في بحثنا هذا تم تضمين جانبين متعلقين بالعامل البشري لمشكلة مركبات جمع النفايات، وهما مؤشر القيادة الخضراء ومستويات يقظة السائق. لذلك، تم افتراض ثلاثة مستويات لدرجة مؤشر القيادة الخضراء بناء على وعيهم بالقيادة الصديقة للبيئة، بالإضافة إلى ثلاثة مستويات من اليقظة بحيث تعكس درجة النعاس/اليقظة للسائقين. تم التحقق في تأثير المستويات المذكورة أعلاه على عوامل مختلفة مثل التكلفة لمعرفة تأثير اختلاف السائقين على نموذج مشكلة توجيه مركبات جمع النفايات الخطرة. كذلك، تم تصميم نموذج متعدد الأهداف لمعالجة مشكلة توجيه مركبات جمع النفايات الخطرة في الواقع مع الأخذ بعين الاعتبار تعدد عدد المركبات ووجود عدة أنواع من النفايات، ووجود عدة نقاط مولدة للنفايات ومعالجتها وإعادة تدويرها والتخلص منها. بالإضافة إلى ذلك تم الأخذ بعين الاعتبار مستويات مؤشر القيادة الخضراء لدى السائقين ومستويات يقظة السائقين. يهدف نظام مشكلة توجيه مركبات جمع النفايات الخطرة هذا إلى: (1) تقليل إجمالي التكاليف مثل تكاليف النقل والتوظيف وإنهاء الخدمة والتكاليف المتعلقة بكمية النفايات، (2) تقليل مخاطر النقل على السكان الموجودين على طول طريق النقل، (3) تقليل المخاطر على السكان الذين يعيشون حول مرافق معالجة النفايات، وأخيراً (4) العمل على زيادة مستوى يقظة السائق. تم استخدام الخوارزمية الجينية للفرز (NSGA-II) لحل النموذج نظراً لشيوع استعمالها في حل مثل هذه المشكلات بطريقة فعالة وفي وقت جيد. تم استعمال مشكلات ذات

احجام مختلفة لغرض التحقق من صحة النموذج، بالإضافة الى ذلك تم إجراء تحليل للحساسية حول تأثير المتغيرات المختلفة على قرارات السائق ومخرجات النموذج للتأكد من أن النتائج منطقية ومرتبطة بالواقع. أظهرت النتائج علاقة مباشرة بين مستويات مؤشر القيادة الخضراء للسائقين والتكاليف الإجمالية، حيث تؤدي الزيادة في مستوى القيادة الخضراء للسائق إلى خفض التكاليف إلى نقطة معينة وتبدأ في الزيادة مرة أخرى بسبب تكاليف التدريب والرواتب للسائقين رفيعي المستوى. علاوة على ذلك، تم العثور على صلة غير مباشرة بين مستويات اليقظة ومخاطر النقل، حيث أدى زيادة مستوى يقظة السائق إلى تقليل مخاطر النقل، على الرغم من عدم وجود علاقة رياضية بين الوظيفتين.