7-6-2021 12:00 PM

Multi-Objective Optimization of Green Transportation Operations in Supply Chain Management

Nayera Elgharably, *The University of Western Ontario*

Supervisor: El Damatty, Ashraf, *The University of Western Ontario*
: Easa, Said, *Ryerson University*
: Nassef, Ashraf, *American University in Cairo*

A thesis submitted in partial fulfillment of the requirements for the Doctor of Philosophy degree in Civil and Environmental Engineering

Abstract

Supply chain is the integration of manufacturing process where raw materials are converted into final products, then delivered to customers. Supply chains consists of two basic integrated process that interact together: (1) production and inventory and (2) distribution and logistics. Maximizing competitiveness and profitability are of the main goals of a supply chain. Accounting only for economic impacts as variable and fixed costs does not serve the main goal of the supply chain. Therefore, considering customer satisfaction measures in distribution models is essential in supply chain management. This thesis focuses on the multi-objective Vehicle Routing Problem (VRP) in green environment. Models that addressed the three objectives simultaneously handled one of the objectives as a constraint with a certain threshold in the problem, while others used weighted utility functions to address the problem objective in deterministic environment. The proposed Green VRP (GVRP) deals with three different objectives simultaneously that considers economic, environmental, and social aspects. A new hybrid search algorithm to solve the capacitated VRP is presented and validated in Chapter 2. The developed algorithm combines the evolutionary genetic search with a new local search heuristic that considers both locations and demand quantities of the nodes to be visited in routing decisions, not just the distances travelled. The algorithm is then used to solve the multi-objective GVRP in Chapter 3. The objectives of the developed GVRP model are minimizing the total transportation operations cost, minimizing the fuel consumption, and maximizing customer satisfaction. Moreover, a new overlap index is developed to measure the amount of overlap between customers' time windows that provides an indication of how tight/constrained the problem is. The model is then adapted to consider the uncertainty in travel times, service times, and unpredictable demands of customers in Chapter 4. Pareto fronts were obtained and trade-offs between the three objectives are presented in both deterministic and stochastic forms. Furthermore, analysis of the effects of changing vehicle capacity and customer time windows relaxation are presented.

Keywords

Supply Chain Management, Capacitated Vehicle Routing, Green Vehicle Routing, Stochastic, Transportation, Optimization, Evolutionary Search.

Summary for Lay Audience

Supply chain is the combination of all manufacturing process where raw materials are converted into final products, then delivered to customers. Supply chains consists of two basic integrated process that interact together: (1) production and inventory and (2) distribution and logistics. Maximizing competitiveness and profitability are of the main goals of a supply chain. Best value supply chains are the chains most likely to prosper within this today's competition and are the ones that use strategic supply chain management in an effort to excel in terms of speed, quality, cost, and flexibility. Accounting only for economic impacts as variable and fixed costs does not serve the main goal of the supply chain. Therefore, considering customer satisfaction measures in distribution models is important in supply chain management. Freight transportation is considered one of the most important parts of logistics that occupies one-third of the logistics cost. On the other hand, one of the side effects of vehicle transportation is the emission of Greenhouse Gases (GHGs). With a growing attention to environmental impact in logistics, a lack of multi objective models that considers the economic, environmental, and social aspects is found in literature. Moreover, in real life, uncertainty plays an important role in the process of routing and scheduling of logistics. Ignoring these sources, may lead to inaccurate modeling of the VRP. Sources of uncertainty can be travel times, service times and unpredictable demands of customers.

The purpose of the thesis is to study the freight distribution problem considering the environmental impact and at the same time accounting for the total travel costs and customer satisfaction. The presented models deal with three different objectives simultaneously that considers economic, environmental, and social aspects and is adapted to consider the uncertainty in travel times, service times and unpredictable demands of customers. Trade-offs between the three objectives are presented in both deterministic and stochastic studies. Furthermore, analysis on the effect of changing the capacity of the vehicle and the effect of customer time windows relaxation is presented.

Co-Authorship Statement

This thesis has been prepared in accordance with the regulations for an Integrated Article format thesis stipulated by the School of Graduate and Postdoctoral Studies at Western University. Statements of the co-authorship of individual chapters are as follows:

Chapter 1: Introduction

Literature review and the framework presented was conducted by N. Elgharably under close supervision of Prof. S. Easa and Prof. A. El Damatty. A paper titled "Implementing Performance-Based Analysis in Supply Chain Management: Review and Extension" co-authored by N. Elgharably, S. Easa, and A. El Damatty was submitted and presented at the CSCE conference 2017, Vancouver, British Columbia, Canada.

Chapter 2: New Hybrid Search Algorithm for the Capacitated Vehicle Routing Problem

All numerical work and Analysis were conducted by N. Elgharably under close supervision of Prof. A. Nassef, Prof. S. Easa and Prof. A. El Damatty. A paper titled "New Hybrid Search Algorithm for the Capacitated Vehicle Routing Problem" co-authored by N. Elgharably, A. Nassef, S. Easa, and A. El Damatty was submitted to the CSCE conference 2021, paper accepted.

Chapter 3: Multi-objective Green Vehicle Routing Model with Customer Satisfaction

All numerical work and Analysis were conducted by N. Elgharably under close supervision of Prof. A. Nassef, Prof. S. Easa and Prof. A. El Damatty. A paper co-authored by N. Elgharably, A. Nassef, S. Easa, and A. El Damatty will be submitted to the Journal of Transportation Research.

Chapter 4: Stochastic Multi-objective Vehicle Routing Model in Green Environment with Customer Satisfaction

All numerical work and Analysis were conducted by N. Elgharably under close supervision of Prof. S. Easa, Prof. A. Nassef, and Prof. A. El Damatty. A paper co-authored by N. Elgharably, S. Easa, A. Nassef, and A. El Damatty will be submitted to the IEE: Intelligent Transportations System Society Journal, Special Issue: Intelligent Supply Chain in modern Challenges.

Chapter 5:

Conclusion drawn from this work was assessed by N. Elgharably under close supervision of Prof. A. Nassef, Prof. S. Easa and Prof. A. El Damatty.

To my adorable girls, ***Rokaya*** and ***Farida***

To my lovely husband, ***Mohamed Hamada***

To my beloved parents, ***Sanaa Aloufy*** and ***Essam Elgharably***

To my dear brothers, ***Omar*** and ***Nour***

To my role model, my aunt, *Prof.* ***Affaf Aloufy***

For their love, patience, support, and encouragement through these years of hard work

Acknowledgments

With these few words, I would like to express my appreciation and gratitude to the people who have helped me. Without them, this thesis would have not been completed.

I would like to express my deep and sincere gratitude to my research supervisors *Prof. Said Easa*, *Prof. Ashraf El Damatty*, and *Prof. Ashraf Nassef* without their guidance and persistent help this work would not have been possible. It has been a great privilege and honor to work with them.

I would like to thank all the staff members at the Civil and Environmental Engineering department for their support especially *Kristen Edwards* for her, endless assistance and for all the effort.

For all my colleagues who supported me and shared their valuable experience with me, thank you.

I would like to thank *Prof. Khaled S. El-Kilany* for the unconditional support, and consistent encouragement throughout my post-graduate years.

Last but not least, I owe my deepest gratitude to my beloved family who has been a source of constant support, love, and encouragement during those challenging years.

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List of Abbreviations

AFS	Alternative Fuel Stations
AFV	Alternative Fuel Vehicle
AVRP	Asymmetric Vehicle Routing Problem
CCP	Chance Constrained Program
CFLP	Capacitated Facility Location Problem
CVRP	Capacitated Vehicle Routing Problem
DM	Decision Maker
FCR	Fuel Consumption Rate
FCVRP	Fuel Consumption Vehicle Routing Problem
GA	Genetic Algorithm
GHG	Green House Gases
GLND	Green Logistics Network Design
GVRP	Green Vehicle Routing Problem
HIC	Heuristic Inheritance Crossover
HVRP	Heterogeneous Vehicle Routing Problem
ILS-SP	Iterated Local Search heuristic with Set Partitioning approach
IRR	Internal Rate of Return
MDVRP	Multi-Depot Vehicle Routing Problem
MOOP	Multi-Objective Optimization Problem
m-TSP	Multiple Travelling Salesman Problem
NP hard	Non-deterministic Polynomial-time Hard

NPV	Net Present Value
OVRP	Open Vehicle Routing Problem
PBP	Pay Back Period
PDPTW	Pickup and Delivery Problem with Time Windows
PRP	Pollution Routing Problem
PVRP	Periodic Vehicle Routing Problem
RAEM	Random Arc Exchange Mutation
RATM	Random Arc transfer Mutation
RIC	Random Inheritance Crossover
RLSH	Resultant Local Search Heuristic
RNEM	Random Node Exchange Mutation
RNTM	Random Node Transfer Mutation
ROI	Return on Investment
RRM	Route Reduction Mutation
RTS	Reactive Tabu Search
SA	Simulated Annealing
SCM	Supply Chain Management
SDVRP	Site-Dependent Vehicle Routing Problem
SPEA	Strength Pareto Evolutionary Algorithm
SPR	Stochastic program with Recourse
SVRP	Stochastic Vehicle Routing Problem
TDGVRP	Time Dependent Green Vehicle Routing Problem
TS	Tabu Search

TSP	Travelling Salesman Problem
TW	Time Windows
UHGS	Unified Hybrid Genetic Search
VRP	Vehicle Routing Problem
VRPB	Vehicle Routing Problem with Backhauls
VRPHTW	Vehicle Routing Problem with Hard Time Windows
VRPSDP	Vehicle Routing Problems with Simultaneous Deliveries and Pickups
VRPSPDP	Vehicle Routing Problems with Split Deliveries and Pickups
VRPTW	Vehicle Routing Problem with Time Windows
VRPTWTD	Vehicle Routing Problem with Time Windows and Temporal Dependencies
VRSP	Vehicle Routing and Scheduling Problem
WIP	Work in Process
3PL	Third-Party Logistics

List of Notations

Y_{i}	Value of the next customer to be visited on the route
X_i	Represents the current visited node
d_{X_i,Y_j}	Distance travelled from node X_i to node Y_j
Z_1	Objective function that minimizes the Total Travel Cost
n	Number of customers to be visited
m	Number of vehicles/ routes
Y_i^k	Value of the next customer to be visited on route k
X_i^k	Represents the current visited node on route k
S_{X_i,Y_j}^k	Binary variable to represent the passing of vehicle k on arc(X_i^k, Y_i^k)
q_{Y_j}	Demand at customer Y_j
Q_k	Capacity of vehicle k
D_i	Quantity of items to be delivered or picked up by the vehicle at the customer i.
α_i	Earliest time a customer i can accept a service (Lower bound)
β_i	Latest time a customer i can be serviced (Upper bound)
t_{Y_j}	Time of travel to next customer Y_j
HR_i	Heuristic Resultant for customer i
λ	Weight given to the distance calculation
DR_i	Demand Remainder for customer i

s_i	Service time for customer *i*
$W^k_{X_i,Y_j}$	Gross weight of the vehicle *k* on a route
SV_i	Customer Satisfaction Value
C_e	cost of early arrival at the customer
C_d	cost of delay (late arrival at the depot)
C_{fuel}	unit fuel cost
C_t	cost per unit time
F	vehicle operating cost
p^*	Full load fuel consumption rate
p_o	No load fuel consumption rate
γ	Coefficient obtained by linear regression between fuel consumption rate and the vehicle's load
δ	Relaxation percentage of the time window's upper bound
${\beta_i}^*$	Relaxed Upper bound of the time window of customer *i*

Chapter 1

1 Introduction

A supply chain consists of multiple firms, both upstream (supply) and downstream (distribution), and the ultimate consumer. It is the network of all organizations involved, in the different processes/ activities that are responsible of adding value in the form of products and services delivered to the ultimate consumer (Mentzer *et al.,* 2001). Supply chain can be defined as the integration of manufacturing process where raw materials are converted into final products, then delivered to customers. A supply chain consists of two basic, integrated processes that interact together: (a) production planning and inventory control process, and (b) distribution and logistics process. The production planning and inventory control process includes all the manufacturing and storage processes. Production planning defines the design and management of the manufacturing process including raw material scheduling and purchase, manufacturing process design and scheduling, operations management, and material handling. Inventory control deals with managing the raw materials, Work in Process (WIP) as well as the final products, where the storage and purchase policies are determined. Inventory retrieval and transportation, whether it is a final product or raw material is defined in the transportation and logistics processes. Products might be delivered to customers directly or may be delivered to distribution centers first and then shipped to the customer (Beamon, 1998).

1.1 Supply Chain Management

Supply Chain Management (SCM) is the management of material and information flows through all the members of the chain, such as vendors, manufacturing, assembly, and distribution centers (Thomas and Griffin, 1996). The coordination of the traditional business functions and its tactics not only within a specific company but across businesses within the supply chain while considering the long-term performance of the chain as a whole is the definition of SCM (Li, 2014).

1.1.1 Supply Chain and Logistics

In 1986, logistics management was stated by the Council of Logistics Management as “The process of planning, implementing, and controlling the efficient, cost – effective flow and storage of raw materials, in-process inventory, finished goods and related information flow from point of origin to point of consumption for the purpose of conforming to customer requirements” (Lambert and Cooper, 2000). SCM is a new term in literature. It appeared in early 1980s focusing on inventory reduction through the whole network involved (Cooper *et al.*, 1997). Supply chain and logistics are usually related in academia. They both are related to the product movement during its whole life cycle, and both are considered the central unit of competitive analysis of model management science. Supply chain is a more broadened concept than logistics dealing with a wider range and perspective. as logistics has no relationship with organizations. Moreover, SCM does not aim at reducing costs and improving profits but the general aim is to increase the competitiveness of the whole chain. (Li, 2014).

1.1.2 SCM Objectives

The objective of SCM is to maximize competitiveness and profitability for the company as well as the whole supply chain network including the ultimate customer, aiming at increasing the total process efficiency and effectiveness across members of the supply chain (Lambert *et al.,* 1998). Moreover, reducing the total amount of resources used to provide the necessary customer service level, reducing inventory investment in the whole chain, and increasing customer service (Cooper *et al.,* 1997).

1.1.3 SCM Components

The supply chain involves the combination of three elements: the structure of the chain, its business processes, and SCM components shown in Figure 1-1. The supply chain structure is the network of members and the links between them. Business processes, second element in SCM, are the activities needed to produce a specific output to the ultimate customer. The management components, third element in the SCM, are the managerial variables by which the business processes are integrated and managed across the supply chain. The identification of the supply chain members is one of the important points in managing the supply chain, then determining their links with each other and their link to the processes done in the chain (Lambert *et al.*, 1998). According to Thomas and Griffin (1996), the following important elements should be considered in SCM:

- The restructuring of value-added activities may offer great opportunities for improvement which can be done through co-ordinated modelling.
- A key element is choosing performance measures that correspond with the supply chain goals and objectives.
- Transportation cost accounts for more than the half of the total logistics cost, which is the largest component of the logistics costs.
- Life cycle constraints and costs should be considered in long supply chains. Quick response to customers' requirements can be constrained in long supply chains. With products of short life cycle, a high risk of inventory obsolescence can occur.
- The coordination between stages of the supply chain in the design and modelling is important.
- Decomposition methods fail to solve these problems as the models becomes too large/complicated to be solved.
- A great attention should be taken to the supply chain activities environmental impact (Thomas and Griffin, 1996).

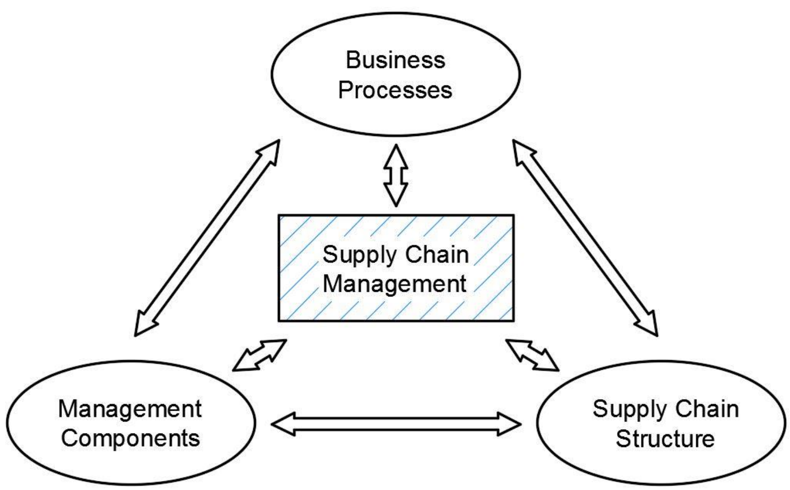

Figure 1-1: Supply Chain Management Components

1.1.4 SCM Complexity and Performance Measures

Figure 1-2 shows a four level Supply Chain consisting of suppliers, manufacturing plants, distribution, and customers. Each level of the supply chain may include several facilities. The complexity of the supply chain depends on the number of levels in the chain and the number of facilities in each level. The selection of the most suitable performance measures of the supply chain is a critical decision, due to the complexity of the supply chain (Beamon, 1999).

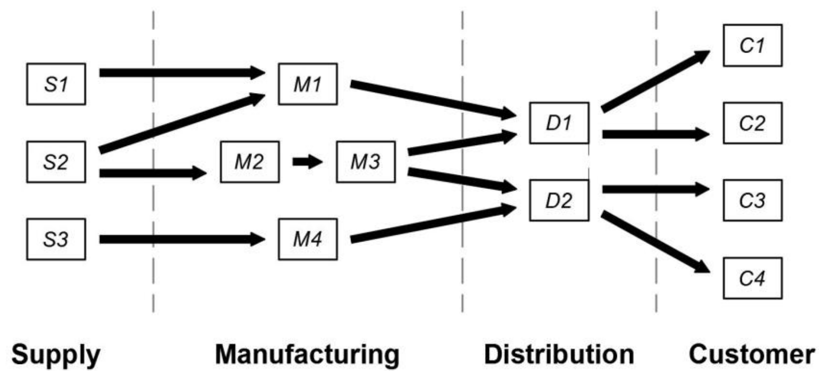

Figure 1-2: Example of a Supply Chain

Mentzer *et al.*, (2001) defined three degrees of supply chain, as shown in Figure 1-3 which illustrates the complexity of a supply chain system:

- Direct Supply Chain: consists of a company, a supplier, and a customer (Figure 1-3 (i)),
- Extended Supply Chain: consists of all the suppliers and customers involved in flow of products, services, finances, and/or information (Figure 1-3 (ii)), and
- Ultimate Supply Chain: includes all the organizations involved in the chain (Figure 1-3 (iii)). A third-party financial provider and a Third-Party Logistics (3PL) exist.

Traditional performance measures concentrate on using financial measures such as Return on Investment (ROI), Net Present Value (NPV), Internal Rate of Return (IRR), and PayBack Period (PBP). Financial measures could be used in evaluating noncomplex supply chains of small sizes although they will not give an overview of the whole chain performance. (Bhagwat and Sharma, 2007).

Beamon (1996) presented several characteristics that can aid in evaluating supply chains. These characteristics are:

- Inclusiveness: measuring all aspects,
- Measurability: data used could be measured, quantitative not qualitative data,
- Universality: to allow for comparison under various operating conditions,
- Consistency: measures meet the organization goals and objectives (Beamon, 1996).

Figure 1-3: Degrees of Supply Chain Complexity

Supply chain models have mainly used either cost, and or a combination of cost and customer responsiveness. Costs may include inventory costs and operating costs. Customer responsiveness includes lead time, stock out probability, and fill rate. Other performance measures have been identified to measure supply chains, yet they are not used in research due to their qualitative nature. These measures include customer satisfaction, information flow, supplier performance, and risk management.

Beamon (1999) presented a framework for the selection of performance measurement systems for manufacturing supply chains that include measures for the use of resources, the desired output and flexibility. Each one of these three measures is important and affect each other. Beamon (1999) stated that the supply chain performance measurement system should contain at least one single measure from each of the three identified types that is consistent with the organization's strategic goals and objectives. The three types of measures are listed below:

1. Resources: which are the minimum requirements (quantity) or an efficiency measure, that measures the utilization of the resources in the system. The use of too few resources can affect the system in a negative way affecting the output and as a result affects the systems flexibility and ability to respond to customers' requests.
2. Output: include measures for customer responsiveness, quality, and the quantity of final product produced. Output measures are mainly quantitative measures, however customer satisfaction; and Product quality are qualitative measures that need to be interpreted quantitatively.
3. Flexibility: is a measure of the ability of the system to respond to customer requests by cooping with volume and schedules changes from suppliers, manufacturers, and customers. Flexibility is vital to the success of the supply chain as supply chains exist in uncertain environments (Beamon, 1999).

Gunasekaran *et al.*, (2001) stated that there is a great need to study the performance measures of SCM in the context of following reasons:

- Lack of a balanced approach as most of the approaches in literature focused on financial measures (stakeholders' measures), not giving enough attention to operational measures,
- Lack of determining the suitable evaluation measures for SCM and the number of measures used. Good few metrics are better than many measures not related to the goals and objectives.
- Lack of differentiation of the measures required at strategic, tactical, and operational levels (Gunasekaran *et al.*, 2001).

1.2 Modelling of Transportation Operations in SCM

According to the 23rd annual Council of Supply Chain Management Professionals State of Logistics Report, the USA transportation costs represented 64 % of the total logistics costs in 2011, while inventory costs represented 33% and 4% for administrative costs. The use of mathematical programming techniques in SCM is one of the most important techniques in latest decades. A review of historic modeling of the transportation function, from 1974 to 2008, in supply chain optimization models and recent papers, from 2009 to 2012, done by Bravo and Vidal 2013 shows that:

- Integrated models have been frequently used. However, those models did not deal with the stochastic nature of transportation time. As this may result in computational complications.
- The number of vehicles used in the fleet and transportation times were considered as model parameters not as decision variables.
- Most of the research used the cost function as the objective function in optimizing the problem. The objectives related to minimizing the travel time, minimizing the distance travelled and, minimizing the order delay were ignored, which means that cost minimization is preferred over customer satisfaction.
- It was found that 10% of the variability in transportation costs is due to the travelled distance, which is calculated using cost per unit shipped or cost per unit distance. This shows that there is a gap in modeling the transportation operations and the modeling of the transportation cost function.
- Recently, transportation models paid attention to service times and considered time windows for serving customers. Moreover, different types of transportation vehicles and modes are considered in the models.
- The speed of the vehicles, its acceleration, the road's topography, and CO_2 emissions were rarely considered.
- Transportation fleet in most of the papers is not determined whether it is private or outsourced, and homogeneous or heterogeneous.
- The use of trade-off considerations between transportation costs and other aspects has decreased rather than increased in research for the recent years (Bravo and Vidal, 2013).

1.3 Objectives of the Study

The main objectives of this research are:

1. Develop a transportation framework that integrates the performance measures and decision variables relevant to Green Supply Chain Management,
2. Develop a new hybrid search algorithm for the Vehicle Routing Problem (VRP) that combines the evolutionary genetic search with a new local search heuristic to solve the Capacitated Vehicle Routing Problem (CVRP),
3. Develop a multi-objective Green Vehicle Routing Problem (GVRP) model that considers the considers economic, environmental, and social aspects that offers the decision maker a set of solutions to trade-off between the total transportation operational costs, the environmental costs and customer satisfaction,
4. Develop a stochastic multi-objective optimization model for routing decisions through the green supply chain under uncertainties of travel time, service time, and customer demands with the objective of minimizing the total travel cost, minimizing fuel consumption rate, and maximizing customer satisfaction.

1.4 Methodology

The study deals with the distribution and logistics operations of the green supply chain in uncertain environment. The green vehicle routing problem of study deals with a set of customers/retailors with variable demand, variable service times and variable travel time between any two locations. Moreover, the stochastic nature of travel times, service times and customer demands will be considered. A homogeneous fleet of vehicles will be used to initiate the routes serving the costumers. However, the utilization of vehicles and a cost-effective route solutions will be studied as a decision will be made regarding the number of vehicles/routes used. The objectives of the GVRP proposed will be minimizing the fuel consumption rate, the total travel time (variable costs), minimizing the number of vehicles used (fixed costs) and maximizing the customer satisfaction.

The current study should achieve the main objectives mentioned in Section 1.4 by developing a transportation framework for the GVRP that adopt Beamon's performance measures in supply chain. The framework uses customer satisfaction, fuel consumption rate and total travel costs as performance measures. The framework introduced in Chapter 1. Then followed by the development of the supply chain transportation optimization model. The transportation optimization model will be divided into three parts. A diagram presenting the stream of the models developed in the study is presented in Figure 1-4. First, a new hybrid search algorithm will be introduced to the Capacitated Vehicle Routing Problem (CVRP). The new algorithm combines the evolutionary genetic search with a new local search heuristic that considers both locations and demand quantities of the nodes to be visited not just distances travelled which will be presented in Chapter 2. Second, a deterministic multi-objective transportation model in green environment will be developed where all the input variables will be considered deterministic, presented in chapter 3. The model considers the economic, environmental, and social aspects objectives. The third part will consider the randomness in the variables where a stochastic multi-objective Green transportation model will be developed in Chapter 4.

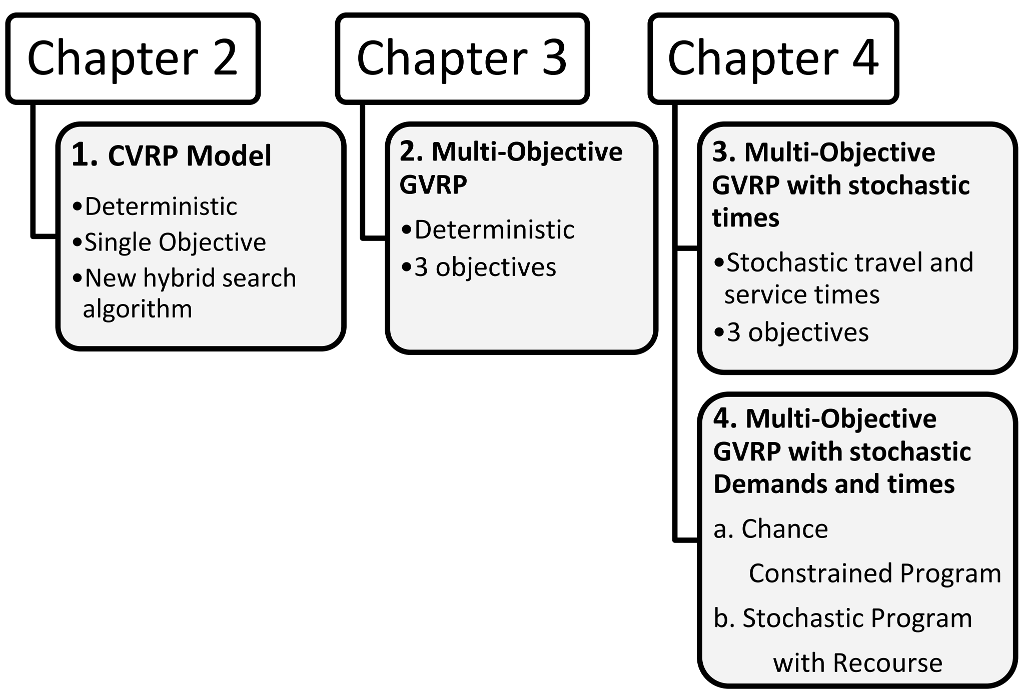

Figure 1-4: Optimization models developed

1.5 Organization of the thesis

This thesis is organized following the "Integrated Article" format. The current chapter introduces the studied topic, along with the key points targeted by the research as objectives of the study. The following chapters address the objectives mentioned as follows:

Chapter 2: New Hybrid Search Algorithm for the Capacitated Vehicle Routing Problem

This chapter aims to develop a new hybrid search algorithm that combines the evolutionary genetic search with a new local search heuristic to solve the CVRP. The proposed heuristic calculates a resultant objective function based on both the distance travelled and the demand associated with the given customer. A new set of genetic operators suited for the problem was employed. Several computational experiments were conducted. The algorithm was validated and was capable of converging to the optimum solution of the tested benchmark instance.

Chapter 3: Multi-objective Green Vehicle Routing Model with Customer Satisfaction

In this chapter the multi-objective vehicle routing problem in green environment is studied. The Green VRP (GVRP) presented deals with three different objectives simultaneously that considers economic, environmental, and social aspects. The model utilizes a new hybrid search algorithm to solve the GVRP. Pareto fronts were obtained and trade-offs between the three objectives are presented. Furthermore, an analysis of the effect of changing the capacity of the vehicles is presented.

Chapter 4: Stochastic Multi-objective Vehicle Routing Model in Green Environment with Customer Satisfaction

The purpose of this chapter is to study the stochastic multi-objective vehicle routing problem in green environment. The stochastic Green VRP (GVRP) presented deals with three different objectives simultaneously that consider economic, environmental, and social aspects. A new hybrid search algorithm to solve the VRP is presented and validated.

The algorithm is then employed to solve the stochastic multi-objective GVRP. Pareto fronts were obtained and trade-offs between the three objectives are presented. Additionally, an analysis on the effect of customers' time window relaxation is presented.

Finally, the last chapter of the thesis presents the conclusions obtained from the performed research, as well as recommendations for future work based on the results of this study.

1.6 Proposed Framework

In the past, manufacturers were considered the main drivers of the supply chain. They controlled the way at which products were manufactured and distributed. Today, customers are the main drivers, and manufacturers are competing to meet their demands by manufacturing products that are different in options, styles, features, quick order fulfillment, and fast delivery (Jain *et al.*, 2010). Best value supply chains are the chains most likely to prosper within this today's competition and are the ones that use strategic SCM in an effort to excel in terms of speed, quality, cost, and flexibility (Muysinaliyev and Aktamov, 2014). As shown in the literature, supply chain models have mainly used two different quantitative performances, either cost; and or a combination of cost and customer responsiveness, ignoring important measures such as output measures. The selection of performance measures in supply chain is considered one of the critical steps in the SCM. A Framework that adopts Beamon's performance measures in supply chain (Beamon, 1999) is proposed (Figure 1-5), emphasizing on the three different types of measures: resource, output, and flexibility measures. These three measures are all interrelated as the output of the supply chain is affected by the resources used and the flexibility of the system is determined by the output whether it is a product or service.

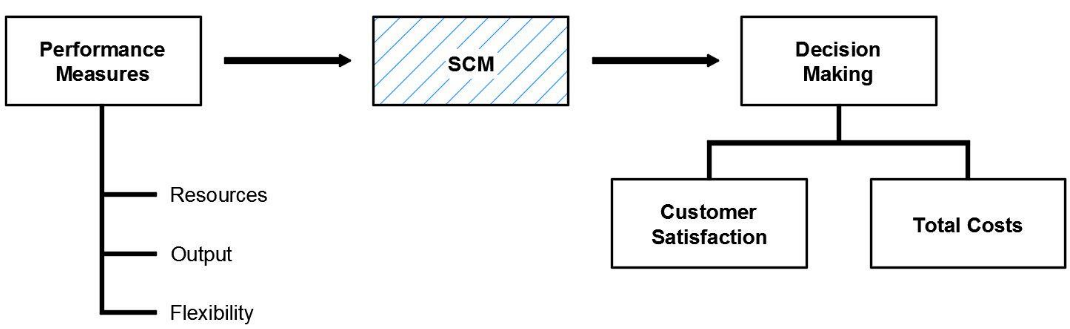

Figure 1-5: Supply Chain Management Framework

The framework includes developing a transportation optimization model that takes into account not only the transportation cost per unit distance or cost per unit shipped, but also other transportation operations involved and trade-offs between transportation costs and other aspects done using a decision support system. The transportation model framework (Figure 1-6) includes routing decisions using private or outsourced fleet, Homogenous or nonhomogeneous fleet. Furthermore, supplier poor management, customer orders uncertainties, carrier delays, lack of updated/accurate data, and other external circumstances are considered sources of risk. Implementation of risk management is to minimize supply chain disruptions and uncertainties, where stochastic analytical models are considered. This is done by identifying the sources of risk in the model, their consequences, actions, and backup scenarios and finally monitoring risks to detect the them when they occur (Tuncel and Alpan, 2010). The proposed framework should be a valuable assessment tool for the newer generation of SCM applications.

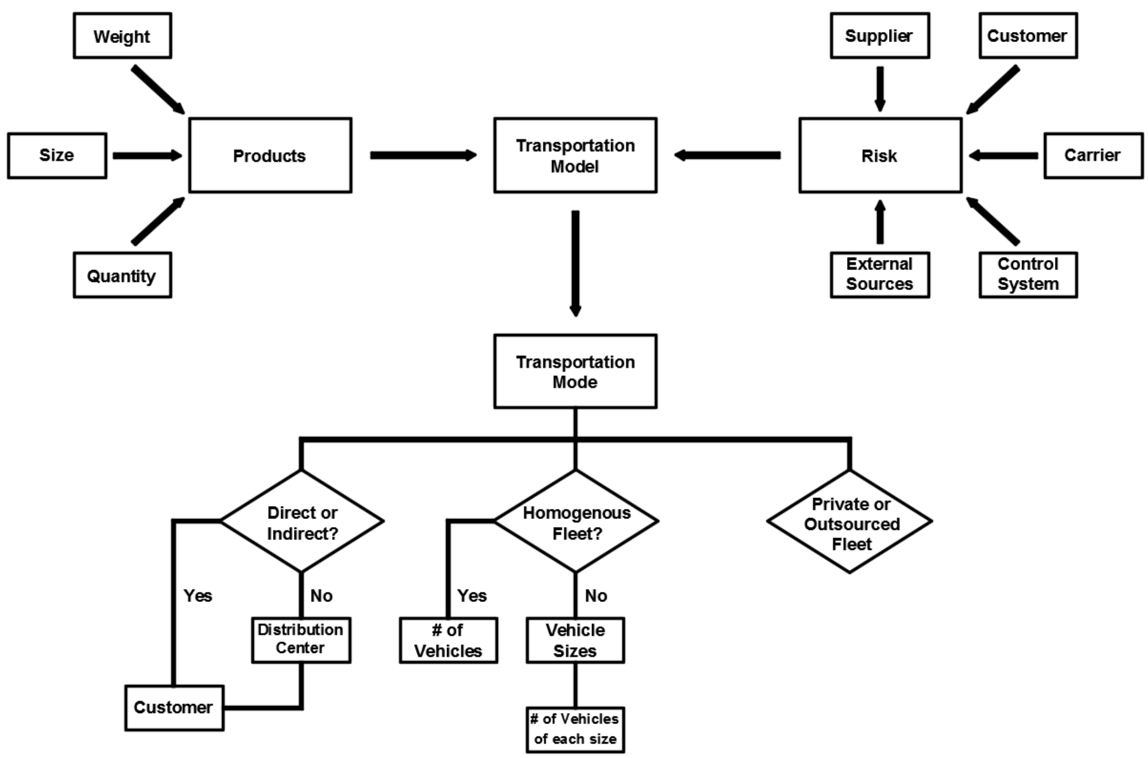

Figure 1-6: Transportation Model Framework

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Chapter 2

2 New Hybrid Search Algorithm for the Capacitated Vehicle Routing Problem

The vehicle routing problem is one of the most studied combinatorial optimization problems in operations research. The problem deals with a homogenous fleet of capacitated vehicles that operates from a central depot serving a set of customers with known demands. The objective of the problem is to design a set of routes serving customers with minimum cost. The vehicle routing problem is classified as NP-hard problem. Exact and approximate algorithms have been developed in the literature to solve the Capacitated Vehicle Routing Problem (CVRP). However, exact methods can only solve relatively small size problems while approximate algorithms have been able to reach near-optimum solutions. The purpose of this chapter is to develop a new hybrid search algorithm that combines the evolutionary genetic search with a new local search heuristic to solve the CVRP. The proposed heuristic calculates a resultant objective function based on both the distance travelled and the demand associated with the given customer. A new set of genetic operators suited for the problem was employed. Several computational experiments were conducted. The algorithm was validated and was capable of converging to the optimum solution of the tested benchmark instance.

2.1 Introduction

The Vehicle Routing Problem (VRP) is one of the most studied combinatorial optimization problems in operations research (Uchoa, *et al.,* 2017). The CVRP is an extension of the well-known Traveling Salesman Problem (TSP) where, a set of minimum distance routes are determined to visit a given set of customers with known demands without violating the capacity constraint of the vehicles used (Derigs and Reuter, 2009). The VRP is classified as NP-hard. Several exact and approximate solution methods have been used to solve the problem. Exact methods can only solve relatively small size problems while approximate algorithms have been able to reach near-optimum solutions (Baldacci *et al.,* 2010). The aim of this chapter is to present a new hybrid search algorithm for the vehicle routing problem using a new local search heuristic and an evolutionary algorithm.

The chapter is divided as follows: Section 2.2 provides a brief literature review on the CVRP and the solutions approaches found. Section 2.3 describes the problem characteristics and the mathematical formulation of the problem of study. Section 2. 4 illustrates the hybrid search algorithm proposed followed by the experimental results in Section 2.5. Finally, in Section 2.6, the conclusions drawn from this work are presented.

2.2 Literature Review

The vehicle routing problem was first introduced by Dantzig and Ramser (1959) as a variant of the travelling salesman problem. The problem was later refined by adding extra realistic constraints such as the capacitation of the vehicle routes (Laporte, 1992). Algorithms employed for solving the problem can be divided into algorithms seeking exact optimum solutions (exact algorithms) and those seeking near-optimal solutions (approximate algorithms). In further research both categories were hybridized. Table 2-1 presents a summary of the characteristics of the reviewed methods, including reference, problem class, solution technique, problem characteristics, type of objective function, and objectives. The solution techniques are classified as exact, approximate, and hybrid.

2.2.1 Exact algorithms

Baldacci *et al.* (2004) briefly discussed the exact methods of solving the capacitated VRP. These methods included: branch-and-cut, branch-and-bound, dynamic programming, and set-partitioning methods. In exact methods, the optimal solution is found for relatively small sized problems if sufficient time and space is given to the problem.

2.2.2 Approximate algorithms

Later research utilized heuristics or pseudo random search algorithms to arrive at near-optimal solutions of larger problem instances. Several heuristics (approximate algorithms) have been proposed for the VRP and are divided into two classes: classical heuristics and metaheuristics.

Table 2-1: Summary of Capacitated vehicle Routing Problem Literature

				Sol. Tech.		**Problem Characteristics**											**Obj. Fn.**		**Objective**			
Author(s)	***Year***	***Problem Class***	***Technique***	*Exact*	*Approximate*	*One visit per customer*	*Vehicle capacity*	*Homogeneous fleet*	*Heterogeneous fleet*	*Single routes per vehicle*	*Multiple routes per vehicle*	*Time windows*	*Total route length*	*Single Depot*	*Multiple Depots*	*Site dependent service*	*Single*	*Multiple*	*Total distance travelled*	*Total Route cost*	*Total travel time*	*Vehicle's fixed cost*
Buxey	1979	VRP	Classical Heuristics/ Simulation		●	●	●	●		●				●			●		●			
Leeuwen and Volgenant	1983	VRP	Classical Heuristics		●	●	●	●		●			●	●			●		●			
Haimovich *et al.*	1985	VRP	Classical Heuristics		●	●	●	●		●				●			●		●			
Kulkarni and Bhave	1985	TSP/ m-TSP/ VRP/ MDVRP	Mathematical Formulation			●	●	●		●			●	●	●		●			●		
Laporte	1989	MDVRP	Exact	●		●	●	●		●			●		●		●			●		
Achuthan and Caccetta	1991	VRP	Mathematical Formulation			●	●	●		●			●	●			●		●			
Laporte	1992	VRP	Exact/ approx.	●	●	●	●	●		●			●	●			●					
Naddef	1994	VRP	Exact	●		●	●	●		●			●		●		●			●		
Baker and Ayechew	2003	VRP	Metaheuristics (GA)		●	●	●	●		●			●	●			●		●			
Baldacci, *et al.*	2004	VRP	Exact	●		●	●	●		●				●			●			●		

Author(s)	Year	Problem Class	Technique	Sol. Tech.		Problem Characteristics											Obj. Fn.		Objective			
				Exact	*Approximate*	*One visit per customer*	*Vehicle capacity*	*Homogeneous fleet*	*Heterogeneous fleet*	*Single routes per vehicle*	*Multiple routes per vehicle*	*Time windows*	*Total route length*	*Single Depot*	*Multiple Depots*	*Site dependent service*	*Single*	*Multiple*	*Total distance travelled*	*Total Route cost*	*Total travel time*	*Vehicle's fixed cost*
Koo, *et al.*	2004	VRP	Metaheuristics (Tabu Search)		●		●	●		●	●			●			●				●	
Wassan	2006	VRP	Metaheuristics (Tabu Search)		●	●	●	●		●				●			●			●		
Baldacci, *et al.*	2007	VRP	Exact	●		●	●	●		●				●			●			●		
Faulin, *et al.*	2008	VRP	Classical Heuristics/ Simulation		●	●	●	●		●				●			●		●			
Montoya-Torres, et al.	2009	VRP	Classical Heuristics		●	●	●	●		●				●			●			●		
Baldacci and Mingozzi	2009	HVRP/SDVRP/ MDVRP	Exact	●		●	●		●	●				●	●	●	●			●		
Hosny and Mumford	2009	Multi - pickup and delivery VRPTW	Metaheuristics (GA)		●		●			●		●		●		●		●			●	●
Baldacci, *et al.*	2010	CVRP/ HVRP	Exact	●		●	●	●	●	●				●				●		●		●
Baldacci, *et al.*	2010	VRP/ VRPTW/ MDVRP/	Exact	●		●	●	●	●	●		●		●		●	●			●		

Author(s)	Year	Problem Class	Technique	Sol. Tech.		Problem Characteristics													Obj. Fn.		Objective			
				Exact	*Approximate*	*One visit per customer*	*Vehicle capacity*	*Homogeneous fleet*	*Heterogeneous fleet*	*Single routes per vehicle*	*Multiple routes per vehicle*	*Time windows*	*Total route length*	*Single Depot*	*Multiple Depots*	*Site dependent service*	*Single*	*Multiple*	*Total distance travelled*	*Total Route cost*	*Total travel time*	*Vehicle's fixed cost*		
		HVRP/ SDVRP																						
Vidal, *et al.*	2012	VRP/MDVRP / PVRP	Hybrid		●	●	●	●		●			●	●	●	●	●		●					
Weyland, et al.	2013	VRP	Classical Heuristics		●					●				●			●				●			
Subramanian, *et al.*	2013	AVRP/ OVRP/ MDVRP	Hybrid		●	●	●	●		●				●	●	●	●			●				
Vidal, *et al.*	2014	VRP/ MDVRP/ PVRP	Hybrid		●	●	●	●		●			●	●	●	●	●		●					
Karakatic and Podgorelec	2015	MDVRP	Metaheuristics (GA)		●	●	●	●		●			●		●			●		●		●		
Wang *et al.*	2017	Stochastic demand VRP	Metaheuristics (GA)		●	●	●	●		●			●	●			●			●				
Biesinger *at al.*	2018	Stochastic demand VRP	Metaheuristics (GA)		●	●	●	●		●			●	●			●			●				

Some of the classical heuristics related to the capacitated VRP as the sweep algorithm, the Clarke and Wright algorithm, and the Christofides-Mingozzi-Toth two-phase algorithm were addressed by Laporte (1992). Buxey (1970) adapted the classical Clarke and wright Heuristic and calculated a saving heuristic to find the best set of routes where a combination of the savings heuristic and Monte Carlo simulation is used to plan the routes of the fleet. Leeuwen and Volgenant (1983) introduced a heuristic algorithm that can be considered as the basis for an exact algorithm, where asymmetrical transformation of the symmetrical VRP is used. The proposed algorithm allows for violating capacity constraints and then adjust the solution to satisfy the constraint using subtour elimination. Haimovich, *et al*. (1985) implemented a regional partitioning heuristic that geometrically divide customers into subsets/regions that allow them to be served by a single vehicle. Montoya-Torres, *et al.* (2009) used random based heuristic algorithm to design vehicle routes. Faulin, *et al.* (2009) introduced the SR1 simulation-based heuristic algorithm that uses initial good solutions from the classical clarke and wright heuristic then a random oriented local search is used to find the list of best solution routes. Weyland *et al.* (2013) proposed a local search heuristic that assigns different collection points to vehicles to solve a real-world oil collection problem of the VRP.

Metaheuristic approaches as Genetic Algorithms (GA), Tabu Search (TS), and Simulated Annealing (SA) are discussed in literature to solve several classes of the vehicle routing problem. Metaheuristics are general solution procedures that provides both a general structure and strategy guidelines for developing a specific heuristic method (Hillier and Lieberman, 2005). Metaheuristics explore the solution space, identify good solutions, and often embed some of the standard route construction and improvement heuristics. Metaheuristics allow deteriorating and even infeasible intermediate solutions during the search process (Bräysy and Gendreau, 2005).

Baker and Ayechew (2003) applied a straightforward Genetic Algorithm to the VRP and showed that incorporating neighborhood search into the GA produces significant improvement to the solution. Koo *et al.* (2004) proposed a two-phase heuristic procedure. The first phase finds the lower bound of the fleet size, while the second phase applies a tabu search to find the solution set of routes. Wassan (2006) introduced a Reactive Tabu Search (RTS) with a new escape mechanism to solve the CVRP. Hosny and Mumford (2009) applied Genetic algorithm to a special class of the vehicle routing problem, a multi pickup and delivery VRP with time windows. The GA handled both grouping and routing aspects simultaneously. A study by Karakatic and Podgorelec (2015) presented a survey of genetic algorithms that are designed for solving the multi depot vehicle routing problem and stated that GA is preferred for solving large NP-hard problems over exact and other heuristic methods due to their main advantage of the linear scaling with growing problem size. Wang *et al.* (2017) applied a genetic algorithm-based approach to solve a 2-echlon CVRP with stochastic demands with 4 satellites and 20 customers. Biesinger *et al.* (2018) introduced a GA that uses a solution archive to solve the VRP to store all generated solutions and avoid adding duplicates to the population. The main feature of this approach is the bounding extension that is similar to the branch and bound search.

2.2.3 Hybrid Algorithms

A limited number of hybrid search algorithms are proposed in literature. Subramanian *et al.* (2013) proposed ILS-SP hybrid algorithm that combines the Iterated Local Search heuristic with the Set Partitioning approach to find new solutions based on known routes from previous local optimums. Vidal *et al*. (2012 and 2014) proposed the Unified Hybrid Genetic Search (UHGS) that finds not only good but diverse solutions by applying a continuous diversification procedure to modify the objective function during parents and survivors' selection (Uchoa *et al*., 2017).

In this chapter a new hybrid search algorithm is proposed. The algorithm combines the evolutionary genetic search with a new local search heuristic. In routing decisions, the heuristic considers both locations and demand quantities of the nodes to be visited not just distances travelled as the proposed model will serve as a basis to subsequent multi-objective green vehicle routing model that will be developed in the upcoming chapters. The objectives of these models will be minimizing the fuel consumption rate, the total travel time, minimizing the number of vehicles used and maximizing the customer satisfaction, where fuel consumption rate will be calculated as a cost function of the distance traveled and the vehicle's load to determine fuel consumption cost. For this reason, it was important to consider both the location and the demand associated with each node/customer in routing decisions as implemented in the new local search heuristic proposed. In addition, the GA operators will use the resultant local search heuristic as a tool to adjust the routes created in the process of applying the mutation and crossover operators to guarantee the feasibility of the routing decisions. The generation of infeasible solutions that goes through further processing to handle and repair the infeasibility during the search, increases the processing time and the complexity of the algorithm (Hosny,and Mumford, 2009). Therefore, the proposed hybrid algorithm utilizes the resultant local search heuristic in applying the GA operators so that the solution produced requires no repairing.

2.3 Problem Description

2.3.1 Characteristics of the Problem

The CVRP of study consists of *n+1* points, *n* customers and a depot. Distances ($d_{i,j}$) between each two points is known. The objective is to determine a set of minimum cost routes to be performed by a homogeneous fleet of vehicles (*m*) to serve a given set of customers (*n*) with known demands (*q*); where, each route starts and ends at a single depot. Each customer must be assigned to only one vehicle and the total demand of all customers assigned to a vehicle does not exceed its capacity (*Q*).

Table 2-2: Problem Characteristics

Element	Characteristics
Size of fleet	Unbounded
Type of fleet	Homogenous
Origin of vehicles	Single depot
Demand type	Deterministic Demand (Known)
Location of demand	At the customer (node)
Maximum time on route	No constraint
Objective	Minimize total distance
Constraints	1. Single visit at customers, 2. Routes start and end at depot, 3. Nodes served by single vehicle, 4. Vehicle capacity cannot be exceeded

The number of vehicles (routes) to be used is not fixed but to be determined by the solution approach. In some studies, the number of vehicles is fixed, while others define a minimum possible number of vehicle routes (K_{min}). According to Uchoa *et al.* (2017) there are two reasons for not fixing the number of vehicles used. The first reason is that fixing the number of routes is an indirect way of minimizing the fixed cost associated with the cost per vehicle, in other words ignoring the trade-off between variable and fixed costs associated with the suggested set of routes. The second reason is that in literature the original CVRP proposed by Dantzig and Ramser (1959) did not consider fixing the number of routes to the problem as it requires adding the cost of unused capacity to the model which in practice is of minor importance. According to the authors, minimization of the travel distance is independent on the number of vehicles used. Table 2-2 summarizes the characteristics of the CVRP of the study.

2.3.2 Mathematical Modeling

The formulation of the problem is presented in a previous publication where integer decision variables are used where the formulation has been validated using several tools (Elgharably *et al.*, 2013). The VRP problem is a generalization of the Travelling salesman Problem (TSP) that introduces more than one salesman (*m*); hence, *m* number of tours can be done; each starting and ending at the depot. For formulating the *VRP*, the starting customer is considered node 1 (depot); where X_i represents the current visited node and Y_i represents the next node to be visited, where *i* varies from 1 to *n*, and n is the number of nodes to be visited by a given vehicle *k*. Now, *m* routes are introduced to the model; where, distance d_{X_i,Y_j} is associated with each arc and represents the distance travelled from node X_i^k to node Y_j^k on route *k*, as shown in Figure 2-1.

The decision variable is Y_i^k; where, Y_i^k determines the value of the next customer *i* to be visited on route *k*. The X_i^k variable represents the value of the start node of the arc on route *k*. The use of loop segments is not allowed (leaving a node then arriving to same node, $X_i^k \neq Y_j^k$), as all nodes must be visited exactly once. The binary variable S_{X_i,Y_j}^k is the set of all possible arcs connecting any two nodes on route *k*. S_{X_i,Y_j}^k is given a value of 1 if arc (X_i^k, Y_j^k) belongs to route *k*; 0 otherwise. Both X_i^k and S_{X_i,Y_j}^k are considered uncontrollable variables.

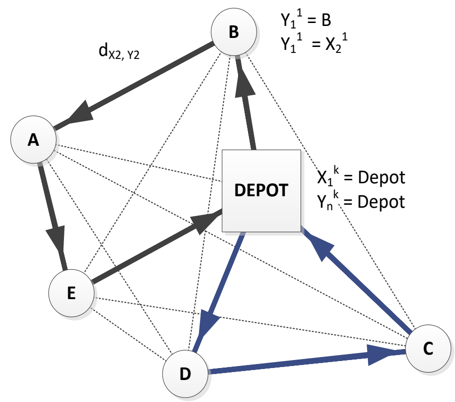


Figure 2-1: Illustration of the VRP (Elgharably *et al*., 2013)

The problem is formulated as follows:

$$Minimize\ Z = \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} S_{X_i,Y_j}^{k} * d_{X_i,Y_j} \tag{1}$$

Subject to

$$X_1^k = 1 \quad \forall k = 1,\dots,m \tag{2}$$

$$Y_n^k = 1 \quad \forall k = 1,\dots,m \tag{3}$$

$$X_i^k = Y_{i-1}^k \quad \forall\, i = 2,\dots,n,\ \forall k = 1,\dots,m \tag{4}$$

$$X_i^k \le n \quad \forall k = 1,\dots,m \tag{5}$$

$$Y_i^k \le n \quad \forall k = 1,\dots,m \tag{6}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{m} S_{X_i,Y_j} = 1 \quad \forall\, i = 2,\dots,n \tag{7}$$

$$\sum_{i=1}^{n}\sum_{k=1}^{m} S_{X_i,Y_j} = 1 \quad \forall\, j = 1,\dots,n-1 \tag{8}$$

$$\sum_{j=1}^{n}\sum_{i=1}^{n} S_{X_i,Y_j}^{k} * q_{Y_j} \le Q_k \quad \forall k = 1,\dots,m \tag{9}$$

$$X_i^k, Y_j^k > 0\ and\ integer \tag{10}$$

The objective function (1) minimizes the total travel distance on all *k* routes; where, *m* is the number of routes proposed. Constraints (2) and (3) ensure that each route starts and ends at the depot. Constraint (4) ensures that each route of the *k* routes is not segmented, that is, if a vehicle arrives at a customer, it eventually leaves the customer again. Constraints (5) and (6) state the range of values given, whereas constraints (7) and (8) state that every customer is visited exactly once. Knowing that at each customer, customer's demand (q_{Y_j}) is present and that each vehicle has limited capacity Q_k; constraint (9) ensures that the total demand of all customers assigned to a route k does not exceed the vehicle's capacity. Finally, constraint (10) is the non-negativity constraint and guarantees that the variables can assume integer values only.

2.4 New Hybrid Search for VRP

The proposed hybrid search algorithm combines the evolutionary genetic search algorithm with a new local search heuristic that calculates a heuristic resultant based on both the distance travelled or the location of the nodes/customers and the demand associated with the given node/customer. Genetic algorithm is considered an approximate solution approach (metaheuristic) that is used to solve NP-hard class of problems to obtain not necessarily optimum but near-optimum solutions. GA's performance and results on time constraints and limited computer power obtains competitive solutions compared to other metaheuristic approaches. GA is a stochastic adaptive optimization algorithm which a subset of evolutionary algorithms, that adopts Darwin's theory of evolution, consisting of the reproduction, selection and diversity nature basic principles. It was first introduced in 1960 by John Holland (Karakatic and Podgorelec, 2015).

2.4.1 Resultant Local Search Heuristic (RLSH)

In the implemented local search method, a heuristic resultant for each customer was used as follows:

$$HR_i == \lambda \, d_{i,j} + (1 - \lambda) \, DR_i \tag{11}$$

where HR_i = Heuristic Resultant for customer i, λ and $(1 - \lambda)$ = weights of the distance and demand (used to achieve diversity and not to be caught in local optimum), $d_{i,j}$ = Euclidian distance to be travelled from the current node (*i*) to the expected following node (*j*) by customer i, and DR_i = Demand Remainder for customer i, which is the difference between the vehicle's capacity and the demand *(i)*, where demand (*i*) is the quantity of items to be delivered or picked up by the vehicle at the customer i. For example, at the beginning of constructing the route, the current location would be the depot, while in the middle of the route the current location would be the last visited node/customer as shown in Table 2-3.

The function identifies the nearest route (heuristic) based on the RLSH function between the remainder of the demand of each node compared to the vehicle capacity and the distance from the current location to the following node.

Table 2-3: Resultant Local Search Heuristic Process

Resultant Local Search Heuristic steps
Step 1: Normalize X and Y coordinates for depot and nodes/customers, Step 2: Find the number of nodes in the problem, Step 3: Create a list with all nodes, Step 4: Initialize the Routes Matrix, Step 5: While number of nodes > 0 Loop to find all routes, Step 6: Start with the Depot, current node = Depot, $X_{Current} = X_{Depot}$; $Y_{Current} = Y_{Depot}$; Step 7: Calculate Euclidean distance from current node to all nodes, Step 8: Calculate the Normalized remainder of the demand to all nodes, Remainder Demand Normalized = (VehicleCapacity – Node Demand) / VehicleCapacity; Step 9: Calculate the Heuristic resultant for each node, HeuristicResultant = alpha x DistancesCurrent + (1-alpha) x Remainder Normalized Demand. Step 10: Find the node with the minimum Heuristic Resultant, Node*(i),* Step 11: Update the total demand for the current route/vehicle, Step 12: If TotalRouteDemand <= VehicleCapacity Insert the selected node to the Route, Step 13: Update the location of the vehicle to the selected node, $X_{Current} = X_{NodesNormalized(i)}$; $Y_{Current} = Y_{NodesNormalized(i)}$; Step 14: Update the number of nodes and the nodes list, Delete the identified node from the node list, Step 15: Update the location of the vehicle to the selected node, Step 16: Repeat from step 7 to continue forming the route, Step 17: Otherwise: (TotalRouteDemand >= VehicleCapacity) Do not insert the selected node to the Route, Insert the identified route to the Routes matrix, Step 18: Start a new route from depot, Repeat from step 5, Step 19: Return the Routes Matrix after all nodes are inserted.

Routes are constructed using the nodes *(i)* of the nearest heuristic resultant until the vehicle capacity is reached then a new route is initiated. The developed resultant heuristic is used in the initialization process of the population generation and in deterministic operators described in the following subsections. As stated by Baker and Ayechew (2003) incorporating neighborhood searches to the GA resulted in more improvements to solution. Therefore, a portion of the evolutionary search population is filled heuristically using the RLSH heuristic, while the remaining portion is filled randomly.

2.4.2 Initial population and fitness function

In GA, the first step is the initialization of population that consists of several solutions to the problem. Each solution is called a chromosome. A fitness function associated to each chromosome is calculated to evaluate the goodness of each solution. In case of CVRP, the lower scores of the fitness function are favored, since CVRP is a minimization problem of the total distance travelled by the vehicles. The chromosome representation is shown in Figure 2-2 for the problem described in Appendix A.

Number of nodes assigned to the given Route

Number of Routes

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	2	11	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	6	4	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	5	7	10	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	3	8	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	9	12	14	15	19	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Route 1	2	11	13		
Route 2	6	4	16		
Route 3	5	7	10	17	
Route 4	3	8	18		
Route 5	9	12	14	15	19

Figure 2-2: Chromosome representation

Each chromosome is a matrix *(n, n)*, n is the number of nodes/customers to be visited in the given problem of study that represents a feasible solution to the problem. Each row in the chromosome matrix represents a route that starts and ends at the depot with no violations to the capacity constraints. A portion of the initial population is filled heuristically using the local search heuristic developed, the remaining portion is filled randomly to achieve diversity and not to be caught in a local optimum. The random part of the initial population is based only on the vehicle capacity ignoring any distance calculations.

A set of operators are then performed to the initial population to mimic the nature of evolution. Operators as selection, mutation and crossover are used to widen the search space and inherit good solutions to the next generations. The flowchart in Figure 2-3 shows the process of the genetic algorithm. An elitist selection process is performed, where a portion of the existing population is used to breed the new generation. Individuals are selected based on their fitness function.

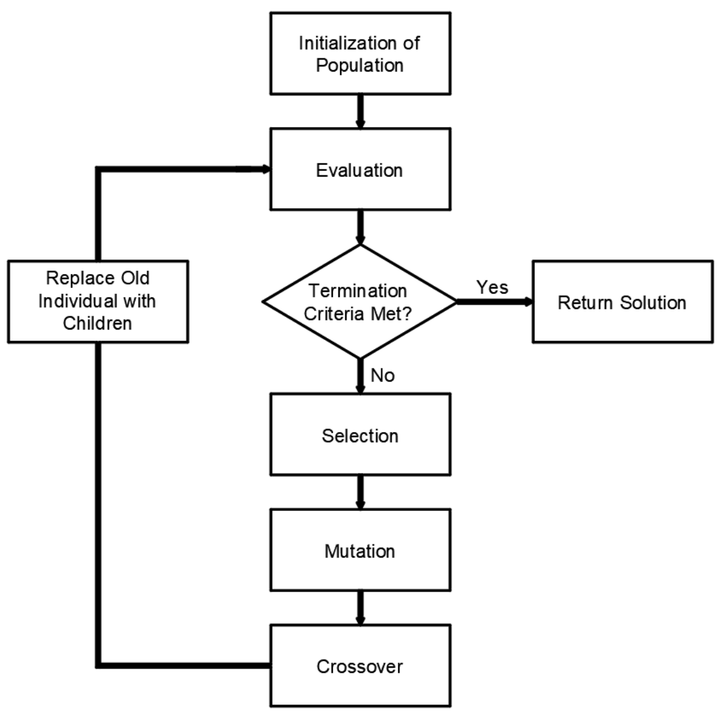


Figure 2-3 Genetic Algorithm Process (Karakatic and Podgorelec, 2015)

2.4.3 Mutation Operators

To achieve diversity and to widen the span of the search space, a set of one deterministic and four random mutation operators is applied. A deterministic Route Reduction Mutation (RRM) is performed that decreases the number of routes in a solution without violating any constraints. The aim is to lower the number of routes considering only capacity and demand calculations. The routes found in an individual solution are sorted based on the highest remaining demand compared to the vehicle capacity. Routes with maximum remaining capacity are combined with the ones with min demand Figure 2-4. While routes with remaining capacity less than the minimum demand in the route remain unchanged. The routes are then adjusted using the resultant local search heuristic illustrated in Section 2.4.1. Comparably, Hosny, and Mumford (2009) applied a vehicle merge operator to a pickup and delivery VRP that merges two vehicles selected at random. The nodes of the selected vehicles are placed in a relocation pool and distributed on the existing vehicle routes before constructing new routes.

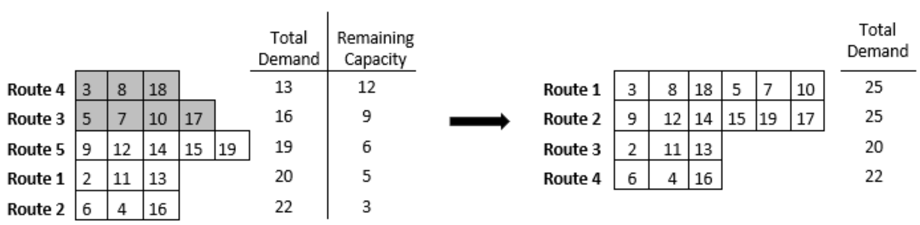


Figure 2-4: Illustration of the Route Reduction Mutation (RRM)

Random Node Exchange Mutation (RNEM) is a mutation operator that exchanges nodes from randomly selected routes without violating any capacity constraints. Two nodes are selected at random from the previously chosen routes and are then exchanged yielding to different routes with updated total demand for each route (Figure 2-5(a)). The routes are then adjusted using the resultant local search heuristic. The random node exchange mutation was used by Baker (2003), and Ayechew, and Biesinge (2018).

Random Node Transfer Mutation (RNTM) is a mutation operator that transfers a randomly selected node from one route to another. The two selected routes are chosen randomly

(Figure 2-5(b)) where if a node is transferred from a one-node route the number of routes will decrease by one. The routes are then adjusted using the developed resultant heuristic with no capacity violation. Similarly, a mutation operator called relocation heuristic by *Wang et al.* (2017) and an insertion mutation by Pereira *et al.* (2002) and Ursani *et al.* (2011) were applied in literature. However, these operators remove one customer from its location and reinsert it in a different location whether in the same route or a different one with no demand and vehicle capacity considerations.

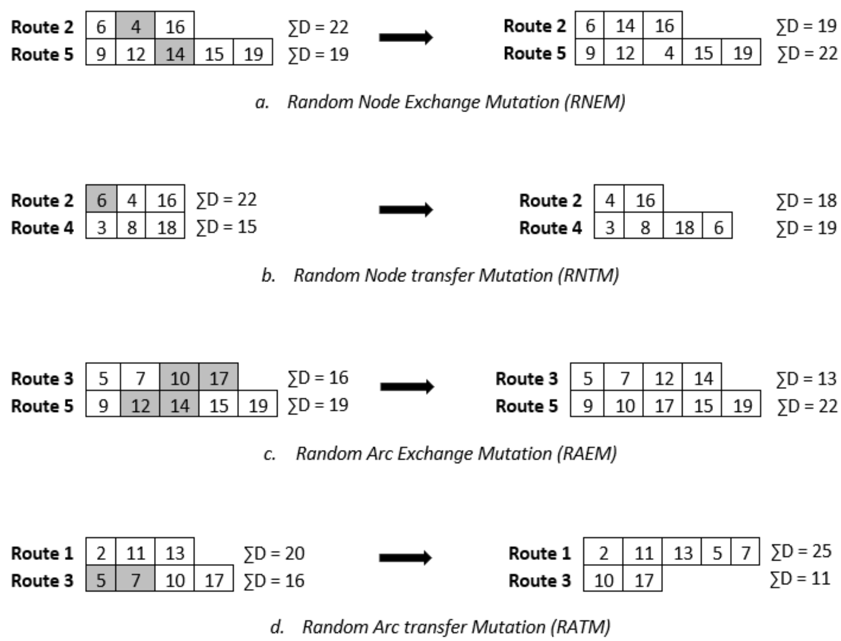


Figure 2-5: Illustration of the Random Mutation Operators

Random Arc Exchange Mutation (RAEM) illustrated in Figure 2-5(c) and Random Arc Transfer Mutation (RATM) illustrated in Figure 2-5(d) follows the same process of the Random Node Exchange Mutation (RNEM) and Random Node Transfer Mutation (RNTM) but instead of selecting nodes at random, arc within the route are selected at random. Taking into consideration if an arc is transferred from a two-node route the number of routes will decrease by one, in case of the RATM operator. A route insertion mutation by Garcia-Najera and Bullinaria (2011) applies the same concept of the arc transfer mutation.

2.4.4 Crossover operators

Crossover is the process which two individual chromosomes act as two parents and are combined to produce two children where the children inherit characteristics from the parents. Two crossover operators are performed, one at random while the other is deterministic that inherits good characteristics from parents.

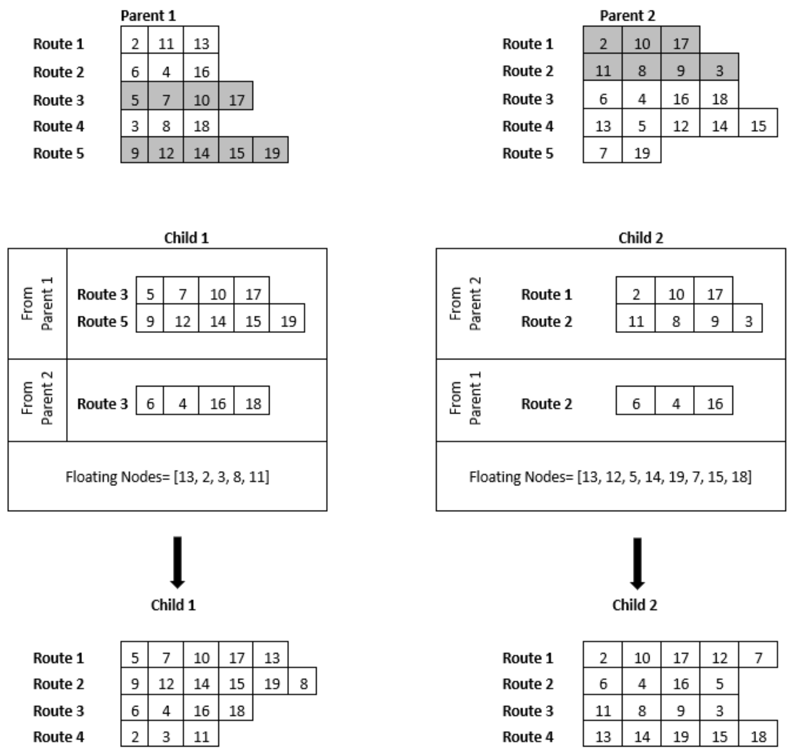


Figure 2-6: Illustration of the Crossover Operators

Hosny, and Mumford (2009) applied a vehicle copy crossover that copies a random number of good routes from each parent, where good routes are ranked according to the number of nodes served in each route. If the number of routes is similar, then routes are ranked based on the total distance travelled. Wang *et al.* (2017) modified the vehicle copy crossover to use a different insertion heuristic to construct routes for the remaining node in the relocation pool rather than the construction algorithm applied by Hosny and Mumford (2009). The Heuristic Inheritance Crossover (HIC) is a deterministic crossover operator that perform changes to the routes within a given solution inheriting good routes without violating any constraints. The HIC is used for intensification of good solutions in the breeding generation rather than diversification. In each chromosome the heuristic resultant is calculated based on distances and demands for each route and is sorted. The number of good routes to be inherited by each child is predetermined. Then the best predetermined number of routes from Parents 1 and 2 are sent to each child correspondingly. From the other parent, the routes with no common nodes are inherited and sent to each child. The remaining set of nodes that are not present in any of the selected parent routes are considered floating nodes that are found in a relocation pool and are to be distributed among the routes or to form new routes in each child without violating capacity constraints (Figure 2-6). The new routes are then adjusted using the resultant local search heuristic in Section 2.4.1.

Random Inheritance Crossover (RIC) follows the same process as the HIC operator, the only difference is that the routes to be inherited from parent 1 and 2 are chosen at random not based on good routes. The RIC operator acts as a diversification operator.

2.5 Computational Study

To evaluate the performance of the developed algorithm a computational study is conducted. Several benchmark data sets were proposed in literature. Uchoa *et al.* (2017) proposed a new benchmark dataset that provides a more comprehensive and balanced experimental setting to the classic CVRP.

2.5.1 The benchmark problem instance

In order to check the validity of the proposed solution algorithm, Problem instance: X-n101-k25 is taken from Uchoa *et al.* (2017) new benchmark instances and is implemented in MATLAB.

Instance: X-n101-k25 (Appendix B) consists of a depot and 100 customers, the number of vehicles to be used is not fixed but the minimum feasible number of vehicles is known (K_{min} = 25). The vehicle capacity is 206 units. Demands of customers [0,100] are deterministic. Euclidian distances are calculated from the given X and Y co-ordinates. The depot and customer positioning of the X-n101-k25 instance is random and the optimal solution of the instance is known (Total Distance = 27591). Figure 2-7 shows the location of both the depot and the customers for instance X-n101-k25.

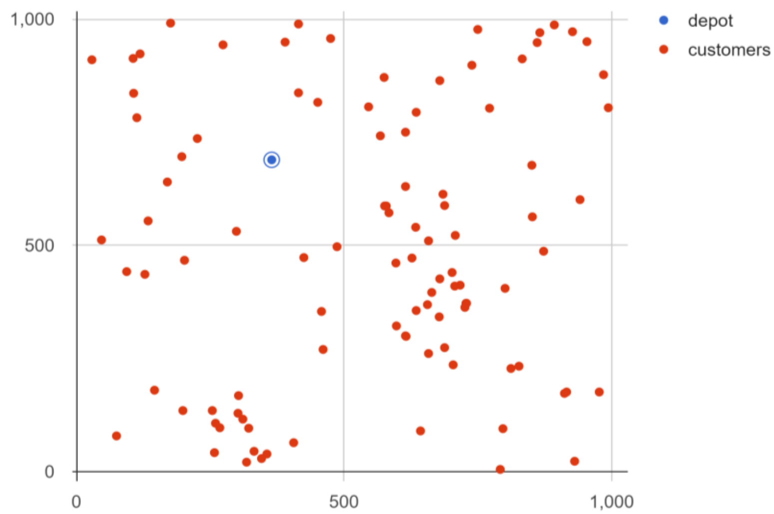


Figure 2-7: Location grid for instance X-n101-k25 (Uchoa *et al.*, 2017)

The validation of the proposed solution algorithm is a two-step process. First, the percentage of the heuristic local search used in the initial population of the hybrid algorithm is to be determined (Section 2.5.2). Then, the second step is to determine the best set of model parameters to be used in the evolutionary model (Section 2.5.3).

2.5.2 Effect of usage of the local search Heuristic

In the developed algorithm, a portion of the initial population is filled heuristically using the local search heuristic developed while the remaining portion is filled randomly to achieve diversity. To determine the portion of the initial population to be filled heuristically, a set of runs with different percentages of the local search Heuristic are performed. The algorithm is tested several times at different percentages ranging from 10 to 90 percent of the population. Figure 2-8 shows a sample of the runs performed at the different levels of the heuristic H at 10%, 30% and 60 % of the initial population to be filled heuristically using the Local search Heuristic. H in the figure denotes the percentage of local search heuristic usage in the initial population of the hybrid algorithm. At thirty percent (H=0.3), the figure shows that the model converges to better solutions rather than the ten and sixty percent.

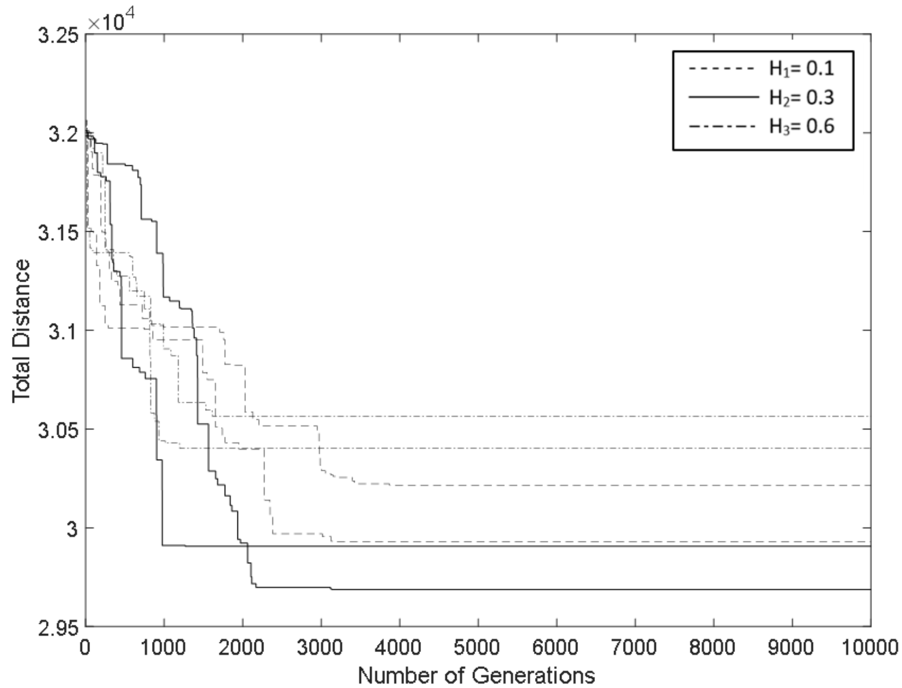


Figure 2-8: Sample runs to determine the Heuristic (H) portion of the initial population

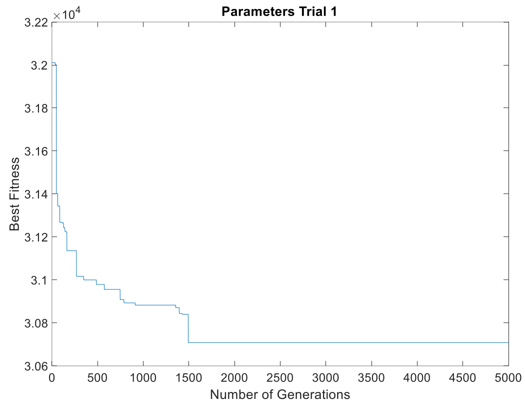
2.5.3 Evolutionary Model Parameters

To determine the evolutionary model parameters, a second set of runs is performed. Five different trials of the paramaters configuration are performed to determine the number of times to perform the mutation and crossover operators. Each trial is experimented at different levels of lambda (λ) in Equation 11.

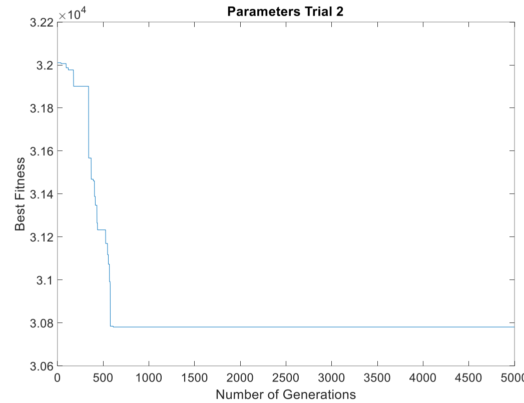
Table 2-4 shows the configuration of each trial. The scenario assumed for each trial is as follows:

- Trial 1: reduced crossovers and increased random node exchange and transfer mutations,
- Trial 2: reduced crossovers and increased random arc exchange and transfer mutations,
- Trial 3: reduced crossovers and route reduction mutation, and increased all other operators,
- Trial 4: increased route reduction mutation and reduced all other operators,

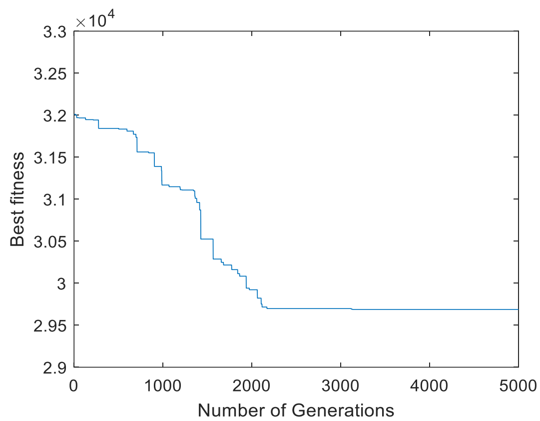
- Trial 5: increased random crossover and reduced all other operators.



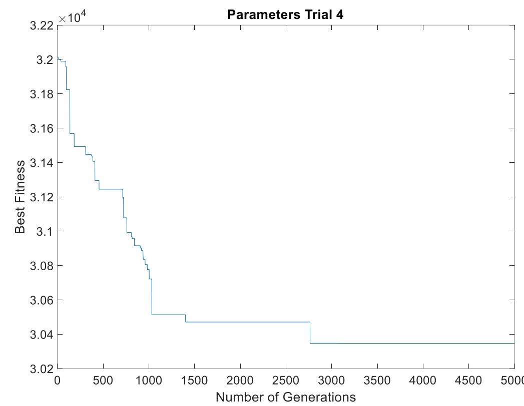
a) Best Solution results for trial 1



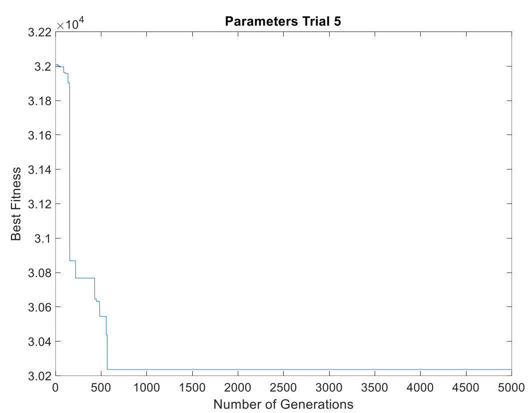
b) Best Solution results for trial 2



c) Best Solution results for trial 3



d) Best Solution results for trial 4



e) Best Solution results for trial 5

Figure 2-9: Best solution reached at each trial

Table 2-4: Mutation and crossover operator configuration of each trial

Trial Number	Number of times to apply the Operator						
	Route Reduction Mutation	*Node Exchange Mutation*	*Node Transfer Mutation*	*Arc Exchange Mutation*	*Arc Transfer Mutation*	*Heuristic Inheritance Cross-over*	*Random Inheritance Cross-over*
1	12	10	10	4	4	5	5
2	10	5	5	10	10	5	5
3	6	10	10	10	10	2	2
4	20	5	5	5	5	5	5
5	5	5	5	5	5	5	20

The best results of the runs performed to each of the five trials are illustrated in Figure 2-9, where Figure 2-9 (c) shows that the configuration of Trial 3 achieved the best fitness value; shortest total distance compared to the other trials. More runs were performed on Trial 3 configuration. More time and a greater number of generations were used to run the algorithm to test its capability of reaching the best-known solution.

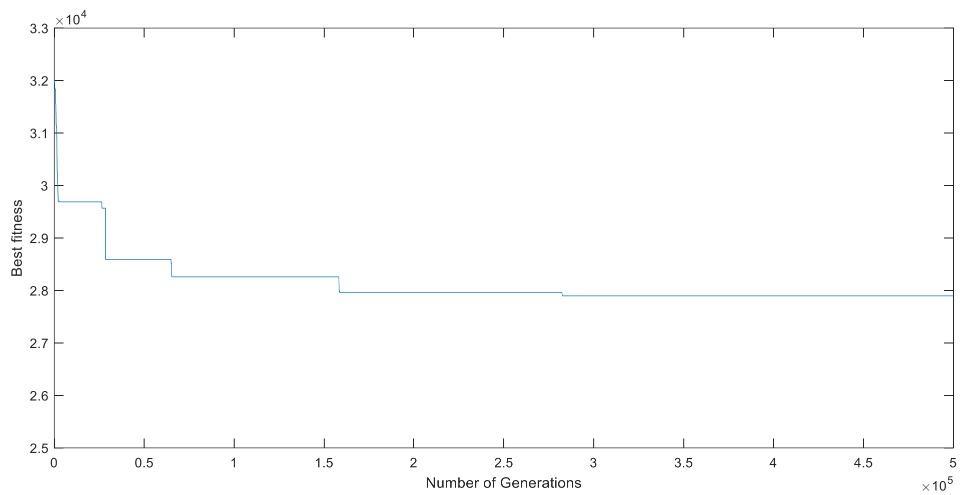


Figure 2-10: Validation of the proposed hybrid algorithm

The introduced new hybrid search algorithm was capable of finding the best-known solution to the Uchoa *et al.* (2014) benchmark X-n101-k25 data instance as shown in Figure 2-10.

2.6 Conclusion

A new hybrid search algorithm that combines the evolutionary genetic search with a new local search heuristic is developed to solve the capacitated vehicle routing problem. The proposed heuristic calculates a heuristic resultant based on both the distance travelled and the demand associated with the given customer not only distances as previously considered in the literature. The developed algorithm will be a fundamental tool for the development of a multi-objective green VRP that considers demand quantities in the calculation of fuel consumption rates. For this reason, the demand quantity consideration was included as an aspect in the routing decisions. In addition, a new set of simple genetic operators that requires no further repairing after application were developed and implemented in the algorithm. Several computational experiments were conducted to define the best set of model parameters. The proposed algorithm was validated and found to be satisfactory. The developed algorithm was capable of converging to the optimum solution of the tested benchmark instance. The developed algorithm is considered the base model to be used in the subsequent chapters, where the hybrid algorithm will be implemented in solving multi-objective green vehicle routing problems in both deterministic and stochastic environments.

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Chapter 3

3 Multi-Objective Green Vehicle Routing Model with Customer Satisfaction

The Vehicle Routing Problem (VRP) is one of the most studied combinatorial optimization problems in operations research. The problem deals with a homogenous fleet of capacitated vehicles that operates from a central depot aiming at finding the minimum cost set of routes that serves a set of customers with known demands. The vehicle routing problem is classified as NP-hard problem. Exact and approximate algorithms have been developed in literature to solve the capacitated VRP. Exact methods can only solve relatively small size problems while approximate algorithms have been able to reach near-optimum solutions. In further research both categories were hybridized. Recently, the area of green logistics and the environmental issues associated received great attention. The concern of studying fuel consumption and greenhouse gases (GHG) grow to be essential. The purpose of this chapter is to study the multi-objective vehicle routing problem in green environment. The Green VRP (GVRP) presented deals with three different objectives simultaneously that considers economic, environmental, and social aspects. The model utilizes a new hybrid search algorithm to solve the GVRP. Pareto fronts were obtained and trade-offs between the three objectives are presented. Furthermore, an analysis of the effect of changing the capacity of the vehicles is presented.

3.1 Introduction

The vehicle routing problem is known to be one of the most studied combinatorial optimization problems. The study of the problem first emerged in the late 1950s, when Dantzig and Ramser introduced the truck dispatching problem. Different variants of the capacitated vehicle routing problem were introduced later in literature. The variants differ according to the characteristics of the problem such as: Vehicle Routing Problem with Time Windows (VRPTW) where customers are to be supplied within a specific time frame, Multi-depot Vehicle Routing Problem (MDVRP) where supply is provided from different depots, Multi-Pickup and Delivery Vehicle Routing Problem (MPDVRP) when customers may require different services of pickup and delivery, and Heterogenous Vehicle Routing

Problem (HVRP), where different types of vehicles with different capacities are used. This chapter will focus on the vehicle routing problem with time windows in green environment. In addition to routing decisions, the aspect of scheduling will be added to the problem of study, where time windows will be introduced at each customer and service times will be considered. The aim of this chapter is to study the Green Vehicle Routing Problem (GVRP) and to present a multi-objective GVRP model. The proposed model handles three different objectives simultaneously. The model minimizes the total operational cost, minimizes the environmental cost, and maximizes customer satisfaction simultaneously, without converting one of the objectives to a constraint with a given threshold as previously handled in literature. The developed model utilizes the hybrid search algorithm developed in chapter 2. The study presented in this chapter is deterministic.

The chapter is divided as follows: Section 3.2 provides a review on the green vehicle routing problem addressed in literature, and how customer satisfaction was tackled. Section 3.3 describes the characteristics of the problem, followed by the mathematical formulation of the problem of study. Section 3.4 presents the development of the hybrid multi-objective optimization model. Section 3.5 presents the computational results of the developed model, followed by the numerical analysis in Section 3.6. The conclusions drawn from this study is then presented in Section 3.7.

3.2 Literature review

One of the primary activities of supply chain is logistics. Freight transportation is considered one of the most important parts of logistics that occupies one-third of the logistics cost. On the other hand, one of the side effects of vehicle transportation is the emission of Greenhouse Gases (GHGs). In 2014, the United States Environmental Protection Agency stated that transportation is responsible of 28% of the total emission in the US (Afshar-Bakeshloo *et al.*, 2016).

The concern of studying the environmental issues as fuel consumption and greenhouse gases (GHG) in the VRP research area began in the early 2000s (Park and Chae, 2014). Sbihi and Eglese (2007) surveyed the area of green logistics and the combinatorial optimization formulations related to it. In green logistics, environmental and social factors of distributing goods such as environmental impact, usage of energy and waste, are taken into consideration not only economic factors. According to Sbihi and Eglese (2007) the area of green logistics is divided into three categories: Reverse Logistics, Waste Management, and Vehicle Routing and Scheduling. The authors stated that there is not much literature that links the Vehicle Routing and Scheduling Problem (VRSP) with environmental concerns. The article also highlighted the importance of directly measuring the environmental benefits in VRSP rather than assuming that the reduction of the total distance itself provides environmental benefits due to less travel time and fuel consumption. Yong and Xiaofeng (2009) presented a VRP based on reducing fuel consumption by solving a small-scale problem that includes one vehicle and seven customers by enumeration method. They showed that different routing decisions can be found when considering fuel consumption rather than considering distances only. Ubeda *et al*. (2011) presented a case study conducted in Spain that aimed at reducing the environmental impact of transportation activities at Eroski Group by applying a distance-based method to calculate CO_2 emissions. Later, Xiao *et al*. (2012) stated that the amount of fuel consumed is of greater concern to transportation companies than the travel distance. Xiao *et al.* (2012) developed a mathematical optimization model to calculate fuel consumption as a load dependent function. Park and Chae (2014) reviewed the solution approaches of solving the of GVRP and discussed the several exact, heuristics and metaheuristics approaches developed to solve the GVRP. They indicated that metaheuristic were the major approaches used to solve the GVRP.

According to the survey presented by Lin *et al.* (2014), Green Vehicle Routing problems can be classified into three problem scenarios:

1. Energy consumption vehicle routing models, that deal with designing routes with minimum energy consumption, and analysis of AFV and facilities,
2. Pollution and pollution reduction-based models, that focus mainly on the environmental impact and the reduction of CO_2 emissions explicitly,
3. Waste management and reverse logistics (Jabir *et al.,* 2017).

More efforts in the green Logistics were done. Harris *et al.* (2014) studied the Capacitated Facility Location Problem (CFLP) in green logistics that considered CO_2 emissions. Tiwari and Chang (2015) used a distance-based approach to calculate the CO_2 emission in solving GVRP and considered the truck load and average distance travelled to calculate the CO_2 emission factor.

Table 3-1: Summary of literature review on GVRP

Author	Year	Problem Class	Obj. Fn.		Objective	
			Single	**Multiple**	Operational Costs	Environment Impact/Cost
Sbihi and Eglese	2007	Time-dependant VRP	●		●	
Yong and Xiaofeng	2009	FCVRP	●			●
Ubeda *et al.*	2011	VRPB	●			●
Xiao *et al.*	2012	FCVRP	●		●	●
Erdogan and Hooks	2012	GVRP with AFVs	●		●	
Harris *et al.*	2014	CFLP		●	●	●
Tiwari and Chang	2015	GVRP	●		●	●
Koc and Karaoglan	2016	GVRP with AFVs	●		●	
Bruglieri *et al.*	2016	GVRP with AFVs	●		●	
Andelmin and Bartolini	2017	GVRP with AFVs	●		●	
Leggieri and Haouari	2017	GVRP with AFVs	●		●	
Kadzinski *et al.*	2017	GVRP		●	●	●
Jabir *et al.*	2017	Multi depot GVRP	●		●	●
Saharidis	2017	PRP	●			●
Cimen and Soysal	2017	TDGVRP	●			●
Affi *et al.*	2018	GVRP with AFVs	●		●	
Macrina *et al.*	2019	GVRP	●		●	●

A Green Vehicle Routing Problem (GVRP) that utilizes Alternate Fuel Vehicles (AFV) to reduce the environment impact was presented by Erdogan and Hooks (2012), Burugelieri *et al*. (2016), Koc and Karaoglan (2016), Leggieri and Haouarri (2017), Andelmin and Bartolini (2017) and Affi *et al.* (2018), all aiming at reducing fossil-fuel use to decrease GHG emissions. Green Vehicle Routing Problem with Alternative Fuel Vehicles (GVRP with AFV) is a variant of the GVRP that utilizes vehicles employing different fuel sources such as natural gas, electricity, and ethanol other than gasoline and diesel-powered vehicles (Andelmin and E. Bartolini, 2017). GVRP with AFV requires including refueling stops to be encountered in planning vehicle routes. Conventional vehicles have a long driving range and are known for short fueling time. On the other hand, AFV have limited fuel autonomy and require stopping for refueling with relatively long fueling delays as Alternative Fuel Stations (AFS) are not widespread along the road networks (Burugelieri et *al.*, 2016, and Koc and Karaoglan, 2016).

Cimen and Soysal (2017) proposed an approximate dynamic GVRP with stochastic vehicle speeds to obtain environmentally friendly solutions by changing the objective function from cost minimization to emission minimization. The model first determines the routes that minimizes emissions exclusively. Secondly, the fuel and wage cost are calculated to determine the routes that minimize the total expected travel cost, where wage cost is computed by each driver's working time and fuel cost estimation depends on vehicle type, vehicle speed, and travel distance. Then the results are evaluated by four key performance indicators: travelled distance, travel duration, emissions, and travel cost. These key performance indicators consider the economic and environmental impact of the results, where CO_2 emissions are estimated by assuming that each liter of fuel consumption generates 2:63 kg CO_2, while customer satisfaction measures are not considered.

In terms of Multi-objective GVRP, a multi-objective model by Kadzinski *et al.* (2017) analyzed a case study with the objectives of minimizing operational costs and lowering CO_2 emissions, then approximated the Pareto front using scalarization methods. In an effort of modeling the emissions associated with the routing decisions, Saharidis (2017) introduced an emission factor called Environmental Emission Score (EES) which acts as a measure of transportation network factors to model the Pollution Routing Problem (PRP). Macrina *et al.* (2019) extended the model presented by Erdogan and Hooks (2012) and considered a mixed vehicle fleet with partial battery recharging and time windows to solve the GVRP. The literature review on GVRP in a deterministic aspect is summarized in Table 3-1.

A literature survey on VRPs that considered customer satisfaction in modeling is presented in Table 3-2. The table shows the way VRP is modeled in literature whether environmental impacts were considered or not and indicates if any of the objectives are converted to constraints. It also discusses the characteristics of the problem studied such as type of vehicle fleet, number of vehicles modeled and whether they are considered as a decision variable or a fixed predetermined set of vehicles, type of time windows used and whether the problem is deterministic or stochastic.

Studies that addressed the VRPTW as Tang *et al.* (2009), Zhang *et al.* (2013), and Goel *et al.* (2019) considered both the operational and customer satisfaction measures with no consideration of the environmental impact of the proposed solution routes, in which customer satisfaction was handled as a constraint in the problem rather than an objective. Both Zhang *et al.* (2013), and Goel *et al.* (2019) studied the problem with uncertainty considerations.

Tang *et al.* (2009) proposed the VRP with fuzzy TW and solved the problem to minimize the cost and maximize the sum of service levels of all customers by modeling the service level as a constraint. Tang *et al.* (2009) determined the customer satisfaction level as the deviation of service time from the customer's TW, also referred to as supplier's service level. Zhang *et al.* (2013) proposed a Stochastic VRP with soft time windows to minimize total cost at a minimum service level probability at each customer. Goel *et al.* (2019) studied the VRPTW with stochastic demands and service times to minimize transportation cost at a determined satisfaction preference index. Tas *et al.* (2014) introduced the concept of flexible time windows where customers accept services outside their original time windows concerning a given tolerance.

Several studies used a utility function approach to model the objective function in VRPs as: Fan (2011), Barkaoui *et al.* (2015), and Yang *et al.* (2015). These studies solved the routing problem deterministically. Fan (2011) used a combined objective function to model the VRP with simultaneous Pickup and Delivery (VRPSPD) with customer satisfaction. Barkaoui *et al.* (2015) modeled a dynamic VRPTW with customer satisfaction, where customer requests are dynamically changing. The study deals with services as diagnosis or detection problems where customers may require more than one visit to reach a satisfactory level.

Table 3-2: Summary of literature on VRP with customer satisfaction

			Obj. Fn.		Objectives			Problem Characteristics				
Author	**Year**	**Problem Class**	**Single**	**Multiple**	Operational Costs	Environment cost/impact	customer satisfaction	**Objectives handled as constraints**	**Type of Vehicle fleet**	**Number of vehicles**	**Time Window**	**Feature**
Tang *et al.*	2009	VRPTW	●		●		●	Customer satisfaction	Homogenous	Fixed	Fuzzy	Deterministic
Fan	2011	VRPSPD	●		●		●		Homogenous	Fixed	Hard	Deterministic
Zhang *et al.*	2013	VRPTW	●		●		●	Customer satisfaction	Homogenous	Decision Variable	Soft	Stochastic
Tas *et al.*	2014	VRPTW	●		●				Homogenous	Decision Variable	Flexible	Deterministic
Yang *et al.*	2015	GVRP	●		●	●	●	Emission	Heterogenous	Decision Variable	Soft	Deterministic
Barkaoui *et al.*	2015	Dynamic VRPTW	●		●		●		Homogenous	Fixed	Soft	Deterministic
Afshar-Bakeshloo *et al.*	2016	GVRP		●	●	●	●	Customer satisfaction	Heterogenous	Decision Variable	Fuzzy	Deterministic
Goel *et al.*	2019	VRPTW	●		●		●	Customer satisfaction	Homogenous	Fixed	Hard	Stochastic

Yang *et al.* (2015) proposed a multi-objective model that minimizes the total cost, minimizes carbon emission, and maximizes customer satisfaction using a weighted utility function to convert the problem to a single objective function and impose a limit on the carbon emissions as a constraint. Weighted linear utility functions work well when a convex Pareto front is expected between the objective functions, which is not guaranteed.

Afshar-Bakeshloo *et al.* (2016) studied a multi-objective GVRP that minimizes operational and environmental costs and maximizes customer satisfaction. The second objective was presented within the model's constraints with a predetermined lower amount of service level. The Pareto front is derived by frequently optimizing the model at different amounts of service level. Afshar-Bakeshloo *et al.* (2016) modeled the problem to solve a set of 10-customers network and the three objectives were not modeled simultaneously.

Based on the literature review conducted in the area of Green Vehicle Routing (GVRP) and the Vehicle Routing Problems (VRP) with customer satisfaction, the following comments are concluded:

- There is a growing attention to green logistics in the Green Vehicle Routing area.
- There is a lack of multi-objective models that considers the three objectives: economic, environmental, and social aspects simultaneously.
- Models that addressed the three objectives simultaneously handled one of the objectives as a constraint in the problem when constructing routes, where a minimum level of service is determined in case of measuring customer satisfaction, or a maximum level of emission is considered a constraint in case of lowering the environmental impact.

In this chapter, a multi-objective green vehicle routing model that handles economic, environmental, and social aspects is proposed. The proposed model takes into consideration; (1) operational costs that include both variable and fixed costs of travel, (2) Fuel Consumption Rate (FCR) based on the distance traveled and the load of the vehicle, (3) customer satisfaction measured as the deviation from the desired time window provided by the customer to accept the service, while all customer demands are fulfilled. The model will utilize the hybrid search algorithm developed in Chapter 2. Pareto fronts between costs and customer satisfaction will be obtained and tradeoffs between the three objectives will be presented. A numerical analysis of the effect of changing the capacity of the vehicles used on the total operational costs, environmental costs and customer satisfaction is examined.

3.3 Problem Description

There are several variants of the VRP in the literature. The problem variants differ according to the characteristics of the problem. The Vehicle Routing Problem with Time windows (VRPTW) of study considers customer satisfaction criteria along with the environmental aspect of reducing fuel consumption. In VRPTW, the special aspect of routing is blended with the temporal aspect of scheduling. The characteristics of the proposed multi-objective Green VRP is presented followed by the mathematical formulation of the problem.

3.3.1 Characteristics of the Problem

The Multi-Objective Green Vehicle Routing Problem (GVRP) of study consists of $n+1$ points, n customers and a depot. The distances ($d_{i,j}$) between each two points is known. The objective is to determine the set of routes to be performed by a homogeneous fleet of vehicles (m) to serve a given set of customers (n) with known demands (q). Each customer(i) is associated with a Time Window, TW $[\alpha_i, \beta_i]$ and a given service time (s_i). α_i is the earliest time a customer can accept a service, while β_i is the latest time a customer can be serviced by vehicle k. The routes of the multi-objective GVRP are constructed to minimize total travel costs, minimize fuel consumption rate, and maximize customer satisfaction where, each route starts and ends at a single depot. Each customer must be assigned to only one vehicle and the total demand of all customers assigned to a vehicle does not exceed its capacity (Q). The number of vehicles (routes) to be used is not fixed but to be determined by the solution approach. In some studies, the number of vehicles is fixed, while others define a minimum possible number of vehicle routes (K_{min}).

Table 3-3: Problem Characteristics of the GVRP

Element	**Characteristic**
Size of fleet	Unbounded
Type of fleet	Homogenous
Origin of vehicles	Single depot
Demand type	Deterministic Demand (Known)
Location of demand	At the customer (node)
Maximum time on route	Constrained
Time windows	Soft Time windows
Objective	1. Minimize Total Travel Cost 2. Minimize Fuel Consumption Rate 3. Maximize Customer satisfaction
Constraints	1. Single visit at customers, 2. Routes start and end at depot, 3. Nodes served by single vehicle, 4. Vehicle capacity cannot be exceeded

Uchoa *et al.* (2017) discussed the reasons for considering the number of vehicles used in the problem as a decision variable rather than fixing it. One of the main reasons is that fixing the number of routes is an indirect way of minimizing the fixed cost associated with the cost per vehicle. In other words, this means ignoring the trade-off between variable and fixed costs associated with the suggested set of routes. Additionally, Uchoa *et al.* (2017) stated that the original Capacitated Vehicle Routing Problem (CVRP) proposed by Dantzig and Ramser (1959) did not consider fixing the number of routes to the problem as it requires adding the cost of unused capacity to the model which in practice is of minor importance. According to the authors, minimization of the travel distance is independent of the number of vehicles used. Table 3-3 summarizes the characteristics of the green vehicle routing problem of study.

3.3.2 Mathematical Modeling

The VRP problem is a generalization of the Travelling Salesman Problem (TSP) that introduces more than one salesman (m); hence, m number of tours can be done; each starting and ending at the depot. For formulating the VRP, the starting customer is considered node 1 (depot); where X_i represents the current visited node and Y_i represents the next node to be visited, where i varies from 1 to n, and n is the number of nodes to be visited by a given vehicle k. Now, m routes are introduced to the model; where, distance

d_{X_i,Y_j} is associated with each arc and represents the distance travelled from node X_i^k to node Y_j^k on route k, as shown in Figure 3-1.

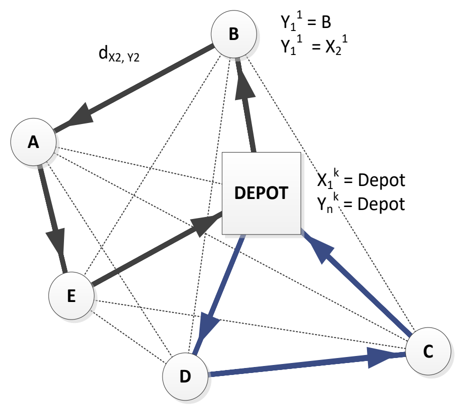


Figure 3-1: Illustration of the VRP (Elgharably et al., 2013)

The decision variable is Y_i^k; where, Y_i^k determines the value of the next customer i to be visited on route k. The X_i^k variable represents the value of the start node of the arc on route k. The use of loop segments is not allowed (leaving a node then arriving to same node, $X_i^k \neq Y_j^k$), as all nodes must be visited exactly once. The binary variable S_{X_i,Y_j}^k represents all possible arcs connecting any two nodes on route k. S_{X_i,Y_j}^k is given a value of 1 if arc (X_i^k, Y_j^k) belongs to route k; 0 otherwise. Both X_i^k and S_{X_i,Y_j}^k are considered uncontrollable variables. The problem is formulated as follows:

$$Minimize\ f_1 = \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} S_{X_i,Y_j}^k * d_{X_i,Y_j} * C_t + \sum_{k=1}^{m} F * S_{1,Y_j}^k \quad (1)$$

$$Minimize\ f_2 = \sum_{K=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} C_{fuel} * S_{X_i,Y_j}^k * d_{X_i,Y_j}(p_o * +\gamma * W_{X_i,Y_j}) \quad (2)$$

$$Maximize\ f_3 = \sum_{i=1}^{n} SV_i \quad (3)$$

Subject to

$$X_1^k = 1 \quad \forall k = 1, \dots, m \quad (4)$$

$$Y_n^k = 1 \quad \forall k = 1, \dots, m \quad (5)$$

$$X_i^k = Y_{i-1}^k \quad \forall\, i = 2, \dots, n, \quad \forall k = 1, \dots, m \quad (6)$$

$$X_i^k \leq n \quad \forall k = 1, \dots, m \quad (7)$$

$$Y_i^k \le n \quad \forall k = 1, \ldots, m \tag{8}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{m} S_{X_i,Y_j}^k = 1 \quad \forall\, i = 2, \ldots, n \tag{9}$$

$$\sum_{i=1}^{n}\sum_{k=1}^{m} S_{X_i,Y_j}^k = 1 \quad \forall\, j = 1, \ldots, n-1 \tag{10}$$

$$\sum_{j=1}^{n}\sum_{i=1}^{n} S_{X_i,Y_j}^k * q_{Y_j} \le Q_k \quad \forall k = 1, \ldots, m \tag{11}$$

$$\sum_{j=1}^{n}\sum_{i=1}^{n} S_{X_i,Y_j}^k\, t_{Y_j} \ge \alpha_j \quad \forall\, k = 1, \ldots, m \tag{12}$$

$$\sum_{j=1}^{n}\sum_{i=1}^{n} S_{X_i,Y_j}^k\, t_{Y_j} \le \beta_j \quad \forall\, k = 1, \ldots, m \tag{13}$$

$$X_i^k, Y_j^k > 0 \; and \; integer \tag{14}$$

The total transportation operational cost function is minimized in the objective function (1). The first term in the objective function calculates the total travel cost calculated from the travel time on all *k* routes; where, *m* is the number of routes, t_{X_i,Y_j} is the time spent travelling from $X_i^k to\ Y_j^k$, C_t cost per unit time. The second term represents the fixed cost of operating each vehicle, where *F* is the vehicle operating cost. The second objective function (2) minimizes the cost of fuel consumption which was proposed by Xiao *et al.* (2012) where, C_{fuel} is the unit fuel cost, d_{X_i,Y_j} is the distance travelled between two nodes, p_o no load fuel consumption rate, γ the coefficient obtained by linear regression between fuel consumption rate and the vehicle's load, ($\gamma = \frac{(p^* - p_o)}{Q}$) where p^* is the full load fuel consumption rate and W_{X_i,Y_j}^K is the gross weight of the vehicle *k* on a route. The third objective function (3) maximizes the customer satisfaction. Customer Satisfaction Value (SV_i) measures the deviation from TW for each customer, while all customer demands are fulfilled. Constraints (4) and (5) ensure that each route starts and ends at the depot. Constraint (6) ensures that each route of the *k* routes is not segmented, that is, if a vehicle arrives at a customer, it eventually leaves the customer again. Constraints (7) and (8) state the range of values given, whereas constraints (9) and (10) state that every customer is visited exactly once. Knowing that at each customer, customers' demand (q_{Y_j}) is present and that each vehicle has limited capacity Q_k; constraint (11) ensures that the total demand of all customers assigned to a route *k* does not exceed the vehicle's capacity. Constraints as (12) and (13), represent the Time Window constraints, where each customer i has a time window $[\alpha_i, \beta_i]$. α_i is the earliest time a customer can accept a service, while β_i is the latest time a customer can be serviced by vehicle k. The arrival time to next customer is t_{Y_j}. Finally, constraint (14) is guarantees that the variables are non-negative and integers.

3.4 Hybrid Multi-Objective Optimization Model

Multi-objective optimization involves several competing objectives that cannot be combined, making it hard for decision makers since there is no single decision that can be considered an optimum solution to solve the problem. However, there is a set of alternative solutions that are considered optimal known as the Pareto-optimal solutions. This solution set considers all objectives and provides the decision maker with the trade-offs between objectives making it easier for decision makers to choose from based on their own preference and considerations (Zitzler and Thiele, 1998, 1999).

The hybrid multi-objective optimization model developed in this chapter combines both the Strength Pareto Evolutionary Algorithm (SPEA) developed by Zitzler and Thiele (1999) with the Resultant Local Search Heuristic (RLSH) developed earlier in Chapter 2.

3.4.1 Resultant Local Search Heuristic (RLSH)

The resultant local search heuristic calculates a heuristic resultant based on both the distance travelled or the location of the nodes/customers and the demand associated with the given node/customer. In the implemented local search method, a heuristic resultant for each customer was used as follows:

$$HR_i = \lambda\, d_{i,j} + (1 - \lambda)\, DR_i \tag{15}$$

where HR_i = Heuristic Resultant for customer i, λ and $(1 - \lambda)$ = weights of the distance and demand (used to achieve diversity and not to be caught in local optimum), $d_{i,j} =$ Euclidian distance to be travelled from the current node (i) to the expected following node *(j)* by customer i, and DR_i = demand remainder for customer i, which is the difference between the vehicle's capacity and the demand *(i)*, where demand *(i)* is the quantity of items to be delivered or picked up by the vehicle at the customer (i). For example, at the beginning of constructing the route, the current location would be the depot, while in the middle of the route the current location would be the last visited node/customer. The function identifies the nearest route (heuristic) based on the resultant heuristic function between the remainder of the demand of each node compared to the vehicle capacity and the distance from the current location to the following node. A detailed illustration of the resultant local search heuristic process is presented in Chapter 2.

3.4.2 Strength Pareto Evolutionary Algorithm (SPEA)

Evolutionary Algorithms (EA) are believed to be one of the best approaches to solve multi-objective optimization problems due to the fact that solution sets are processed in parallel and at the same time utilize the similarity of the solutions by recombination (Zitzler and Thiele, 1998, 1999).

The Strength Pareto Evolutionary Algorithm (SPEA) developed by Zitzler and Thiele (1999) is used for finding the Pareto-optimal set for multi-objective optimization problems. Similar to other EAs, the SPEA stores the nondominated solutions externally, and also uses the concept of Pareto dominance to evaluate fitness values and performs clustering to reduce nondominated solutions without affecting the trade-off front. In addition, SPEA is unique as it evaluates the fitness of an individual from the external nondominated set, where all solutions of the nondominated set participate in selection and uses a Pareto-based niching method to preserve diversity in the population (Zitzler and Thiele, 1999).

A comparative study performed by Zitzler and Theile (1999) showed that the SPEA achieved the best assessment when compared to other four population-based multi-objective EAs: Vector Evaluated Genetic Algorithm (VEGA), Aggregation by Variable Objective Weighting (AVOW), Niched Pareto Genetic Algorithm (NPGA), and Nondominated Sorting Genetic Algorithm (NSGA). The performance of the EAs was measured quantitatively by two performance measures: the size of the solution space covered and the coverage in how one algorithm dominates the solution of the other. The study was performed on a Knapsack problem. The experimental results showed that the SPEA is capable of finding global optimal trade-off solutions than the solutions found by using a single objective EA optimization that uses a linear combination of the objectives.

There are two major differences between the SPEA and the other existing multi-objective EAs. The SPEA uses a fitness assignment based on the coevolution where a two-stage process of fitness assignment is used, the individuals in the external nondominated set are ranked then the individuals in the population are evaluated. Moreover, the SPEA uses a pareto-based dominance niching technique that is not defined in terms of distance but pareto dominance to achieve diversity in the population and reduces the pareto set by clustering (Zitzler and Theile, 1999).

In terms of computational complexity, the VRP is known to be a NP-hard problem. This means that the problem cannot be solved in polynomial time with a deterministic turning machine. The complexity of the SPEA is known to be O($n_o n_p^3$) for advancing one generation, where n_o is the number of objectives and n_p is the population size. To calculate the actual computational complexity the number of generations used (n_g) should be considered. Thus the complexity of the SPEA shall be O($n_g n_o n_p^3$), (Curry and Dagli, 2014).

3.4.3 Initial Population and Operators

A portion of the initial population is filled heuristically using the local search heuristic developed, while the remaining portion is filled randomly to achieve diversity and not to be caught in a local optimum. The random portion of the initial population is based only on the vehicle capacity ignoring any distance calculations. A set of operators are then performed to the initial population to mimic the nature of evolution.

To achieve diversity and to widen the span of the search space, a set of one deterministic and four random mutation operators is applied.

1. A deterministic Route Reduction Mutation (RRM) is performed that decreases the number of vehicles used in a solution without violating any constraints. The aim is to lower the number of routes considering only capacity and demand calculations.
2. Random Node Exchange Mutation (RNEM) is a mutation operator that exchanges nodes from randomly selected routes without violating any capacity constraints.

3. Random Node Transfer Mutation (RNTM) is a mutation operator that transfers a randomly selected node from one route to another, where routes are adjusted using the developed resultant heuristic with no capacity violation.
4. Random Arc Exchange Mutation (RAEM)
5. Random Arc Transfer Mutation (RATM)

Two crossover operators are performed, one at random while the other is deterministic that inherits good characteristics from parents, as follows:

1. The Heuristic Inheritance Crossover (HIC) is a deterministic crossover operator that performs changes to the routes within a given solution inheriting good routes without violating any constraints. The HIC is used for intensification of good solutions in the breeding generation rather than diversification.
2. Random Inheritance Crossover (RIC) follows the same process as the HIC operator; the only difference is that the routes to be inherited from parent 1 are chosen at random not based on good routes. The RIC operator acts as a diversification operator.

A detailed description of the operators mentioned above, their procedures and figures are presented in Chapter 2 (Section 2.4).

3.4.4 Objective Functions

The multi-objective GVRP model presented in this study deals with three different objectives: economic, environmental, and social aspects.

The economic aspect can be reflected as minimizing the total transportation operations cost function as in Equation (1). While the environmental aspect is measured in terms of minimizing the fuel consumption as shown in Equation (2). Finally, maximizing customer satisfaction, Equation (3), reflects the social aspect, which is one of the main performance measures of the supply chain.

3.4.4.1 Customer Satisfaction

Customer Satisfaction Value *(SV_i)* is calculated as the time deviation between the actual time of service and the customer's time window $[\alpha_i, \beta_i]$, while all customer demands are fulfilled. As mentioned earlier, α_i is the earliest time a customer can accept a service, while β_i is the latest time a customer can be serviced by the vehicle.

Several types of Time Windows (TW) have been addressed in the literature. A traditional VRPTW would deal with customers' time windows as a hard TW in which delivery service must fall within the customer's specified TW. However, in real world transportation, TW may be violated for practical reasons as mentioned by Tang *et al*. (2009) such as:

1. Relaxing the TW constraint can result in a better solution when considering the number of vehicles used, time and cost.
2. Feasible solutions are hard to find if all TW have to be satisfied. Thus, a relaxed TW would result in an executable route plan.
3. It is a fact that customers provide narrow TW, while a little deviation would be considered acceptable to them.

Soft Time Windows accept violations of the customer's specified TW with a penalty cost added once violation occurs. In soft TW, penalty costs are assumed to be linear with the degree of violation (Tang *et al*., 2009). Tas *et al*., (2014) introduced the VRP with flexible TWs, where vehicles are given a certain tolerance in which TW can be deviated.

In the multi-objective GVRP with customer satisfaction model introduced in this chapter, Soft TW are used. If the vehicle arrives after the latest time a customer can accept the service, the customer is then unsatisfied. A satisfaction value will be calculated as shown in Equation (16), which is the time difference between the arrival time of the vehicle and the upper bound (β_i) of the time window.

$$SV_i = \beta_i - t_{Y_i} \qquad \forall\, i = 2, \ldots, n, \tag{16}$$

Customer Satisfaction Value *(SV_i)* is a variable which can be either zero or a negative integer, where the maximum value zero would reflect complete satisfaction. However, if the vehicle arrives early at the customer, the vehicle will wait till the earliest time a customer can accept the service (α_i). This will incur an extra cost due to the increase of the travel time on the route that shall be reflected in the travel cost function.

3.4.4.2 Total Cost Function

The total transportation operations cost function in Equation (1), in Section 3.3.2, consists of both variable and fixed costs. The first term calculates the total travel distance cost calculated from travelling on all routes, while the second term represents the fixed cost of operating each vehicle. The second objective function presented in Equation (2) minimizes the cost of fuel consumption. These two objectives can be combined in the model as a minimization cost function (17) that aims at both minimizing travel costs and minimizing environmental impact by reducing fuel consumption measured in terms of fuel consumption cost as shown in the modified objective function (18).

$$Minimize\ Z_1 = f_1 + f_2 \tag{17}$$

can be written as

$$Minimize\ Z_1 = \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} S_{X_i,Y_j}^{k} * d_{X_i,Y_j} * C_t + \sum_{k=1}^{m} F * S_{1,Y_j}^{k} + \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} C_{fuel} * S_{X_i,Y_j}^{k} * d_{X_i,Y_j}(p_o + \gamma * W_{X_i,Y_j}) \tag{18}$$

Due to the presence of time windows, an extra cost is calculated. Extra cost reflects cases where vehicles arrive early inducing working waiting cost at customers (Equation 19) and waiting cost at depot (Equation 20), reflecting cases of late vehicle arrival at the depot. C_e is the cost of early arrival at the customer, while C_d is the cost of delay (late arrival at the depot).

$$Waiting\ Cost\ at\ customer = \sum_{i=1}^{n} C_e * (\alpha_i - t_{Y_i}) \tag{19}$$

$$Waiting\ Cost\ at\ Depot = \sum_{k=1}^{m} C_d * (t_1^k - \beta_1) \tag{20}$$

Then the total cost objective function is adjusted to

$$
\begin{aligned}
Minimize\ Z_1 = &\sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} S^{k}_{X_i,Y_j} * d_{X_i,Y_j} * C_t + \sum_{k=1}^{m} F * S^{k}_{1,Y_j} \\
&+ \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} C_{fuel} * S^{k}_{X_i,Y_j} * d_{X_i,Y_j}\left(p_o + \gamma * W_{X_i,Y_j}\right) \\
&+ \sum_{i=1}^{n} C_e * (\alpha_i - t_{Y_i}) \\
&+ \sum_{k=1}^{m} C_d * (t^{k}_{1} - \beta_1) \qquad (21)
\end{aligned}
$$

The developed multi-objective model solves the conventional VRP with time windows in green environment and considers customer satisfaction. The model is developed in a way that it can handle either delivery or pickup services. The service to be done is considered as an input to the model as fuel consumption calculations differ in each case while constructing the routes. Fuel consumption rate calculation depends on both the vehicle load and the distance travelled. For this reason, the type of service has to be determined upfront before running the model.

3.5 Computational Study

3.5.1 Dataset generation

In order to study the proposed multi-objective model, two data sets were used: Solomon's VRPTW benchmark data set and Uchoa *et al.* VRP benchmark data set.

Solomon's VRPTW benchmark problems are known to compare computational performance of many algorithms. The problems can be found at: http://web.cba.neu.edu/~msolomon/problems.htm. The larger problems are 100-customer Euclidean problems where travel times are equal to the corresponding distances. For each problem, smaller problems have been created by considering only the first 25 or 50 customers (Solomon 1987, and Fisher *et al.*, 1997). The problem consists of 100 customers and a depot, each with a defined X, Y co-ordinates, service time, demand, and time windows. A homogeneous fleet of vehicles with a capacity of 200 is used. The depot has a zero-service time and is considered a customer with a zero demand and a time window of [0, 230]. This time window is considered the time horizon required for all routes to be fulfilled. The R101 and R102 dataset inputs are presented in Appendix C and Appendix D, respectively.

Uchoa *et al.* (2017) proposed a new benchmark dataset that provides a more comprehensive and balanced experimental setting to the classic CVRP. Problem instance: X-n101-k25 is taken from Uchoa *et al.* new benchmark instances (Appendix B). The problem consists of a depot and 100 customers, the number of vehicles to be used is not fixed but the minimum feasible number of vehicles is known (K_{min} = 25). The vehicle capacity is 206 units. The depot and customer positioning of the X-n101-k25 instance is random.

For both benchmark sets, Euclidean distances are calculated from the given X and Y co-ordinates, where travel times are equal to the corresponding distances and demands of customers [0,100] are deterministic.

Table 3-4: GVRP Problem Sets

Data Set	**Distance and Demands**		**Time Windows**	
	Instance	*Reference*	*Instance*	*Reference*
Problem set 1	X-n101-k25	Uchoa *et al.*, 2017	R101	Solomon 1987
Problem set 2	R101	Solomon 1987	R101	Solomon 1987
Problem set 3	R102	Solomon 1987	R102	Solomon 1987
Problem set 4	X-n101-k25	Uchoa *et al.*, 2017	R102	Solomon 1987

Table 3-4 shows the four problem sets that are used to experiment on the multi-objective GVRP model developed. Sets 1 and 4 are a combination of Uchoa *et al*,.2017 and Solomon,1987 benchmark datasets. The TW of Solomon's R101 and R102 are used with the X-n101-k25 instance from Uchoa *et al.* (2017) to produce two new problem sets; problem set 1 and problem set 4, respectively.

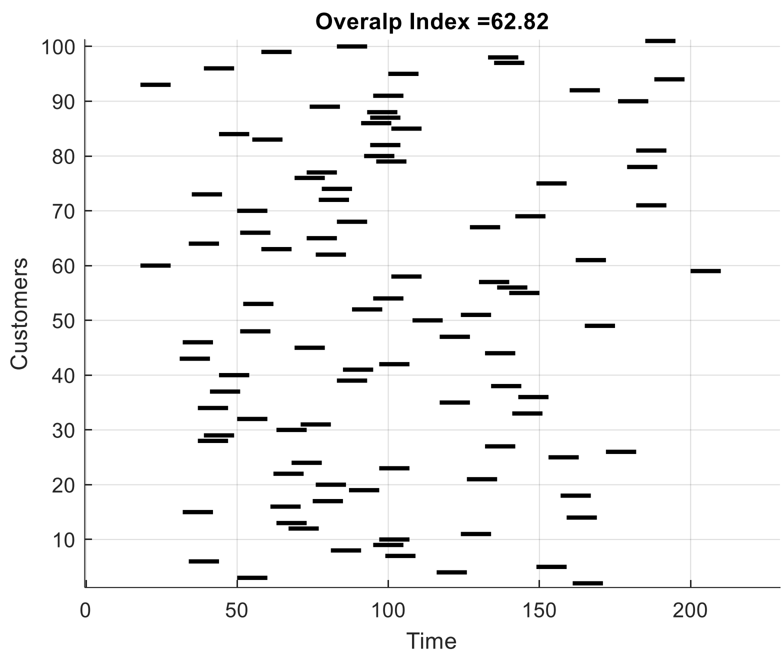
For Solomon's R101 and R102 problems, the customer co-ordinates are identical for all problems within R type dataset. The problems differ with respect to the width of the time windows. Some have very tight time windows, while others have time windows which are hardly constraining (Solomon, 1987).

For this reason, the overlap index is developed to measure how tight are the time windows associated with the customers. The index value is calculated as follows:

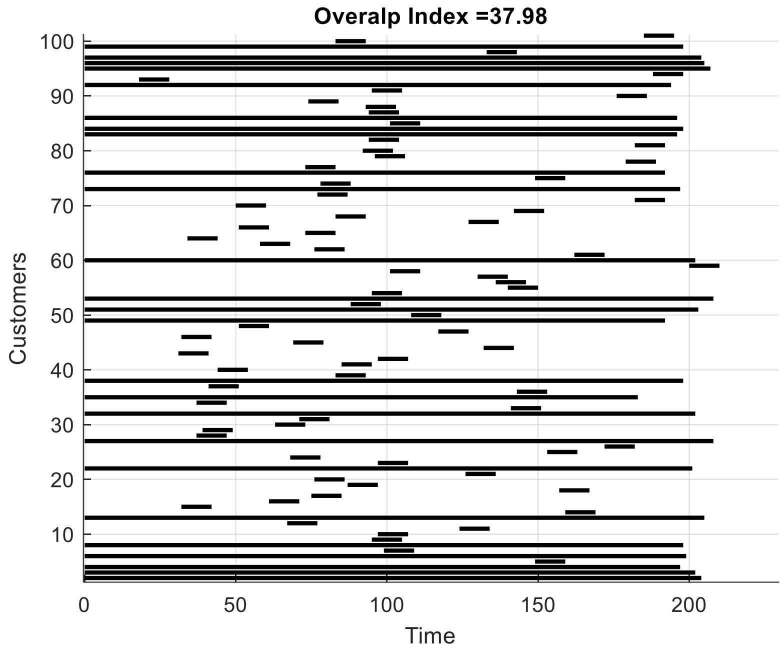
$$Overlap\ Index = \frac{\sum_{i=2}^{n}\sum_{j=2}^{m}(\beta_i - \alpha_i) \cap (\beta_j - \alpha_j)}{n-1} \tag{22}$$

The higher the index, the tighter are the time windows, resulting in more constraining set to achieve customer satisfaction.

Figure 3-2 shows the overlapping time windows of R101 and R102 problems by Solomon. The overlap index is a developed index to show the possibility of satisfying customers given conflicting demands. As shown in Figure 3-2 (a), the time windows are so tight, while Figure 3-2 (b) shows a less conflicting set of demands for customer satisfaction.



a. Time Windows and Overlap index for Solomon's R101



b. Time Windows and Overlap index for Solomon's R102

Figure 3-2: Time windows and Overlap Index representation

3.5.2 Parameter Initialization

The evolutionary model parameters used are shown in Table 3-5. The selection of the number of times each operator is applied is based on the study performed in Chapter 2 (Section 2.5.3). The study explores different configuration settings.

Table 3-5: Configuration of Evolutionary Operators

Operator	Name	Description	Occurrence
Mutation	RRM	Route Reduction Mutation	6
	RNEM	Random Node Exchange Mutation	10
	RNTM	Random Node Transfer Mutation	10
	RAEM	Random Arc Exchange Mutation	10
	RATM	Random Arc Transfer Mutation	10
Crossover	HIC	Heuristic Inheritance Cross over	2
	RIC	Random Inheritance Cross over	2

Runs at different number of generations are done to determine the suitable number of generations to be used in the algorithm. Several runs are performed at different values over an interval [2000, 6000] of the maximum number of generations, while the other parameters are unchanged.

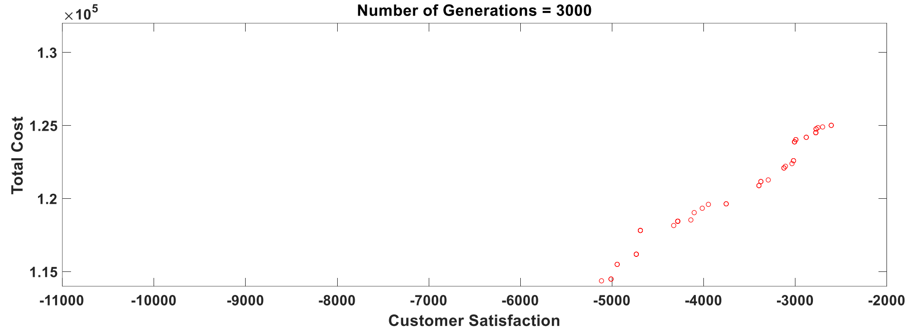
Figure 3-3 shows a sample of the experimental runs performed at different generations settings. The maximum number of generations to be used in the EA is 4000 as shown in Figure 3-3(c) which captures the trade-offs between the two conflicting objectives with a broader set of optimal solutions in the Pareto front.

Table 3-6: Problem sets Characteristics

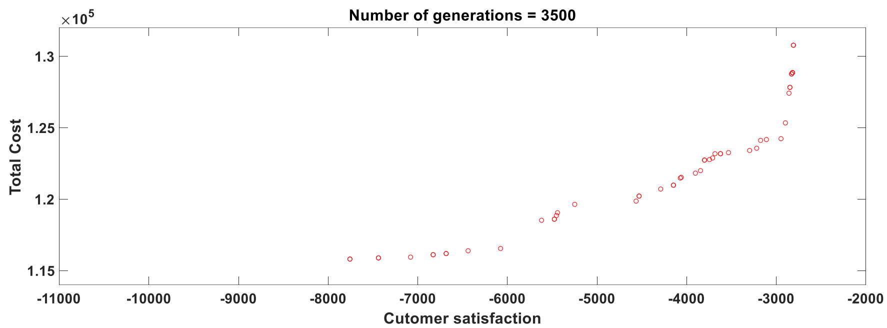
Problem Set	Distance and Demands		Time Windows		Overlap Index	Vehicle Capacity (Q)	Number of customers
	Instance	Reference	Instance	Reference			
Problem 1	X-n101-k25	Uchoa *et al.*, 2017	R101	Solomon, 1987	62.82	206	100
Problem 2	R101	Solomon, 1987	R101	Solomon, 1987	62.82	200	100
Problem 3	R102	Solomon, 1987	R102	Solomon, 1987	37.98	200	100
Problem 4	X-n101-k25	Uchoa *et al.*, 2017	R102	Solomon, 1987	37.98	206	100

3.5.3 Results

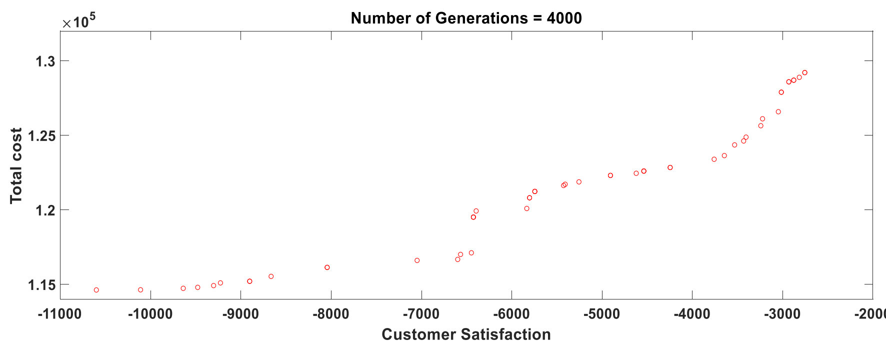
Computational experiments on the four problem data sets (Table 3-6) are performed. All data sets operate from a central depot and routes are constructed using a set of homogenous fleet of vehicles with a limited capacity (Q) to serve a delivery service to a given set of customers with deterministic demands. Euclidean distances are calculated from the given X and Y co-ordinates, where travel times are equal to the corresponding distances. The cost coefficients (C_t , F, C_f, C_e, C_d) are set to (2, 1000, 4, 0.5, 1). The fuel consumption coefficients (p_0, p^*) are set to (1, 2) as in Xiao *et al.* (2012). Using the EA parameters defined in Table 3-5, and a maximum number of generations of 4000, the problem is solved using MATLAB.



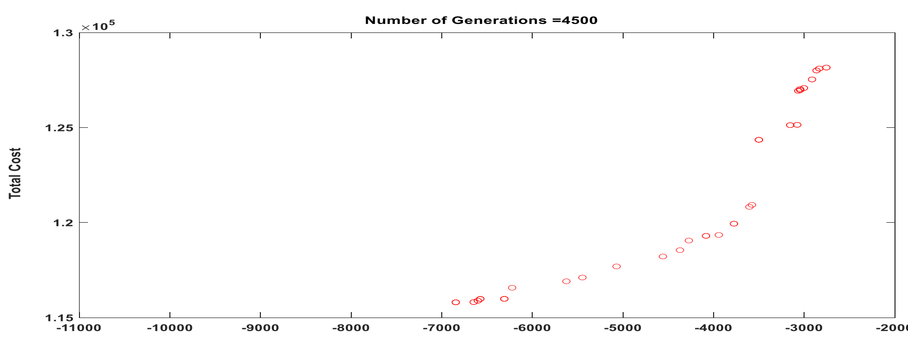
a. Experimental run with 3000 generations



b. Experimental run with 3500 generations

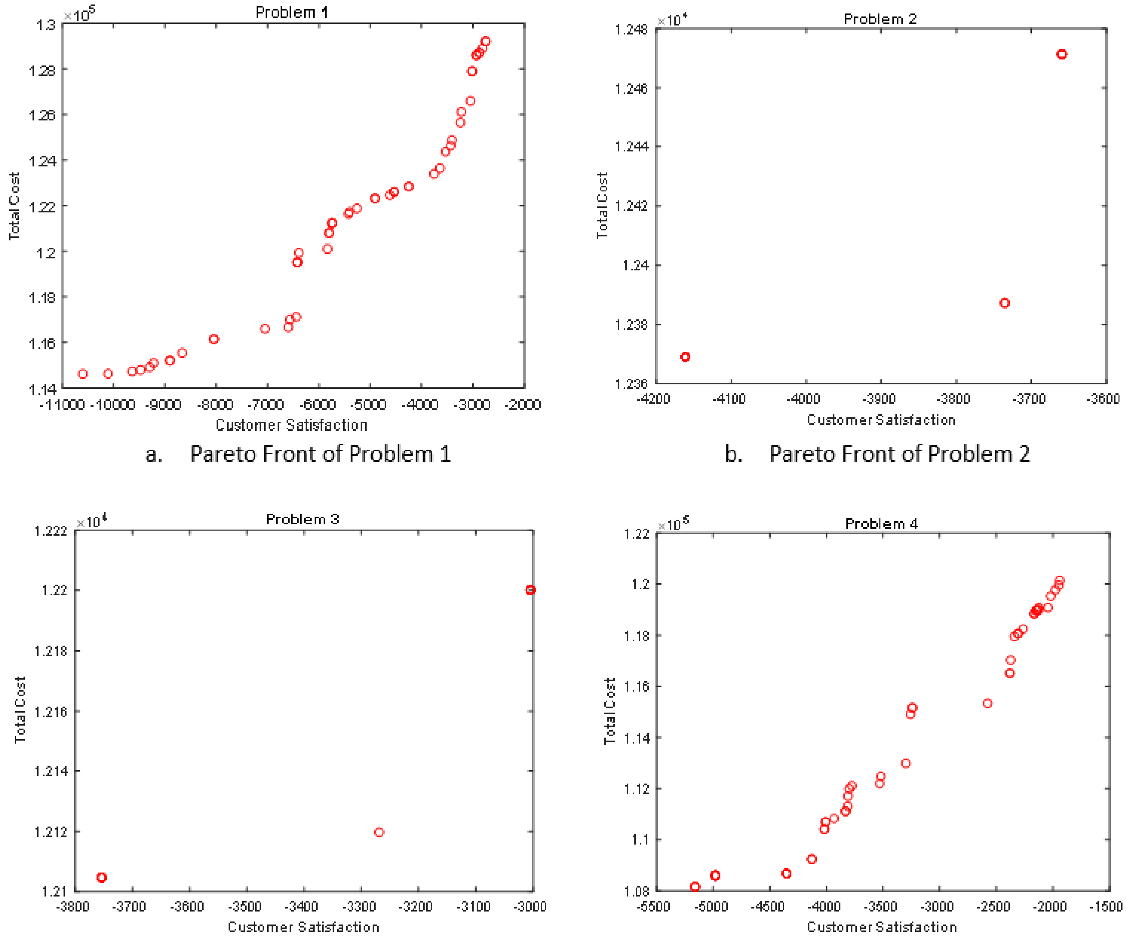


c. Experimental run with 4000 generations



d. Experimental run with 4500 generations

Figure 3-3: Sample runs to determine the number of generations in the EA



a. Pareto Front of Problem 1 b. Pareto Front of Problem 2

c. Pareto Front of Problem 3 d. Pareto Front of Problem 4

Figure 3-4: Pareto Fronts of the multi-objective GVRP

The results of the model runs are presented in Figure 3-4. The figure shows the trade-offs between the two objectives, minimizing total costs and maximizing customer satisfaction. In Figure 3-4 (a) and Figure 3-4 (d), a wide set of Pareto-optimal solutions is found which presents the trade-off solutions between the two objectives. However, Figure 3-4 (b) and Figure 3-4 (c) show a constrained set of Pareto-optimal solutions. The reason for that is the difference in the grid scale, and locations of customer and their demands. As shown in Table 3-7, both problems 1 and 2 have lower customer satisfaction compared to problems 3 and 4. This is due to the tightness of the time windows, which is analyzed using the overlap index values of each set. Both problems 1 and 2 have time windows that are constraining the solution with an overlap index equal to 62.82. On the other hand, problems

3 and 4 has time windows that are more relaxed and are hardly constraining the solution with an overlap index equal to 37.98.

Table 3-7: Results of the Multi-Objective GVRP

	Problem Set	Number of Routes	Customer Satisfaction	Total Travel cost	Variable Cost	Fixed Cost	Cost of Fuel Consumption	Extra Cost
Minimum Total Cost	Problem 1	24	-10602	114630	30423	24000	45913	14294
	Problem 2	8	-4160.9	12369	1077.7	8000	1512.7	1778.7
	Problem 3	8	-3754.1	12105	1060.3	8000	1440.2	1604.2
	Problem 4	23	-5158.8	108160	29366	23000	44639	11157
Compromise case	Problem 1	27	-5426.1	121640	32323	27000	46659	15656
	Problem 2	8	-3735.5	12387	1045.2	8000	1404.9	1937.2
	Problem 3	8	-3269	12120	1070.6	8000	1470.3	1578.8
	Problem 4	26	-3299.1	113000	30370	26000	44325	12304
Maximum satisfaction	Problem 1	29	-2754.6	129210	35370	29000	49736	15106
	Problem 2	8	-3659.6	12471	1065.2	8000	1428.4	1977.7
	Problem 3	8	-3004.5	12200	1065.2	8000	1428.4	1706.6
	Problem 4	27	-1941.7	120140	32964	27000	47997	12183

3.6 Numerical Analysis

A study on the effect of changing the vehicle capacity (Q) on total travel cost, the total environmental cost and the customer satisfaction is conducted on problem 1 and 4. An interval of the vehicle capacity range is [160, 300] with increments of 20s, along with an increase of the vehicle fixed operating cost as in Table 3-8.

Table 3-8: Changes in vehicle capacity and vehicle operating cost

Cost per unit vehicle	800	900	1000	1100	1200	1300	1400	1500
Vehicle Capacity	160	180	200	220	240	260	280	300

For each problem 1 and 4, three points are taken from the Pareto fronts of each problem. These three points represent a midpoint and two extreme endpoints on the Pareto front. The selected points are as follows:

1. Compromise point which is a Pareto-optimum point along the middle of the Pareto front.
2. First extreme endpoint represents minimum total cost and the corresponding customer satisfaction, which is low in this case.

3. Second extreme endpoint represents the maximum customer satisfaction and the corresponding total cost, which is high in this case.

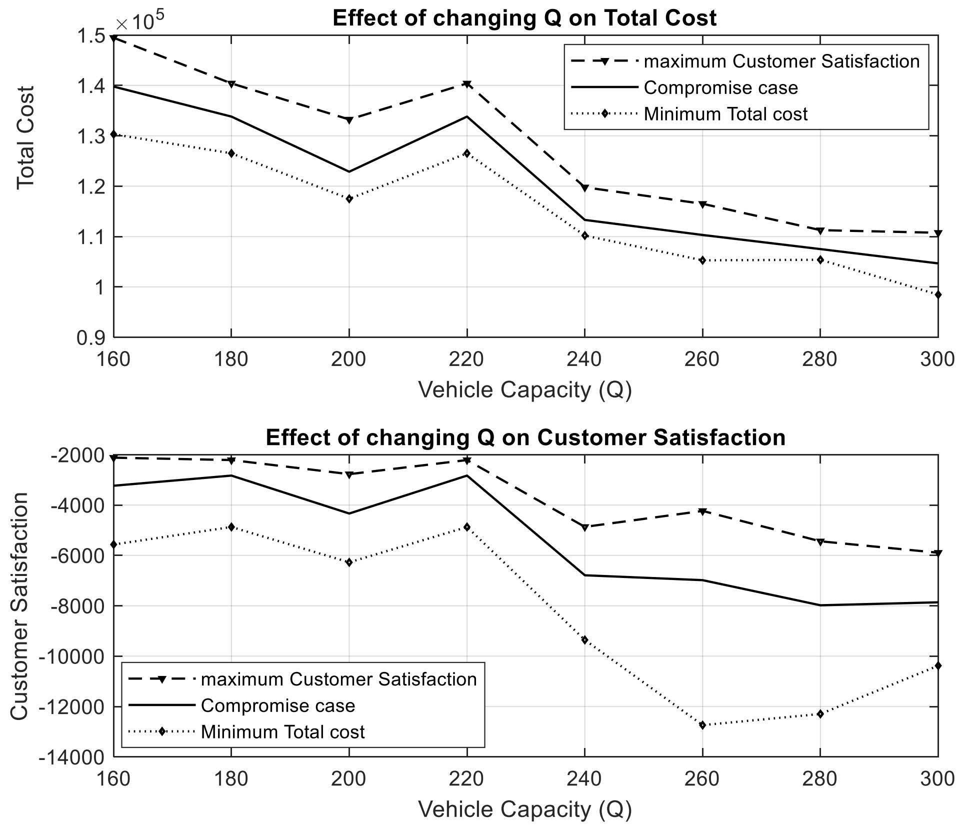


Figure 3-5: Effect of Changing Q on both Total Cost and Customer satisfaction, Problem 1

Figure 3-5 shows the effect of changing the vehicle capacity on both the total cost and the customer satisfaction for problem 1. The total cost of serving the customers decreases with the increase of vehicle capacity. The more the capacity, the less number of vehicles needed to fulfill customer demands. As the vehicles can carry more units, the number of vehicles decreases resulting in low customer satisfaction. On the other hand, the smaller the vehicle capacity, the better customer satisfaction is achieved. Similarly, for problem 4 shown in Figure 3-6, the vehicle capacity is inversely proportional with the total costs of constructing the routes, and the customer satisfaction objective.

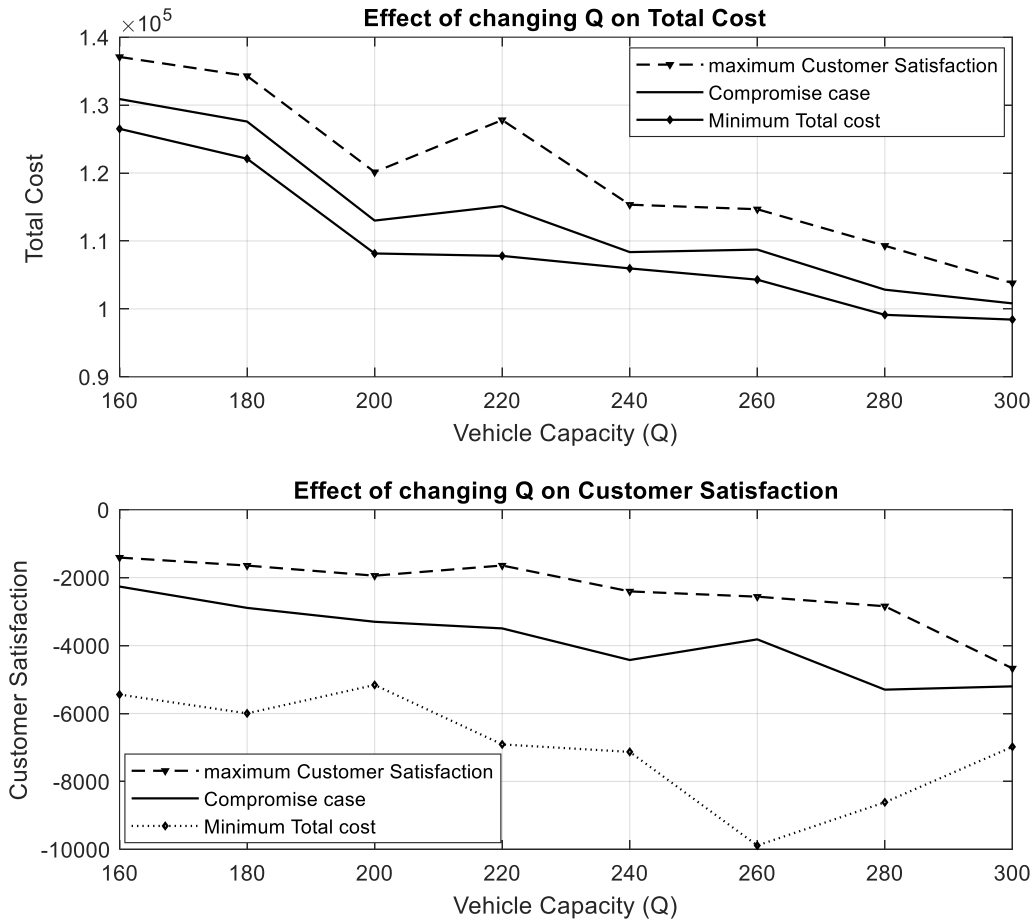


Figure 3-6: Effect of Changing Q on both Total Cost and Customer satisfaction, Problem 4

For the purpose of further investigation, the comprise case is selected from Problem 1 to examine the effect of changing the vehicle capacity (Q) on the economic, environmental, and social aspects considered in this study. Figure 3-7, shows the effect of changing the vehicle capacity on the travel costs and environmental costs separately and customer satisfaction. Tradeoffs between the three objectives are presented in Figure 3-7, and decisions can be taken based on the decision-maker’s perspective.

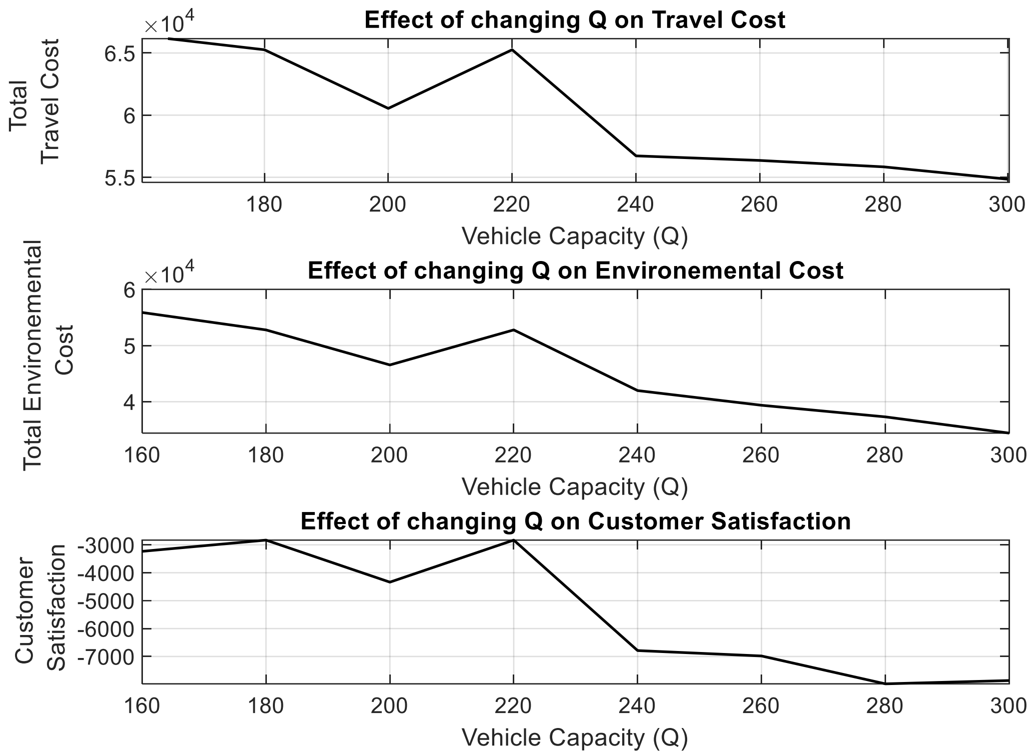


Figure 3-7: Effect of changing Q on economic, environmental, and social aspects

3.7 Conclusion

In this chapter, the multi-objective green vehicle routing problem is investigated. An extensive literature review on Green Vehicle Routing Problems (GVRP) is conducted. In addition, a literature review on VRPs with customer satisfaction in traditional VRPs and GVRPs is done. A model that handles the economic, environmental, and social aspects is developed. Previously in the literature, multi-objective VRPs handled one of the objectives as a constraint, and Pareto fronts were obtained by running the model several times at different levels of the constraint, while others handled the problem using weighted utility functions. Weighted linear utility function methods work well when a convex Pareto front is expected between the objective functions. In the case of nonconvex MOOP, evolutionary methods work better in finding the Pareto optimal solutions (Singh *et al*., 2013). As shown in Figure 3-4, the problem presented in this chapter is a nonconvex problem with disjoint solutions. Genetic Algorithms are known for their ability to search the different areas of the solution space simultaneously, finding a diverse solution set for multi-objective optimization problems with non-convex, discontinuous, and multimodal search spaces (Singh *et al.*, 2015).

The developed model, handles the three objectives simultaneously and Pareto-optimum solutions are found, offering the decision maker a set of solutions to tradeoff between the total travel, environmental costs, and customer satisfaction. Travel costs considers both variable costs associated with the travelled distance and fixed costs for operating the vehicles. Environmental costs reflect the amount of fuel consumption that is measured in terms of travel distance and varies depending on the load of the vehicle. Customer satisfaction is measured as the deviation from the time window specified by the customers. Problem instances from both benchmark problems of Solomon and the new benchmarks by Uchoa *et al.* are used. A new overlap index is developed to measure the amount of overlap between customers' time windows that provides an indication of how tight/constrained the problem is. The multi-objective GVRP studied is solved in MATLAB and evolutionary algorithms are used. The Strength Pareto Evolutionary Algorithm (SPEA) developed by Zitzler and Thiele is combined with the new resultant local search heuristic developed in Chapter 2 to obtain the Pareto fronts of the model. Furthermore, the effect of changing the vehicle capacity is investigated. The total cost of serving the customers decreases with the increase of vehicle capacity. The more the capacity, the less number of vehicles needed to fulfill customer demands, as the vehicles can carry more units. Therefore, the number of vehicles decreases resulting in low customer satisfaction. On the other hand, the smaller the vehicle capacity, the better customer satisfaction is achieved. The analysis shows how each of the three objectives is affected and provides an overall vision of the effect of choosing a different vehicle with a different load capacity.

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Chapter 4

4 Stochastic Multi-Objective Vehicle Routing Model in Green Environment with Customer Satisfaction

The Vehicle Routing Problem (VRP) is one of the most studied combinatorial optimization problems in operations research and are classified as NP-hard. Introducing uncertainty to the problem increases the complexity of solving such problems. Sources of uncertainty in VRPs can be travel times, service times and unpredictable demands of customers. Ignoring these sources, may lead to inaccurate modeling of the VRP. Moreover, the area of green logistics and the environmental issues associated received great attention. The purpose of this chapter is to study the stochastic multi-objective vehicle routing problem in green environment. The stochastic Green VRP (GVRP) presented deals with three different objectives simultaneously that consider economic, environmental, and social aspects. A new hybrid search algorithm to solve the VRP is presented and validated. The algorithm is then employed to solve the stochastic multi-objective GVRP. Pareto fronts were obtained and trade-offs between the three objectives are presented. Furthermore, an analysis on the effect of customers' time window relaxation is presented.

4.1 Introduction

One of the most challenging combinatorial optimization problems is the vehicle routing problem. The VRP was first proposed in the late 1950s by Dantzig and Ramser (Khaliigh and MirHassaani, 2016). Since then, the problem has been studied extensively. Introducing different characteristics to the VRP led to the presence of several variants of the problem. The VRP aims at constructing a minimum cost set of vehicle routes serving a set of known customers. Routes are constructed starting from depots, serving customers, then returning back to the depot. The Capacitated Vehicle Routing Problem (CVRP) is a well-known class of the VRP, where capacity limits are introduced to the vehicles serving customers with known demands. Introducing time boundaries where customers can accept the service provided within those limits is known as the VRP with Time Windows (VRPTW). In VRPTW the aspect of routing is combined with scheduling. Several variants of the VRP are present in literature such as: Multi-depot Vehicle Routing Problem (MDVRP) where supply is provided from different depots, Multi-Pickup and Delivery Vehicle Routing Problem (MPDVRP) when customers may require different services of pickup and delivery, and Heterogenous Vehicle Routing Problem, where different types of vehicles with different capacities are used. Toth and Vigo (2002) presented a comprehensive overview of the VRP along with its formulations, solution methods, and variants.

In real life, uncertainty plays an important role in the process of routing and scheduling of VRPs. It is important for express and logistic industries to consider the uncertainty existing to reduce the costs associated with planning the routes and costs of failures of the planned schedules (Wang *et al.*, 2017). Sources of uncertainty in a VRP can be travel times, service times and unpredictable demands of customers. Ignoring these sources, may lead to inaccurate modeling of the VRP. Applications of Stochastic VRPs (SVRP) are online retail businesses as Alibaba and Amazon (Wang *et al.,* 2017), in-home delivery businesses, milk collection systems, waste collection services (Goel *et al.,* 2019 and Biesinger *et al.,* 2018), cash collection from banks, delivering products to cities under emergencies (Khaligh and Mirhassani, 2016), courier delivery, delivery of goods to supermarkets, routing of maintenance units, routing of sales units and dial-a-ride services (Gounaris *et al.,* and Pandelis *et al.,* 2013).

This chapter studies the stochastic VRP in green environment with customer satisfaction criteria. The multi-objective models proposed take into consideration three main objectives: (1) minimizing the total operational cost, (2) minimizing the environmental cost, and (3) maximizing customer satisfaction, simultaneously, without converting one of the objectives to a constraint with a given threshold. Three models are proposed to address the multi-objective green vehicle routing problem with customer satisfaction and are presented in this chapter. The first model addresses the GVRP with uncertain travel times and service times taking into consideration customer satisfaction. The second and third models handles the GVRP with customer satisfaction under uncertain travel times, service times and customer demands. The uncertain demands are conducted in the second and third models with two different demand policies: chance constrained, and recourse, respectively.

This chapter is divided as follows: Section 4.2 provides a review on the stochastic vehicle routing problem addressed in literature, and how uncertainty was tackled in GVRP. Section 4.3 describes the characteristics of the problem, followed by the mathematical formulation of the problem of study. Section 4.4 illustrates how the hybrid multi-objective optimization model is developed. Section 4.5 presents the multi-objective GVRP with uncertain travel and service times. Section 4.6 presents the multi-objective GVRP with uncertain demands and times followed by the numerical analysis in Section 4.7. Finally, the conclusions drawn from this work are presented in Section 4.8.

4.2 Literature Review

Vehicle Routing Problems are NP-hard. Introducing uncertainty to the problem increases the complexity of solving such problems, making classical optimization methods infeasible (Cimen and Soysal, 2017). Several sources of uncertainty are present in the real-world VRP such as: travel times, service times, and customer demands. Travelling on an arc is stochastic in nature as travel times can be affected by weather, congestion due to car accidents and/or construction, rush hours or any other factors that might affect the time of travel between two locations (Cimen and Soysal, 2017). Ignoring travel times' uncertainty leads to inaccurate estimation of the fuel consumption and scheduling of customers visits, which will lead to customer dissatisfaction. Service times can also be uncertain considering the human factor of performing a service (delivery/pickup of goods) and the correlation to the uncertain demand acquired by the customer. Uncertainty in demands means that the deterministic customer demands are unknown and only demands with known distributions are known. The actual demands are revealed only when the vehicle reaches the customer (Zhang *et al.*, 2016). In literature, two policies are considered when modeling the VRP with stochastic demands; Chance Constrained Program (CCP) and Stochastic Program with Recourse (SPR) (Gendreau *et al.*, 1996).

In an effort to review the VRP with uncertainty, Table 4-1is developed. The table presents a summary of the literature review conducted on VRPs with uncertainty. The table shows the problem class of study, the objectives addressed, whether the objective function is single or multi. The table also determines the elements of uncertainties in the problem.

Table 4-1: Summary of literature on the VRPs with uncertainties

Author	Year	Problem Class	Obj. Fn.		Objectives				Problem Characteristics: Uncertainty			Problem Characteristics: Demand Policy	
			Single	Multiple	Economic impact	Environment impact	Customer satisfaction	Objectives handled as constraints	Time	Service time	Demand	Chance Constrained	Recourse
Laporte *et al.*	2002	VRP	●		●						●		●
Ak and Erera	2007	VRP	●		●						●		●
Tan *et al.*	2007	VRP		●	●						●		●
Maden *et al.*	2010	VRP	●		●				●				
Juan *et al.*	2011	VRP	●		●						●		●
Lei *et al.*	2011	VRP	●		●						●		●
Pishvaee *et al.*	2012	GLND		●	●	●			●		●		
Ahmmadi-Javid and Seddighi	2013	VRP	●		●						●	●	
Gounaries *et al.*	2013	VRP	●		●				●		●	●	
Pandelis *et al.*	2013	VRP	●		●						●		●
Zhang *et al.*	2013	VRPTW	●		●		●	Customer satisfaction	●				
Khaligh and Mirhassani	2016	VRP	●		●						●		●
Zhang *et al.*	2016	VRP	●		●		●	Customer satisfaction			●		●
Cimen and Soysal	2017	GVRP		●	●	●			●				
Wang *et al.*	2017	VRP	●		●						●		●
Biesinger *at al.*	2018	VRP	●		●						●		●
Goel *et al.*	2019	VRPTW	●		●		●	Customer satisfaction		●	●		●

One of the most popular stochastic routing problems is the SVRP with variable demand. Laporte *et al*. (2002), Ak and Erera (2007), Lei *et al. (*2011), Juan *et al.* (2011), Pandelis *et al*. (2013), Khaligh and Mirhassani (2016), Wang *et al*. (2017), and Biesinger *et al.* (2018) studied the single objective SVRP with uncertain demand and used the SPR policy in case of route failures without considering the other objectives; the environmental impact or customer satisfaction considerations.

Juan *et al.* (2011) introduced a SVRP with stochastic demands, intending to reduce costs by considering a vehicle capacity that is lower than the actual capacity in planning the routes and using the extra capacity as a safety stock to handle variations in demand aiming at reducing the probability of route failure.

Ahmmadi-Javid and Seddighi (2013) studied a special variant of the VRP, where location-allocation decisions of a set of potential producers-distributers and the routing decisions associated is to be made to minimize the total annual costs given a stochastic production capacity. A shortage of capacity is handled as a cost of delay, lost sales, or outsourcing without giving much attention to customer satisfaction nor environmental impact.

Modeling the uncertainty in demands, travel times and service times is important in modeling VRPs with customer satisfaction in green environment. Ignoring uncertainty leads to in accurate modeling of transportation operations. Some efforts in modeling uncertainty as simplifying the problem were done as in Gounaris *et al.* (2013) where the problem was converted to a deterministic case by realizing the worst-case scenarios or by using constant average travel times as in Maden *et al*. (2010*).* A study on VRP with time varying data by Maden *et al*. (2010) showed that using constant average travel times leads to a significant inaccurate calculation of travel times resulting in missing the specified time windows. In the stochastic GVRP with customer satisfaction, three main objectives are optimized simultaneously, where economic, environmental, and social aspects are considered in the model. Simplifying the problem to the worst-case scenario considers the most serious or severe outcome that may happen in a given situation. Converting the uncertainty in demand to a deterministic maximum value means more number of vehicles used leading to less utilized vehicles and an increase in the operating cost. Moreover, modeling for the maximum deterministic value of travel times implies inaccurate calculation of the fuel consumption cost and arrival times at customers while modeling resulting in a decrease in customer satisfaction. Considering the worst-case scenario to simplify the presented model and ignoring the uncertainty in the model will lead to an inaccurate calculation of operational costs, environmental costs and customer satisfaction and ignores the trade-off present among them.

Zhang *et al.* (2013) applied a discrete approximation method to generate the arrival time distributions of vehicles in the presence of TW and adjusted customer service level to obtain trade-offs between costs and service levels. Later, Zhang *et al.* (2016) and Goel *et al.* (2019), both considered the SVRP with uncertain customer demands minimizing the total cost, while ensuring a given on-time delivery probability to each customer. Goel *et al.* (2019) added the factor of stochastic travel times to the model. All the previously cited research studied the SVRP without considering the environmental impact of the proposed solutions.

As shown in Table 4-1, not much attention was given to GVRPs with uncertainty and multi-objective models that can address the economic, environmental and customer satisfaction aspects at the same time. The multi-objective model by Tan *et al.* (2007) considered the SVRP with uncertain demand and minimized the travel distance, the driver wage and number of vehicles, all of which are considered economic aspects, ignoring the effect of the suggested routes on the environment, and ignoring customer satisfaction measures. Pishvaee *et al.* (2012) studied the Green Logistics Network Design (GLND) problem that aims at minimizing the environmental and economic impacts of the network under time and demand uncertainties. The GLND is a multi-echelon single product network that involves production, distribution, and customers and strategic decisions regarding locations, numbers, and capacities of required facilities in the logistics network as well as aggregate material flow between them. Cimen and Soysal (2017) proposed an approximate dynamic GVRP with stochastic vehicle speeds to obtain environmentally friendly solutions by changing the objective function from cost minimization to emission minimization. The model first determines the routes that minimizes emissions exclusively. Secondly, the fuel and wage cost are calculated to determine the routes that minimize the total expected travel cost, where wage cost is computed by each driver's working time and fuel cost estimation depends on vehicle type, vehicle speed, and travel distance. Then the results are evaluated by four key performance indicators: travelled distance, travel duration, emissions, and travel cost. These key performance indicators consider the economic and environmental impact of the results, where CO_2 emissions are estimated by assuming that each liter of fuel consumption generates 2:63 kg CO_2, while customer satisfaction measures are not considered.

One of the main goals of a Supply Chain (SC) is to maximize competitiveness in addition to maximizing profitability during both the production and distribution stages of the SC (Lambert at al., 1998). Accounting only for economic impacts as variable and fixed costs does not serve the main goal of the SC. In the past, manufacturers were considered the main drivers of the supply chain. They controlled the way at which products were manufactured and distributed. Today, customers are the main drivers, and manufacturers are competing to meet their demands by manufacturing products that are different in options, styles, features, quick order fulfillment, and fast delivery (Jain *et al.,* 2010). Best value supply chains are the chains most likely to prosper within this today's competition and are the ones that use strategic SCM in an effort to excel in terms of speed, quality, cost, and flexibility (Muysinaliyev and Aktamov, 2014). Therefore, considering customer satisfaction measures in distribution models is essential in supply chain management.

A literature survey on VRPs that considered customer satisfaction is presented in Table 4-2. The table shows how the VRP was modeled in previous studies and state the problem class of study. The table also shows whether environmental impacts, and customer satisfaction were taken into consideration, and states the problem environment whether it is deterministic or stochastic. In case of multi-objective models, the table shows if the objectives were optimized simultaneously or one of the objectives was converted into constraints.

Tang *et al.* (2009) studied the VRPTW to minimize costs and model customer satisfaction as a constraint in the model. Zhang *et al.* (2013 and 2016) and Goel *et al*. (2019), studied the stochastic VRPTW with the aim of minimizing costs at a minimum service level probability at each customer, ignoring environmental impact of the constructed routes.

Table 4-2: Summary of literature on VRPs with customer satisfaction

			Obj. Fn.		Objectives				Problem Feature	
Author	Year	Problem Class	Single	Multiple	Economic impact	Environment impact	Customer satisfaction	Objectives handled as constraints	Deterministic	Stochastic
Tang *et al.*	2009	VRPTW	●		●		●	Customer satisfaction	●	
Fan	2011	VRPSPD	●		●		●		●	
Zhang *et al.*	2013	VRPTW	●		●		●	Customer satisfaction		●
Yang *et al.*	2015	GVRP	●		●	●	●	Emission	●	
Barkaoui *et al.*	2015	Dynamic VRPTW	●		●		●		●	
Afshar-Bakeshloo *et al.*	2016	GVRP		●	●	●	●	Customer satisfaction	●	
Zhang *et al.*	2016	VRP	●		●		●	Customer satisfaction		●
Goel *et al.*	2019	VRPTW	●		●		●	Customer satisfaction		●

Several studies used a utility function approach to model the objective function in VRPs such as: Fan (2011), Barkaoui *et al*. (2015), and Yang *et al.* (2015). These studies solved the routing problem deterministically. Fan (2011) used a combined objective function to model the VRP with simultaneous Pickup and Delivery (VRPSPD) with customer satisfaction. Barkaoui *et al*. (2015) modeled a special variant of VRPTW, where customer requests are dynamically changing. The study dealt with services as diagnosis or detection problems not delivery or pickup of goods, where customers may require more than one visit to reach a satisfaction level. Yang *et al*. (2015) proposed a model that minimizes the total cost, minimizes carbon emission, and maximizes customer satisfaction using a weighted utility function for the objectives and imposing a limit on the carbon emissions as a constraint. Weighted linear utility functions works well when a convex Pareto front is expected between the objective functions which is not guaranteed when solving the multi-objective vehicle routing problem.

Afshar-Bakeshloo *et al.* (2016) studied a multi-objective GVRP that minimizes operational and environmental cost and maximizes customer satisfaction to solve a set of 10-customers network. The study represented the second objective within the model's constraints with a predetermined lower amount of service level, and by frequently optimizing the model at different amounts of service level, the Pareto front is derived. The study is deterministic and does not solve the three objectives simultaneously.

Based on the literature review conducted in the areas of VRPs with uncertainties (Table 4-1) and the VRP–with customer satisfaction (Table 4-2), the following comments are concluded:

1. Studying the stochastic VRP received attention in the last decade with more focus on the economic aspects associated with demand uncertainty and less attention to the environmental impact.
2. The SPR policy is the most common way to handle uncertainties in demand.
3. Few studies are conducted to examine the VRP with customer satisfaction under uncertainty.
4. Research on GVRP with customer satisfaction is limited to the deterministic study as in Yang *et al.* (2015) and Afshar-Bakeshloo *et al.* (2016).
5. Models that addressed the three objectives simultaneously handled one of the objectives as a constraint in the problem when constructing routes, where a minimum level of service is determined in case of measuring customer satisfaction (Afshar-Bakeshloo *et al.*, 2016) or a maximum level of emission is considered a constraint in case of lowering the environmental impact (Yang *et al.*, 2015). Both studies addressed the problem in a deterministic environment.
6. There is a lack of multi-objective models that considers the three objectives: economic, environmental, and social aspects with uncertainty.

This chapter proposes a stochastic multi-objective GVRP that handles economic, environmental, and social aspects simultaneously. Three different models are presented. The first model deals with uncertainties in travel and service time. The second and third models deal with uncertain times and demand, where CCP and SPR policies handle route failures, respectively. The models utilize the hybrid search algorithm developed in chapter

2. Pareto fronts between costs and customer satisfaction are obtained and trade-offs between the three objectives are presented. A numerical analysis is conducted to study the effect of relaxation of time windows on the total operational costs, environmental costs and customer satisfaction is examined.

4.3 Problem Description

4.3.1 Characteristics of the Problem

The stochastic multi-objective GVRP of study consists of $n+1$ points, n customers and a single depot. Distances ($d_{i,j}$) between each two points is known, although stochastic travel times between two locations are considered. The objective is to determine the set of routes to be performed by a homogeneous fleet of vehicles (m) to serve a given set of customers (n) with uncertain demands (q). Customer demands are independent and known only when the vehicle arrives at the customer. Each customer(i) is associated with a Time Window, TW $[\alpha_i,\ \beta_i]$ and an uncertain service time (s_i). α_i is the earliest time a customer can accept a service, while β_i is the latest time a customer can be serviced by vehicle k. The routes of the multi-objective GVRP are constructed to minimize the expected total travel costs, minimize the expected fuel consumption rate, and maximize the expected customer satisfaction where each route starts and ends at a single depot. Each customer must be assigned to only one vehicle and the total demand of all customers assigned to a vehicle does not exceed its capacity (Q). The number of vehicles (routes) to be used is not fixed but to be determined by the solution approach. In some studies, the number of vehicles is fixed, while others define a minimum possible number of vehicle routes (K_{min}). According to Uchoa *et al.* (2017), fixing the number of routes is an indirect way of minimizing the fixed cost associated with the cost per vehicle, ignoring the trade-off between variable and fixed costs associated with the suggested set of routes. Additionally, the original CVRP proposed by Dantzig and Ramser (1959) did not consider fixing the number of routes in the problem as it requires adding the cost of unused capacity to the model which in practice is of minor importance. According to the authors, minimization of the travel distance is independent of the number of vehicles used. In this problem, full-service policy is to be applied when servicing a customer for either pickup or delivery. Split deliveries are not allowed, where customer demand cannot be supplied with two vehicles nor split between two visits of the same vehicle. Splitting service policy is considered a relaxation policy of the full delivery policy (Dror, *et al.*, 1989). Table 4-3 summarizes the characteristics of the stochastic green vehicle routing problem of study.

Table 4-3: Problem Characteristics of the Stochastic GVRP

Element	Characteristic
Size of fleet	Unbounded
Type of fleet	Homogenous
Origin of vehicles	Single depot
Demand type	Stochastic Demand
Service and travel times	Stochastic
Location of demand	At the customer (node)
Maximum time on route	Constrained
Time windows	Soft Time windows
Demand Policy	1. Chance Constrained Programing (CCP) 2. Stochastic Program with Recourse (SPR)
Objectives	1. Minimize Total Travel Cost, 2. Minimize Fuel Consumption Rate, 3. Maximize Customer satisfaction.
Constraints	1. Single visit at customers, 2. Routes start and end at depot, 3. Nodes served by single vehicle, 4. Vehicle capacity cannot be exceeded, 5. No split deliveries.

4.3.2 Mathematical Modeling

The VRP problem is a generalization of the Travelling Salesman Problem (TSP) that introduces more than one salesman (*m*); hence, *m* number of tours can be done; each starting and ending at the depot. For formulating the stochastic GVRP, the starting customer is considered node 1 (depot); where $X_i$represents the current visited node and Y_i represents the next node to be visited, where *i* varies from 1 to *n*, and n is the number of nodes to be visited by a given vehicle *k*. Now, *m* routes are introduced to the model; where, distance d_{X_i,Y_j} is associated with each arc and represents the distance travelled from node X_i^k to node Y_j^k on route *k*, as shown in Figure 4-1.

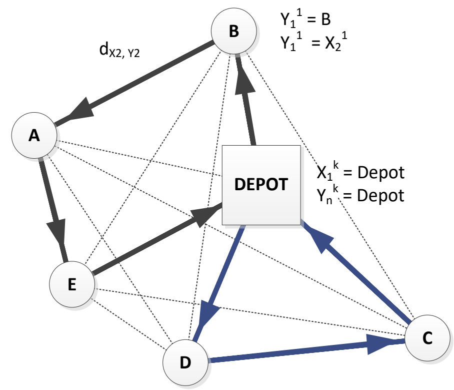


Figure 4-1: Illustration of the VRP [Elgharably *et al.*, 2013]

The decision variable is Y_i^k; where, Y_i^k determines the value of the next customer *i* to be visited on route *k*. The X_i^k variable represents the value of the start node of the arc on route *k*. The use of loop segments is not allowed (leaving a node then arriving to same node, $X_i^k \neq Y_j^k$), as all nodes must be visited exactly once. The binary variable S_{X_i,Y_j}^k represents all possible arcs connecting any two nodes on route *k*. S_{X_i,Y_j}^k is given a value of 1 if arc (X_i^k, Y_j^k) belongs to route *k*; 0 otherwise. Both X_i^k and S_{X_i,Y_j}^k are considered uncontrollable variables. The problem is formulated as follows:

$$\begin{aligned} Minimize\ f_1 = & \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} E(\, S_{X_i,Y_j}^k * d_{X_i,Y_j} * C_t) + \sum_{k=1}^{m} E\left(F * S_{1,Y_j}^k\right) \\ & + \sum_{i=1}^{n} E\left(C_e * \left(\alpha_i - t_{Y_i}\right)\right) \\ & + \sum_{k=1}^{m} E\left(C_d * \left(t_1^k - \beta_1\right)\right) \end{aligned} \tag{1}$$

$$Minimize\ f_2 = \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} E\ [C_{fuel} * S_{X_i,Y_j}^k * d_{X_i,Y_j}(p_o + \gamma * W_{X_i,Y_j})] \tag{2}$$

$$Maximize\ f_3 = \sum_{i=1}^{n} E(SV_i) \tag{3}$$

Subject to

$$X_1^k = 1 \quad \forall k = 1, \dots, m \tag{4}$$

$$Y_n^k = 1 \quad \forall k = 1, \dots, m \tag{5}$$

$$X_i^k = Y_{i-1}^k \quad \forall\, i = 2, \dots, n, \ \forall k = 1, \dots, m \tag{6}$$

$$X_i^k \le n \qquad \forall k = 1, \dots, m \tag{7}$$

$$Y_i^k \le n \qquad \forall k = 1, \dots, m \tag{8}$$

$$\sum_{j=1}^{n} \sum_{k=1}^{m} S_{X_i,Y_j}^k = 1 \quad \forall\, i = 2, \dots, n \tag{9}$$

$$\sum_{i=1}^{n} \sum_{k=1}^{m} S_{X_i,Y_j}^k = 1 \quad \forall\, j = 1, \dots, n-1 \tag{10}$$

$$\sum_{j=1}^{n} \sum_{i=1}^{n} S_{X_i,Y_j}^k * E(q_{Y_j}) \le Q_k \quad \forall k = 1, \dots, m \tag{11}$$

$$\sum_{j=1}^{n} \sum_{i=1}^{n} S_{X_i,Y_j}^k * E\ (t_{Y_j}) \ge \alpha_j \quad \forall\ k = 1, \dots, m \tag{12}$$

$$\sum_{j=1}^{n} \sum_{i=1}^{n} S_{X_i,Y_j}^k * E\ (t_{Y_j}) \le \beta_j \quad \forall\ k = 1, \dots, m \tag{13}$$

$$X_i^k, Y_j^k > 0 \text{ and integer} \tag{14}$$

The expected total transportation operations cost function is minimized in the objective function (1). The first term in the objective function calculates the expected total travel cost calculated from the expected travel time on all k routes; where, m is the number of routes, $E\ (t_{X_i,Y_j})$ is the expected time spent travelling from $X_i^k to\ Y_j^k$, C_t cost per unit time. The second term represents the fixed cost of operating each vehicle, where F is the vehicle operating cost. Due to the presence of time windows, an extra cost is calculated to reflect cases where vehicles arrive early inducing working waiting cost at customers as in the third term of equation (1) and waiting cost at depot (fourth term in equation (1)) reflecting cases of late vehicle arrival at the depot. C_e is the customer's cost of early arrival, while C_d is the cost of delay (late arrival at the depot). The second objective function (2) minimizes the expected cost of fuel consumption. The Fuel Consumption Rate (FCR) proposed by Xiao *et al*. (2012) is applied; where, C_{fuel} is the unit fuel cost, d_{X_i,Y_j} is the distance travelled between two nodes, p_o no load fuel consumption rate, α the coefficient obtained by linear regression between fuel consumption rate and the vehicle's load, ($\gamma = \frac{(p^* - p_o)}{Q}$) where p^* is the full load fuel consumption rate and W_{X_i,Y_j}^K is the gross weight of the vehicle on a route. The third objective function (3) maximizes the expected customer satisfaction. The expected customer Satisfaction Value (E(SV_i)) measures the deviation from TW for each customer, while all customer demands are fulfilled. Constraints (4) and (5) ensure that each route starts and ends at the depot. Constraint (6) ensures that each route of the k routes is not segmented; that is, if a vehicle arrives at a customer, it eventually leaves the customer again. Constraints (7) and (8) state the range of values given, whereas constraints (9) and (10) state that every customer is visited exactly once. Knowing that at each customer, an expected customers' demand $(E(q_{Y_j}))$ is present with a known distribution and that each vehicle has a limited capacity Q_k; constraint (11) ensures that the expected total demand of all customers assigned to a route k does not exceed the vehicle's capacity. Constraints as (12) and (13), represent the time window constraints, where each customer i has a time window $[\alpha_i, \beta_i]$. α_i is the earliest time a customer can accept a service, while β_i is the latest time a customer can be serviced by vehicle k. The expected time of travel to the next customer is $E(t_{Y_j})$. Finally, constraint (14) is the non-negativity constraint and guarantees that the variables can assume integer values only. The expected cost of the routes constructed is dependent on the direction in which the route is travelled, and the type of service performed, whether pickup or delivery.

4.4 Hybrid Multi-Objective Optimization Model

Multi-objective optimization involves several competing objectives that cannot be combined, making it hard for decision-makers since no single decision can be considered an optimum solution to solve the problem. However, there is a set of alternative solutions that are considered optimal known as the Pareto-optimal solutions. This solution set considers all objectives and provides the decision-maker with the trade-offs between objectives, making it easier for decision makers to choose from based on their own preference and considerations (Zitzler and Thiele, 1998, and 1999).

The hybrid multi-objective optimization model presented in this chapter combines both the Strength Pareto Evolutionary Algorithm (SPEA) developed by Zitzler and Thiele (1999) with the resultant local search heuristic developed earlier in chapter 2. The new hybrid solution approach successfully solves the deterministic multi-objective GVRP model developed in Chapter 3.

4.4.1 Resultant Local Search Heuristic (RLSH)

The resultant local search heuristic computes a heuristic resultant based on both the distance traveled calculated from the nodes/customers' location and the demand associated with the given node/customer. In the implemented local search method, a heuristic resultant for each customer is used as follows:

$$HR_i = \alpha\, d_i + (1-\alpha)\, DR_i \tag{15}$$

where HR_i = Heuristic Resultant for customer i, α and (1 – α) = weights of the distance and demand (used to achieve diversity and not to be caught in local optimum), d_i = Euclidian distance to be travelled from the current node to the expected following node by customer i, and DR_i = demand remainder for customer i, which is the difference between the vehicle’s capacity and the demand *(i)*, where demand *(i)* is the quantity of items to be delivered or picked up by the vehicle at the customer (i). For example, at the beginning of constructing the route, the current location would be the depot, while in the middle of the route the current location would be the last visited node/customer. The function identifies the nearest route (heuristic) based on the resultant heuristic function between the remainder of each node's demand compared to the vehicle capacity and the distance from the current location to the following node. A detailed illustration of the RLSH process is presented in Chapter 2.

4.4.2 Strength Pareto Evolutionary Algorithm (SPEA)

Evolutionary Algorithms (EA) are believed to be one of the best approaches to solve multi-objective optimization problems because solution sets are processed in parallel and simultaneously utilize the similarity of the solutions by recombination (Zitzler and Thiele, 1998, 1999). The Strength Pareto Evolutionary Algorithm (SPEA) developed by Zitzler and Thiele (1999) is used for finding the Pareto-optimal set for multi-objective optimization problems. Similar to other EAs, the SPEA stores the nondominated solutions externally. It also uses the concept of Pareto dominance to evaluate fitness values and performs clustering to reduce nondominated solutions without affecting the trade-off front. In addition, SPEA is unique as it evaluates the fitness of an individual from the external nondominated set. All solutions of the nondominated set participate in selection and a

Pareto-based niching method is used to preserve diversity in the population (Zitzler and Thiele, 1999).

4.4.3 Initial Population and Operators

A portion of the initial population is filled heuristically using the local search heuristic developed, while the remaining portion is filled randomly to achieve diversity and not to be caught in a local optimum. The random portion of the initial population is based only on the vehicle capacity ignoring any distance calculations. A set of operators are then performed to the initial population to mimic the nature of evolution.

To achieve diversity and at the same time to widen the span of the search space, a set of one deterministic and four random mutation operators is applied.

1. A deterministic Route Reduction Mutation (RRM) is performed that decreases the number of routes in a solution without violating any constraints. The RRM aims to lower the number of vehicles considering only capacity and demand calculations.
2. Random Node Exchange Mutation (RNEM) is a mutation operator that exchanges nodes from randomly selected routes without violating any capacity constraints.
3. Random Node Transfer Mutation (RNTM) is a mutation operator that transfers a randomly selected node from one route to another, where routes are adjusted using the developed Resultant Heuristic with no capacity violation.
4. Random Arc Exchange Mutation (RAEM) follows the same approach as the RNEM operator; however, arcs are exchanged instead of nodes.
5. Random Arc Transfer Mutation (RATM) follows the same approach as the RNTM operator; however, arcs are transferred instead of nodes.

Two crossover operators are performed. One crossover operator is performed in a random way, while the other is deterministic that inherits good characteristics from parents.

1. The Heuristic Inheritance Crossover (HIC) is a deterministic crossover operator that perform changes to the routes within a given solution inheriting good routes

without violating any constraints. The HIC is used for intensification of good solutions in the breeding generation rather than diversification.

2. Random Inheritance Crossover (RIC) follows the same process as the HIC operator, the only difference is that the routes to be inherited from parent 1 are chosen at random not based on good routes. The RIC operator acts as a diversification operator.

A detailed description of the operators mentioned above, their procedures and figures are presented in Chapter 2, Section 2.4.

4.4.4 Objective Functions

The stochastic multi-objective GVRP model represented in this study deals with three different objectives. The economic aspect can be reflected as minimizing the expected total transportation operations cost function as in Equation (1). While the environmental aspect is measured in terms of minimizing the expected fuel consumption as shown in Equation (2). Finally, maximizing the expected customer satisfaction, Equation (3), reflects the social aspect which is one of the main performance measures of the supply chain.

4.4.4.1 Customer Satisfaction

The expected customer Satisfaction Value *($E(SV_i)$)* is calculated as the time deviation between the actual time of service and the customer's time window $[\alpha_i, \beta_i]$, while all customer demands are fulfilled. As mentioned earlier, α_i is the earliest time a customer can accept a service, while β_i is the latest time a customer can be serviced by the vehicle.

Several types of time windows have been addressed in the literature. A traditional VRPTW would deal with customers' time windows as a hard TW in which delivery service must fall within the customer's specified TW. However, in real world transportation, TW may be violated for practical reasons as discussed by Tang *et al*. (2009) such as:

1. Relaxing the TW constraint can result in better solution when considering the number of vehicles used, time and cost.
2. Feasible solutions are hard to find if all TW has to be satisfied. Thus, a relaxed TW would result in an executable route plan.

3. It is a fact that customers provide narrow TW while a little deviation would be considered acceptable to them.

However, soft time windows accept violations of the customer's specified TW with a penalty cost added once violation occurs. In soft TW, penalty costs are assumed to be linear with the degree of violation (Tang *et al.*, 2009). Tas *et al.* (2014) introduced the VRP with flexible TW, where vehicles are given a certain tolerance in which TW can be deviated.

In the multi-objective GVRP with customer satisfaction model introduced in this chapter, Soft TW are used. If the vehicle arrives after the latest time a customer can accept the service, the customer is then unsatisfied. A satisfaction value will be calculated as shown in Equation (16), which is the time difference between the vehicle's arrival time and the upper bound (β_i) of the time window.

$$SV_i = \beta_i - t_{Y_i} \qquad \forall\, i = 2, \dots, n, \tag{16}$$

Customer Satisfaction Value *(SV_i)* is a variable which can be either zero or a negative integer, where the maximum value zero would reflect complete satisfaction. However, if the vehicle arrives early at the customer, the vehicle will wait till the earliest time a customer can accept the service (α_i). This will incur an extra cost due to the increase of the travel time on the route that shall be reflected in the travel cost function. Finally, the expected number of satisfied customers is measured, which in this case is the number of customers who received their service within the specified time window.

4.4.4.2 Total Cost Function

The expected total transportation operations cost function in equation (1), in Section 4.3.2, consists of the expected variable travel costs, expected vehicle fixed costs, expected waiting cost at customer and at depot. The second objective function presented in equation (2) minimizes the expected cost of fuel consumption. These two objectives can be combined in the model as a minimization cost function (17) that aims to minimize the expected travel costs and minimize the expected environmental impact by reducing fuel consumption measured in terms of fuel consumption cost as shown in the modified objective function (18).

$$Minimize\ Z_1 = f_1 + f_2 \tag{17}$$

Then the total cost objective function is adjusted to:

$$\begin{aligned} Minimize\ Z_1 = & \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} E(S^k_{X_i,Y_j} * d_{X_i,Y_j} * C_t) + \sum_{k=1}^{m} E\left(F * S^k_{1,Y_j}\right) \\ & + \sum_{i=1}^{n} E\left(C_e * \left(\alpha_i - t_{Y_i}\right)\right) \\ & + \sum_{k=1}^{m} E\left(C_d * \left(t^k_1 - \beta_1\right)\right) \\ & + \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} E\,[C_{fuel} * S^k_{X_i,Y_j} * d_{X_i,Y_j}(p_o + \gamma * W_{X_i,Y_j})] \end{aligned} \tag{18}$$

The developed multi-objective model solves the conventional VRP with time windows in green environment and considers customer satisfaction under uncertainty. The model is developed in a way which it can handle either delivery or pickup services. The type of service to be done (pickup/delivery) is considered as an input to the model as fuel consumption calculations differ in each case while constructing the routes. Fuel consumption rate calculation depends on both the vehicle load and the distance travelled. For this reason, the type of service has to be determined upfront before running the model.

4.4.5 Dataset generation

Two data sets are used to study the proposed multi-objective model: Solomon's VRPTW benchmark data set (1987) and Uchoa *et al.* (2017) VRP benchmark data set.

Solomon's VRPTW benchmark problems are known to compare computational performance of many algorithms. The problems can be found at: http://web.cba.neu.edu/~msolomon/problems.htm. The larger problems are 100-customer Euclidean problems where travel times are equal to the corresponding distances. For each problem, smaller problems have been created by considering only the first 25 or 50 customers (Solomon,1987, and Fisher *et al.*, 1997). The problem consists of 100 customers and a depot, each with a defined X, Y co-ordinates, service time, demand, and time windows. A homogeneous fleet of vehicles with a capacity of 200 is used. The depot has a zero-service time as it is not considered a real customer with a zero demand and a time window of [0, 230]. This time window is considered the time horizon required for all routes to be fulfilled. The R101 and R102 dataset inputs are presented in Appendix C and Appendix D, respectively.

Table 4-4: Problem sets characteristics

Problem Set	Distance and Demands		Time Windows		Overlap Index	Vehicle Capacity (*Q*)	Number of customers
	Instance	Reference	Instance	Reference			
Problem 1	X-n101-k25	Uchoa *et al.*, 2017	R101	Solomon, 1987	62.82	206	100
Problem 2	R101	Solomon, 1987	R101	Solomon, 1987	62.82	200	100
Problem 3	R102	Solomon, 1987	R102	Solomon, 1987	37.98	200	100
Problem 4	X-n101-k25	Uchoa *et al.*, 2017	R102	Solomon, 1987	37.98	206	100

Uchoa *et al.* (2017) proposed a new benchmark dataset that provides a more comprehensive and balanced experimental setting to the classic CVRP. Problem instance: X-n101-k25 is taken from Uchoa *et al.* (2017) new benchmark instances (Appendix B) consisting of a depot and 100 customers. The number of vehicles to be used is not fixed but the minimum feasible number of vehicles is known (K_{min} = 25). The vehicle capacity is 206 units. The depot and customer positioning of the X-n101-k25 instance is random.

Euclidean distances are calculated for both benchmark sets from the given X and Y co-ordinates, where travel times are equal to the corresponding distances. Table 4-4 shows the four problem sets used to experiment on the stochastic multi-objective GVRP model developed in this chapter. Sets 1 and 4 are a combination of Uchoa *et al.* (2017) and Solomon (1987) benchmark datasets. The TW of Solomon's R101 and R102 are used with the X-n101-k25 instance from Uchoa *et al.*, (2017) to produce two new problem sets: problem 1 and problem 4, respectively.

For Solomon's R101 and R102 problems, the customer co-ordinates are identical for all problems within R type dataset. The problems differ with respect to the width of the time windows. Some have very tight time windows, while others have time windows which are hardly constraining [Solomon, 1987]. Thus, the overlap index is developed to measure how tight the time windows are associated with the customers. The index value is calculated as follows:

$$Overlap\ Index = \frac{\sum_{i=2}^{n}\sum_{j=2}^{m}(\beta_i - \alpha_i) \cap (\beta_j - \alpha_j)}{n-1} \tag{19}$$

The higher the index, the tighter are the time windows, resulting in more constraining set to achieve customer satisfaction.

4.4.6 Parameter Initialization

The evolutionary model parameters used are shown in Table 4-5. The selection of the number of times each operator is applied is based on the study performed in Chapter 2 (Section 2.5.3). The study explored different configuration settings. All data sets operate from a central depot and routes are constructed using a set of homogenous fleet of vehicles with a limited capacity (Q) to serve a delivery service to a given set of customers. The cost coefficients (C_t , F, C_f, C_e, C_d) are set to (2, 1000, 4, 0.5, 1). The fuel consumption coefficients (p_0, p^*) are set to (1, 2) as in Xiao *et al*. (2012). Using the EA parameters defined in Table 4-5, and a maximum number of generations of 4000, the problem is solved using MATLAB.

Table 4-5: Configuration of Evolutionary Operators

Operator	Name	Description	Occurrence
Mutation	RRM	Route Reduction Mutation	6
	RNEM	Random Node Exchange Mutation	10
	RNTM	Random Node Transfer Mutation	10
	RAEM	Random Arc Exchange Mutation	10
	RATM	Random Arc Transfer Mutation	10
Crossover	HIC	Heuristic Inheritance Cross over	2
	RIC	Random Inheritance Cross over	2

4.5 Multi-objective GVRP with stochastic service and travel times

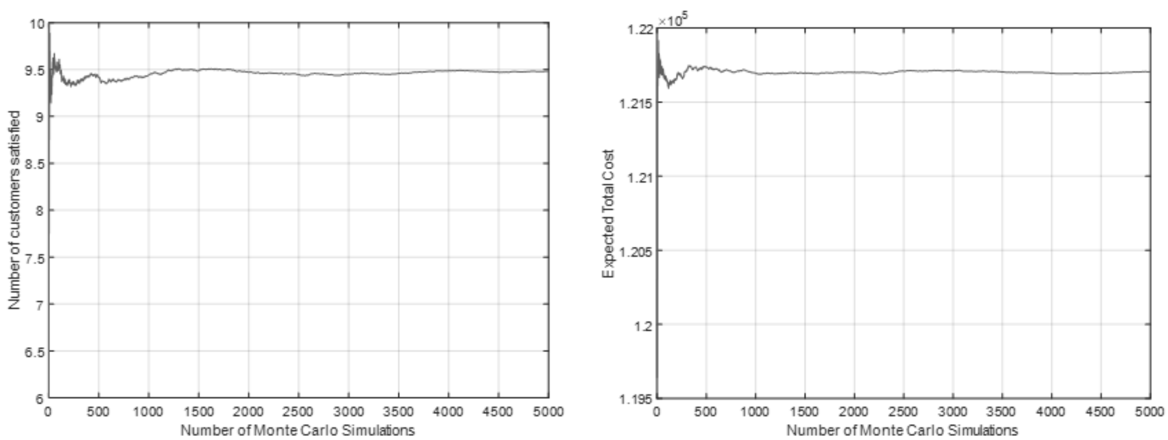
In this model, the demand is assumed to be deterministic. The only source of uncertainty introduced to the model is the variations in travel times between two customers and the service time needed to deliver the service. As demand is assumed to be deterministic, all customers' demands will be fulfilled with no probability of failure for the set of routes proposed.

Table 4-6: Distributions of travel and service times

Source of variability	Distribution	Distribution parameters
Service Time	Normal Distribution	Mean= Deterministic Time COV=0.1
Travel Time	Normal Distribution	Mean= Deterministic Time COV=0.1

Table 4-6 shows the distributions of travel time and service time used in the stochastic GVRP model. The distributions are chosen based on the comprehensive survey by Oyola *et al.* (2018) on the stochastic VRP that shows that the most common way of modeling uncertainties in service time and travel times is the normal distribution.

4.5.1 Model parameters



a. Simulation of the number of satisfied customers

b. Simulation of the expected total cost

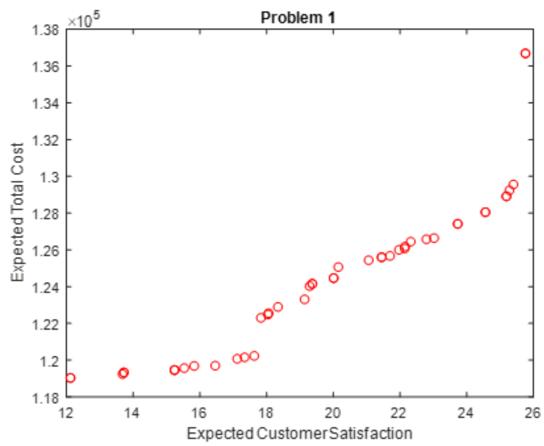
Figure 4-2: Monte Carlo Simulations

Monte Carlo simulation is used to simulate the variability in the travel time, service time and demands. Experimental runs are performed to determine the ideal number of Monte

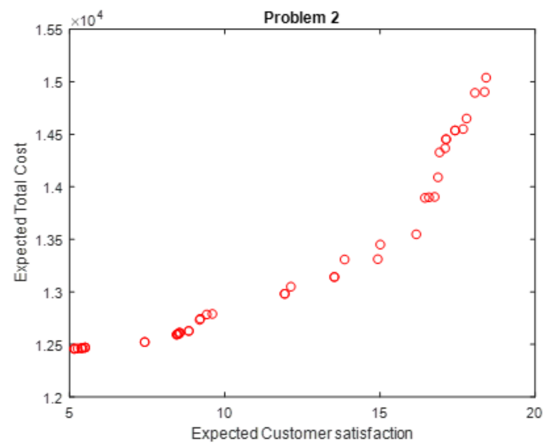
Carlo simulations so that the model reaches a stable solution. Figure 4-2 shows the number of simulations needed to reach a stable solution.

4.5.2 Results of multi-objective GVRP with uncertain travel and service times

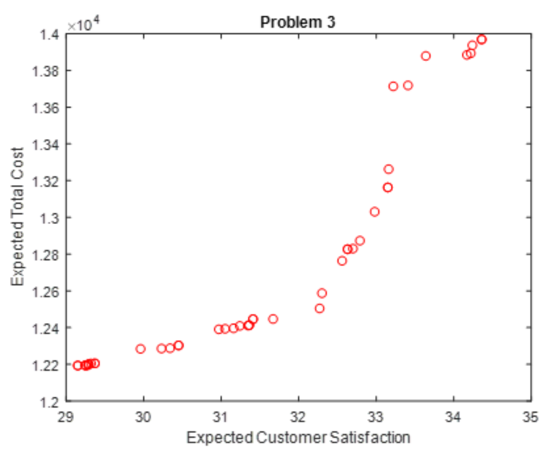
Computational experiments on the four problem data sets (Table 4-4) are performed. Using the EA parameters defined in Table 4-5, a maximum number of generations of 4000, and the number of Monte Carlo simulations of 1000, the problem is coded in MATLAB and solved for a delivery service.



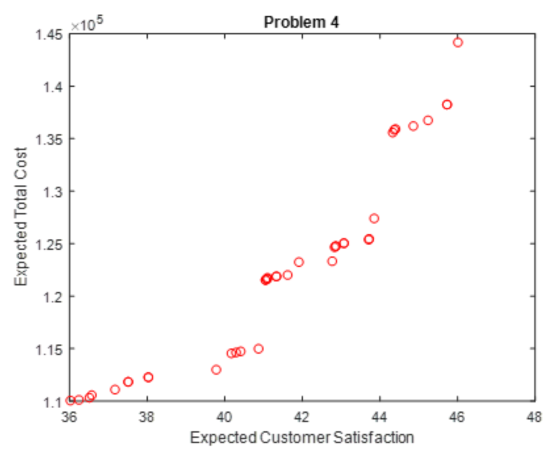
a. Pareto Front of Problem 1



b. Pareto Front of Problem 2



c. Pareto Front of Problem 3



d. Pareto Front of Problem 4

Figure 4-3: Pareto fronts of stochastic GVRP with uncertain times

Pareto fronts are obtained and presented in Figure 4-3. In case of stochastic service times and travel times, note the difference in Pareto fronts of problems 1 and 2. Even though both use the same time windows of instance R101 by Solomon (1987) but the expected number of customers to be fully satisfied in problem 1 is more than the expected number of customers to be fully satisfied in problem 2 due to the difference in the locations of customers in each data set.

Similarly, for problems 3 and 4, the expected number of customers to be fully satisfied in problem 4 is more than the expected number of customers to be fully satisfied in problem 3. This is because the grid/scale for problems 1 and 4 is larger than that of problem 2 and 3. Furthermore, the number of satisfied customers in problems 1 and 2 is less than that of problems 3 and 4. The reason for that is the tighter time windows of problems 1 and 2 (higher overlap index) as shown in Table 4-4.

Table 4-7: Results of the Multi-objective stochastic GNRP with uncertain times

	Problem Set	Number of Routes	Expected Customer Satisfaction	Expected Total cost	Expected Variable Cost	Expected Fixed Cost	Expected Cost of Fuel consumption	Expected Extra Cost
Minimum Total Cost	Problem 1	26	12	119150	31394	26000	45654	16107
	Problem 2	8	5	12480	1067.7	8000	1431.6	1981
	Problem 3	8	29	12214	1152.8	8000	1582.9	1478
	Problem 4	24	36	110400	30225	24000	45171	11003
Compromise case	Problem 1	26	19	124420	34025	26000	49883	14511
	Problem 2	8	14	13302	1372.5	8000	1876.8	2052.4
	Problem 3	8	32	12762	1341.6	8000	1868.2	1551.9
	Problem 4	27	41	122320	34452	27000	49640	11227
Maximum satisfaction	Problem 1	27	25	136710	38278	27000	55533	15903
	Problem 2	8	18	15048	1790.2	8000	2488.5	2769.2
	Problem 3	8	34	13969	1586.9	8000	2256.5	2125.4
	Problem 4	29	45	144220	42482	29000	59736	13006

As shown in Table 4-7, the customer satisfaction for problems 1 and 2 is always lower than problems 3 and 4. The reason for that is the presence of time windows with different levels of tightness. For both problems 1 and 2 (overlap index= 62.82), the time windows are tighter than that given for problems 3 and 4 (overlap index= 37.98). In addition, extra costs for problems 2 and 3 are lower than that for problems 1 and 4. This is due to the difference in the locations and the larger grid of problems 1 and 4. Expected extra incurred costs are due to either early arrival at customer or late arrival at depot.

4.6 Multi-objective GVRP with stochastic service time, travel time, and customer demands

In this model, the uncertainty in demand is added to the uncertainties of travel and service times handled in the previous model discussed in Section 4.5. Uncertainty in demands means that the deterministic customer demands are unknown and only demands with known distributions are known. The actual demands are revealed only when the vehicle reaches the customer (Zhang *et al.*, 2016). In real life situation, demand distribution is calculated from historical data to assume the anticipated customer demand. The forecast for future demand depends on both the application of the problem and the type of customer. Modeling demand uncertainties is important to capture the variability in customers' demand. Ignoring such variability may result in vehicle routes that are less utilized or overloaded with demands, resulting in more costs and less satisfaction.

There is a difference between the deterministic VRP and the VRP with stochastic demand, in the SVRP, the decision-maker has to interfere at least partially with the solution before the exact values are revealed. The decision-maker has complete information when planning routes in the deterministic problem. However, in the stochastic VRP there is a probability of route failure and violation of constraints (Oyola *et al.*, 2018). Route failure occurs when the demand of customers on a route exceeds the capacity of the vehicle.

In literature, two ways of modeling the route failure in VRPs with stochastic demands are known: Chance Constrained Program (CCP), and Stochastic Program with Recourse (SPR). In the CCP, route failure is accepted with a probability of failure and no corrective action is taken to satisfy customer demands. While in SPR, a corrective action is considered to account for the failure of routes (Gendreau *et al.*, 1996; and Oyola *et al.*, 2018).

4.6.1 Model parameters

The distributions of travel time, service time, and demands used in the model are shown in Table 4-8. A literature review paper on stochastic VRPs by Oyola *et al.* (2018) presented a summary on the research papers dealing with stochastic demands. It was found that most studies used normal distribution in modeling continuous demand. While in case of modeling discrete demands, Poisson and uniform distributions are the most common distributions.

Table 4-8: Distributions of travel time, service times, and demands

Source of variability	Distribution	Distribution parameters
Service Time	Normal Distribution	Mean= Deterministic Time COV=0.1
Travel Time	Normal Distribution	Mean= Deterministic Time COV=0.1
Demand	a. Discrete: Poisson	Lambda= Deterministic Demand
	b. Continuous: Normal	Mean= Deterministic Demand COV=0.25

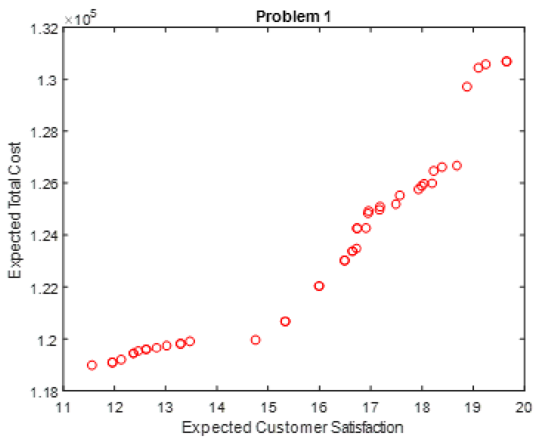
4.6.2 Chance Constrained Stochastic Multi-Objective Green Vehicle Routing Problem

One approach to deal with demand uncertainty is the chance constrained programming of the VRP. A CCP model's objective is to design a set of routes with minimum costs with an acceptable level of route failure. No corrective action is done to account for route failures and costs of those failures are ignored (Tan *et al*., 2007). The chance constrained stochastic multi-objective GVRP model presented in this section deals with demand uncertainties where no course of action is taken in case of shortage or excess of quantities compared to the customer's required demand.

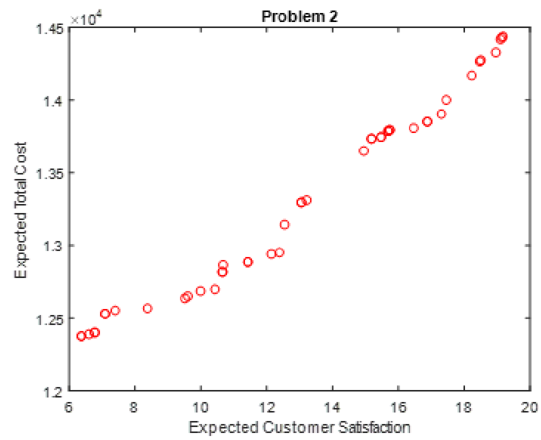
A change in the customer satisfaction objective function is performed as two aspects of customer satisfaction criteria are considered in chance-constrained programing presented in this study: (1) fulfillment of demand, and (2) time window satisfaction. The first aspect that measures the fulfillment of demand checks for whether the customer demand is fulfilled or not, while the second aspect measures the deviation from TW at the customer in case of being serviced. The expected number of satisfied customers is then calculated. Those are the customers who received their demand and at the same time were serviced within the specified time window. The total cost objective function remains unchanged. In the CCP, the route is terminated in case of failure (demand exceeds capacity) then the vehicle returns to the depot and no corrective action occurs.

4.6.2.1 Results of the stochastic GVRP with CCP

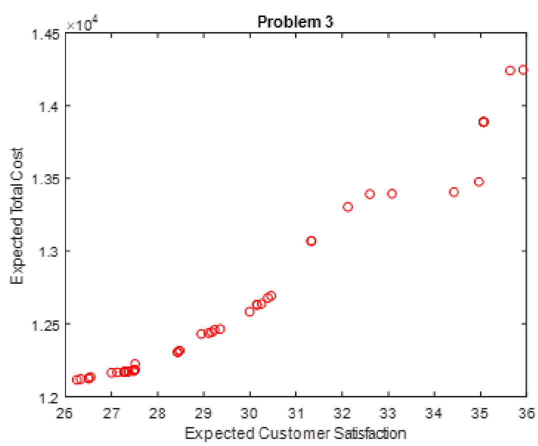
The demand distributions are assumed to be continuous and Pareto fronts of the four problem sets are obtained as shown in Figure 4-4.



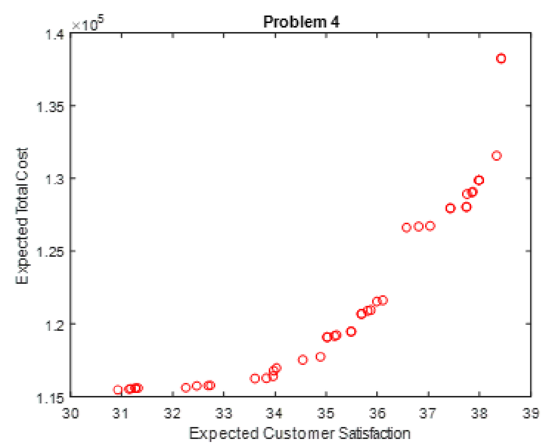
a. Pareto Front of Problem 1



b. Pareto Front of Problem 2



c. Pareto Front of Problem 3



d. Pareto Front of Problem 4

Figure 4-4: Pareto fronts of the CCP-GVRP with Normally distributed demands

A second set of runs of the chance constrained multi-objective GVRP is performed assuming discrete demands (Figure 4-5). The results of both the normally distributed and the Poisson distributed demands for the CCP-GVRP models are shown in Table 4-9 and Table 4-10.

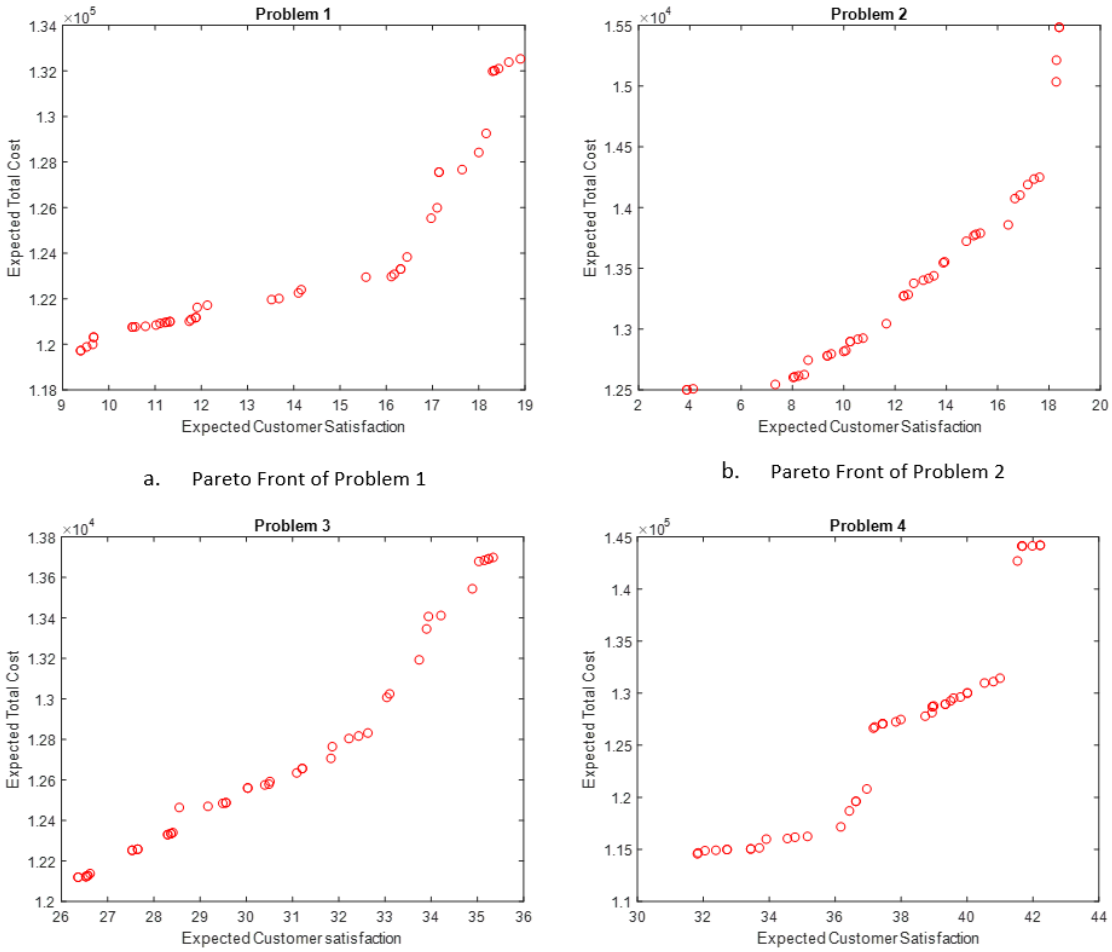
Table 4-9: Results of the CCP-GVRP with Normally distributed demands

	Problem Set	Number of Routes	Expected Customer Satisfaction	Expected Total cost	Expected Variable Cost	Expected Fixed Cost	Expected Cost of Fuel consumption	Expected Extra Cost
Minimum Total Cost	Problem 1	25	12	119290	31123	25000	48406	14758
	Problem 2	8	6	12398	1076.1	8000	1527.8	1794.3
	Problem 3	8	26	12141	1077.2	8000	1529.1	1534.2
	Problem 4	25	31	115820	30831	25000	47434	12554
Compromise case	Problem 1	25	16	123290	32662	25000	50829	14795
	Problem 2	8	13	13321	1411.9	8000	2029.4	1880.1
	Problem 3	8	30	12644	1325	8000	1854.1	1465.4
	Problem 4	25	35	121790	34394	25000	53109	9291
Maximum satisfaction	Problem 1	25	12	119290	31123	25000	48406	14758
	Problem 2	8	6	12398	1076.1	8000	1527.8	1794.3
	Problem 3	8	26	12141	1077.2	8000	1529.1	1534.2
	Problem 4	25	31	115820	30831	25000	47434	12554

Table 4-10: Results of the CCP-GVRP with Poisson distributed demands

	Problem Set	Number of Routes	Expected Customer Satisfaction	Expected Total cost	Expected Variable Cost	Expected Fixed Cost	Expected Cost of Fuel consumption	Expected Extra Cost
Minimum Total Cost	Problem 1	25	8.69	120440	31305	25000	48522	15610
	Problem 2	8	3.72	12516	1079.4	8000	1467.8	1968.6
	Problem 3	8	26.3	12135	1073.2	8000	1524.1	1538.1
	Problem 4	25	31.4	115110	30579	25000	47767	11763
Compromise case	Problem 1	26	16.32	124220	33219	26000	50594	14407
	Problem 2	8	13.13	13445	1436.1	8000	2014.1	1995.1
	Problem 3	8	31.4	12708	1336.8	8000	1918.8	1452.1
	Problem 4	28	35.67	127360	35324	28000	53755	10282
Maximum satisfaction	Problem 1	26	17.63	133030	36701	26000	56073	14260
	Problem 2	8	17.27	15511	1946.9	8000	2679.7	2884.7
	Problem 3	8	34.72	13708	1573.8	8000	2253.1	1881
	Problem 4	26	40.67	145530	43022	26000	64442	12065

In Figure 4-4 and Figure 4-5, the trade-offs between the expected total costs and the customer satisfaction measure are demonstrated. Moreover, the effect of different customers' locations is present. When comparing the results of problem 1 with the results of problem 2, even though they have the same TW, but due to the difference in the locations and grid scale, the expected total costs are higher for problem 1. Similarly for comparing problem 3 with 4. The effect of TW overlapping is clearly present when comparing problems 1 and 2 with problems 3 and 4, as the tighter is the TW, the less expected satisfaction is achieved, and more is the total expected costs.



a. Pareto Front of Problem 1

b. Pareto Front of Problem 2

c. Pareto Front of Problem 3

d. Pareto Front of Problem 4

Figure 4-5: Pareto fronts of the CCP-GVRP with Poisson distributed demands

4.6.3 Recourse Stochastic Multi-Objective Green Vehicle Routing Problem with stochastic Demands

In contrast, SPR routing problem considers a corrective action in modeling demand uncertainty. Three common recourse policies are used in the literature:

1. Simple recourse policy is known as Detour to Depot (DTD), in which the vehicle returns to the depot in case of route failure to restock or unload,
2. Preventive restocking of vehicle capacity can be done before a route failure,

3. The remaining portion of the route is optimized after each customer visit or after each failure where a decision is taken after each stop (Tan *et al*., 2007; and Oyola *et al*., 2018).

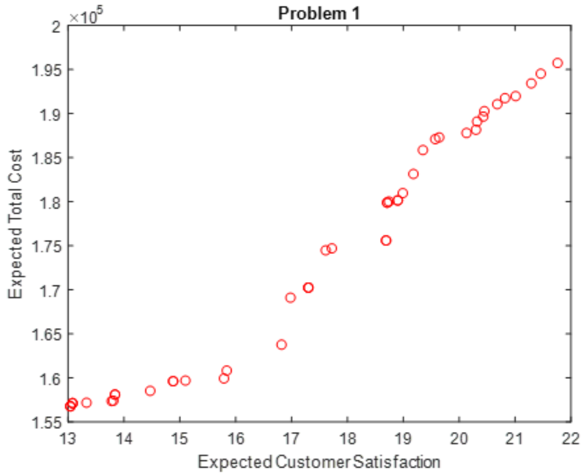
VRPs with recourse policy are modeled as a two-stage solution. In stage one, the vehicle routes are planned in advance, while stage two takes place when a recourse action is implemented to account for route failures (Juan *et al.*, 2011). In stochastic programming with Recourse (SPR), the goal is to determine a first stage solution that minimizes the expected cost of the second stage solution: this cost is made up of the cost of the first stage solution, plus the expected net cost of recourse. SPRs are typically more difficult to solve than CCPs, but their objective function is more meaningful (Gendreau *et al.*, 1996).

The model presented in this section considers a multi-objective stochastic GVRP with recourse policy to handle any route failures. The model takes into consideration the operational cost, environmental impact, and customer satisfaction simultaneously. The detour to depot recourse policy is adapted in the model. The recourse model is adjusted to consider extreme cases of demand due to uncertainty. In deterministic modeling, customer demands are known in advance and are known to not exceed the capacity of the vehicle. However, in stochastic modeling, an extreme case of demand might occur, where the demand could exceed the vehicle capacity. Only at that case, split services are considered where the vehicle would detour to depot and return to the same customer to fulfill the required demand.

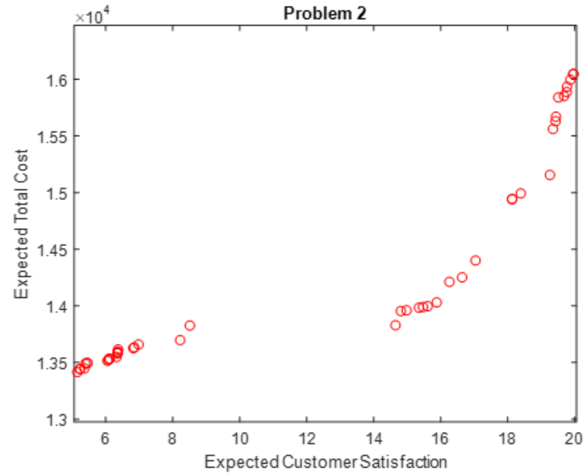
4.6.3.1 Objective Functions

The goal of the SVRP with recourse programming is to generate a set of routes that minimizes the expected costs of both the cost of constructing the routes (stage 1) and costs incurred due to recourse action (stage 2) in case of route failure. Meanwhile, the expected number of satisfied customers is measured in terms of the number of customers who received their service within the specified time window.

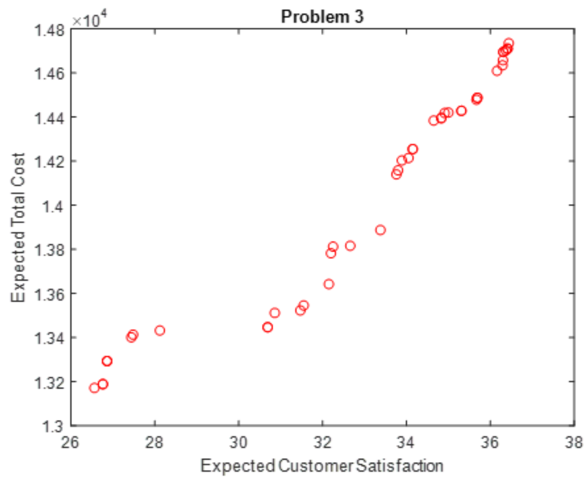
4.6.3.2 Results of the stochastic GVRP with DTD policy



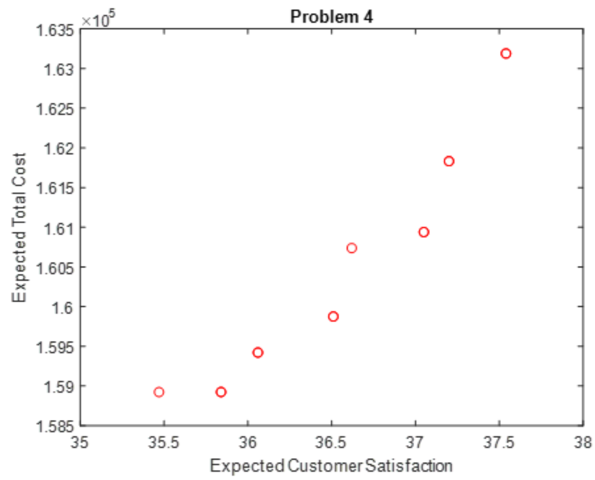
a. Pareto Front of Problem 1



b. Pareto Front of Problem 2



c. Pareto Front of Problem 3



d. Pareto Front of Problem 4

Figure 4-6: Pareto fronts of the DTD-GVRP with Normally distributed demands

Trade-offs between the expected customer satisfaction and the expected total cost including recourse cost are presented in Figure 4-6 and Figure 4-7, where demands are modeled assuming continuous and discrete distributions, respectively. The effect of the customer locations and the TW overlapping are clearly present.

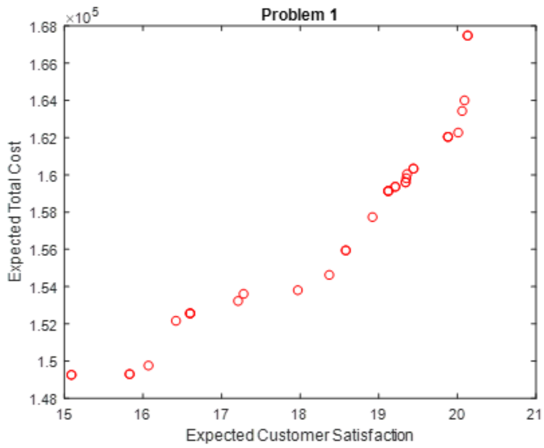
Table 4-11: Results of the DTD-GVRP with Normally distributed demands

	Problem Set	Number of Routes	Expected Customer Satisfaction	Expected Total cost	Expected Variable Cost	Expected Fixed Cost	Expected Cost of Fuel consumption	Expected Extra Cost
Minimum Total Cost	Problem 1	26	12.89	159390	45292	26000	67101	20995
	Problem 2	8	5.06	13497	1342.8	8000	1742.1	2412.1
	Problem 3	8	26.35	13342	1391.4	8000	1862.3	2088.6
	Problem 4	27	35.6	161250	46511	27000	66332	21402
Compromise case	Problem 1	26	17.38	175820	50330	26000	74115	25375
	Problem 2	8	16.89	14260	1643.7	8000	2252.5	2363.6
	Problem 3	8	33.48	14259	1709.8	8000	2351.4	2197.6
	Problem 4	27	36.31	163350	46965	27000	66498	22885
Maximum satisfaction	Problem 1	27	20.33	196230	56970	27000	82908	29349
	Problem 2	8	19.19	16097	2118.3	8000	2881.3	3096.9
	Problem 3	8	36.24	14765	1832.6	8000	2523.8	2408.3
	Problem 4	27	36.47	167060	48048	27000	67992	24019

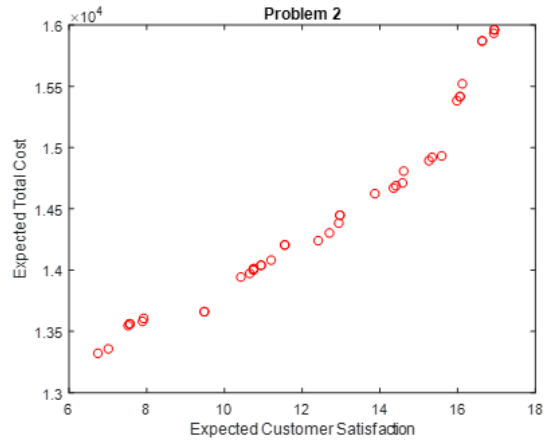
When comparing problem set 1 and 2 with problem sets 3 and 4, as the tighter is the TW, the less expected satisfaction achieved, and more is the total expected costs as presented in Table 4-11 and Table 4-12.

Table 4-12: Results of the DTD-GVRP with Poisson distributed demands

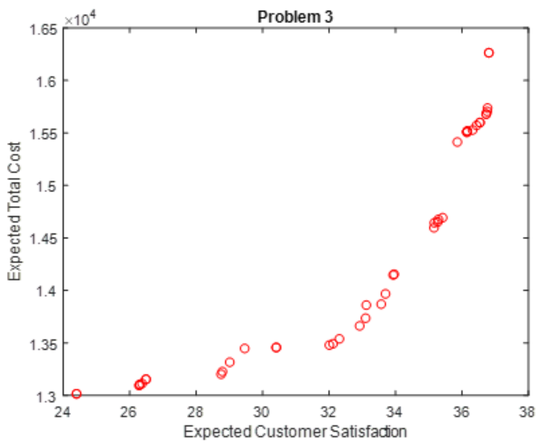
	Problem Set	Number of Routes	Expected Customer Satisfaction	Expected Total cost	Expected Variable Cost	Expected Fixed Cost	Expected Cost of Fuel consumption	Expected Extra Cost
Minimum Total Cost	Problem 1	25	15.91	153010	43874	25000	62870	21261
	Problem 2	8	6.5	13485	1366.8	8000	1836.6	2281.3
	Problem 3	8	24.31	13198	1352.5	8000	1785.4	2059.6
	Problem 4	26	34.21	150900	43220	26000	61874	19810
Compromise case	Problem 1	26	17.76	158500	45308	26000	64210	22981
	Problem 2	8	12.6	14534	1672.6	8000	2247	2614.4
	Problem 3	8	33.5	14148	1664.7	8000	2343.2	2140
	Problem 4	25	36	155730	45275	25000	65301	20155
Maximum satisfaction	Problem 1	27	18.96	167140	47957	27000	68143	24043
	Problem 2	8	16.29	15992	2013.4	8000	2736.4	3242.4
	Problem 3	8	36	16350	2185.7	8000	3011.1	3152.9
	Problem 4	27	36.68	164240	47501	27000	68484	21260



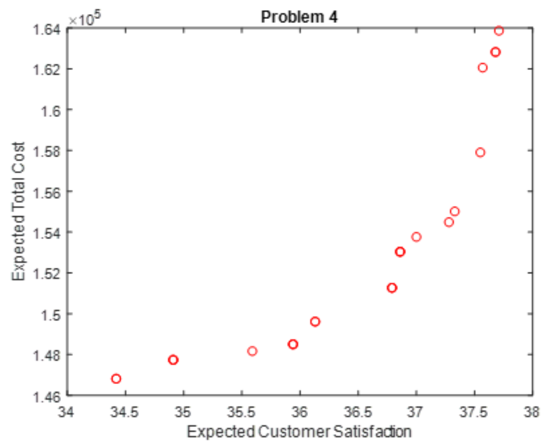
a. Pareto Front of Problem 1



b. Pareto Front of Problem 2



c. Pareto Front of Problem 3



d. Pareto Front of Problem 4

Figure 4-7: Pareto fronts of the DTD-GVRP with Poisson distributed demands

4.7 Numerical Analysis

A study of the effect of TW flexibility on the performance of the supply chain is performed. Flexible TW allows vehicles a certain tolerance in which TW can be deviated (Tas *et al.*, 2014). The analysis is done on the recourse multi-objective GVRP with stochastic demands, where demands are discrete following Poisson distribution.

Relaxation of the upper bound of the time windows is considered (Equation 20), where TW are adjusted from soft to flexible TW. Relaxation with increments of 10% of the upper bound (β_i) is conducted on problem 2 and problem 3, studying the effect on the expected total travel cost, the expected total environmental cost, and the expected customer satisfaction.

$$UB^{*} = UB + \delta\,(UB - LB) \tag{20}$$

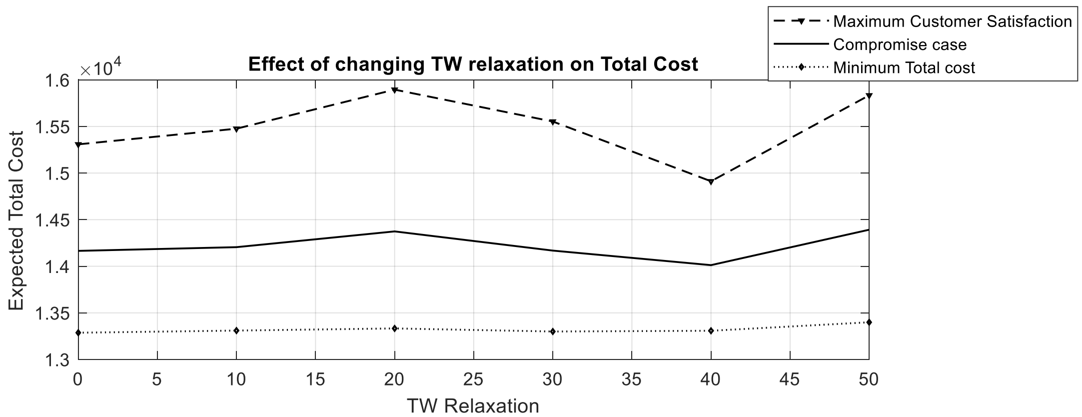
$$\beta_i^{*} = \beta_i + \delta\,(\beta_i - \alpha_i) \tag{21}$$

In equation 21, β_i^{*} is the relaxed time window's upper bound, where δ is the percentage of time window relaxation and β_i and α_i are the upper and lower bounds of the time window at which a customer can accept a service.

Three Pareto-optimal points are taken from problem 2 and problem 3 representing a midpoint and two extreme endpoints on the Pareto front. The selected points are as follows:

1. Compromise point, which is a Pareto-optimum point along the middle of the Pareto front,
2. First extreme endpoint, which represents the expected minimum total cost and the corresponding customer satisfaction that is low in this case,
3. Second extreme endpoint, which represents the expected maximum customer satisfaction and the corresponding total cost that is high in this case.

Figure 4-8 shows the effect of TW relaxation on both the expected total cost and expected customer satisfaction. In the case of extreme optimal points of maximum expected customer satisfaction, with the change in the relaxation of TW, both the expected total costs and expected customer satisfaction are affected. However, in the case of the minimum expected total costs, the expected customer satisfaction is affected and increases significantly at 30% and 40% relaxation, with no significant change in the expected total cost.



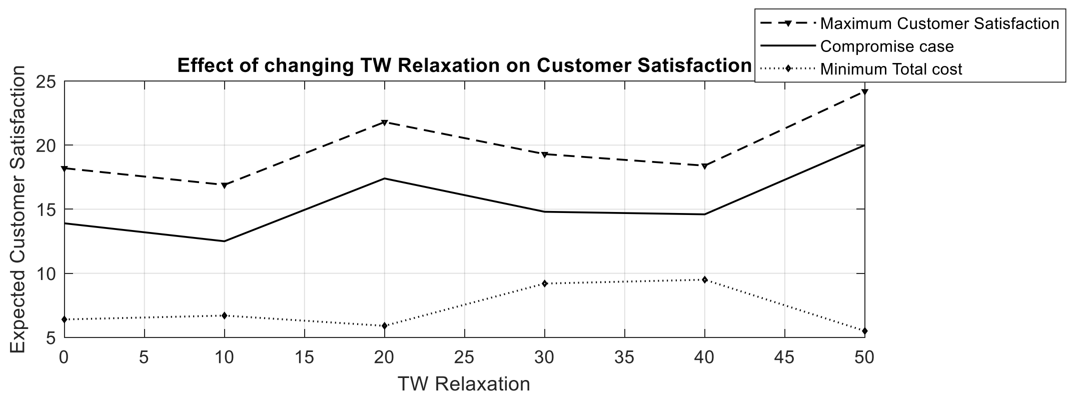


Figure 4-8: Effect of TW relaxation on the total cost and customer satisfaction, Problem 2

For the purpose of further investigation, the comprise case is selected from problem 2 to examine the effect TW relaxation on the economic, environmental, and social aspects considered in this study as shown in Figure 4-9, where trade-offs between the three objectives are presented and decisions can be taken. The minimum expected total travel cost and total environmental cost is achieved at 40% relaxation of the time window, with an increased expected customer satisfaction compared to the case with no TW relaxation (0%) of the upper bound. On the other hand, the maximum expected customer satisfaction is achieved at 50% relaxation of the TW, resulting in an increase in both the expected travel and environmental costs.

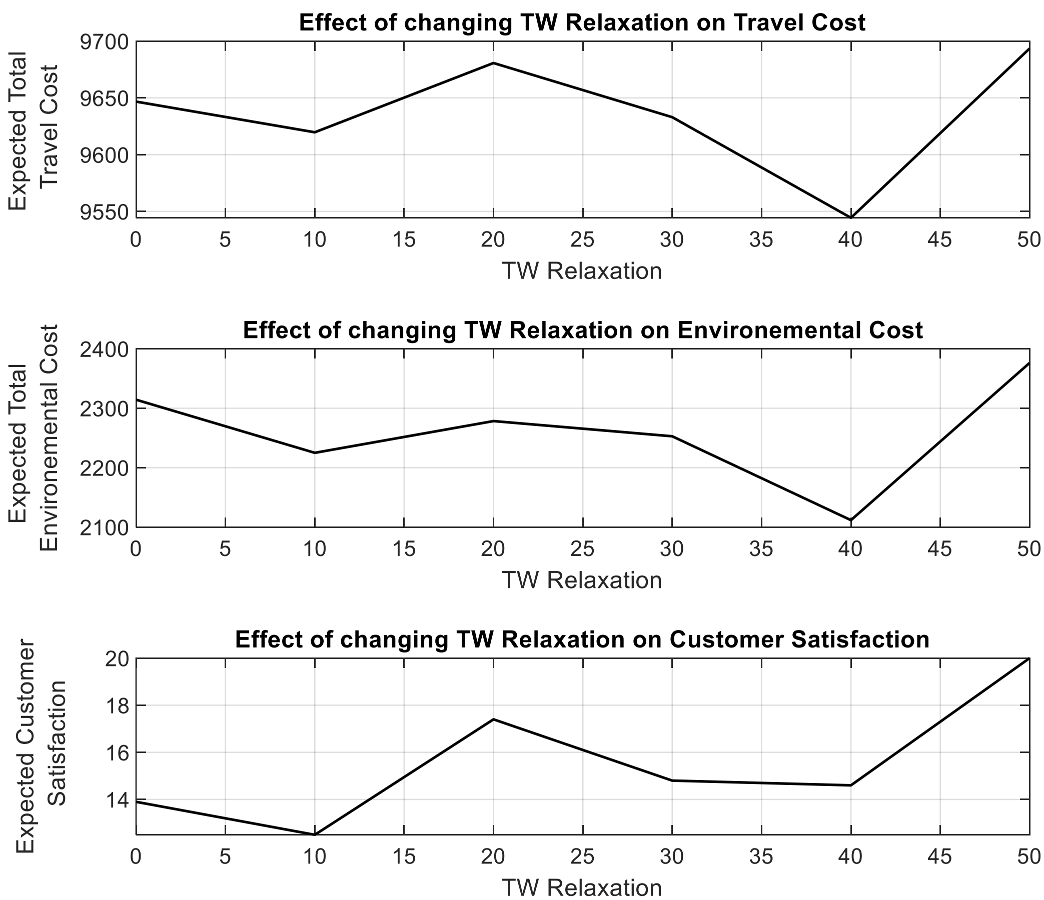


Figure 4-9: Effect of TW relaxation on economic, environmental, and social aspects, Problem 2

Similarly, the effect of TW relaxation on both the expected total cost and the expected customer satisfaction is investigated for problem 3, and the results are shown in Figure 4-10. In case of extreme optimal points of maximum customer satisfaction, an increase in the TW relaxation, decreases the expected total costs at 20%, 30% and 50% TW relaxation, with a slight increase at 40% TW relaxation and increases the expected customer satisfaction at 30%, 40%, and 50%. On the other hand, considering the case of minimum total cost Pareto-optimal points, the expected customer satisfaction increases at 20% and 40% relaxation with no significant change in the expected total cost.

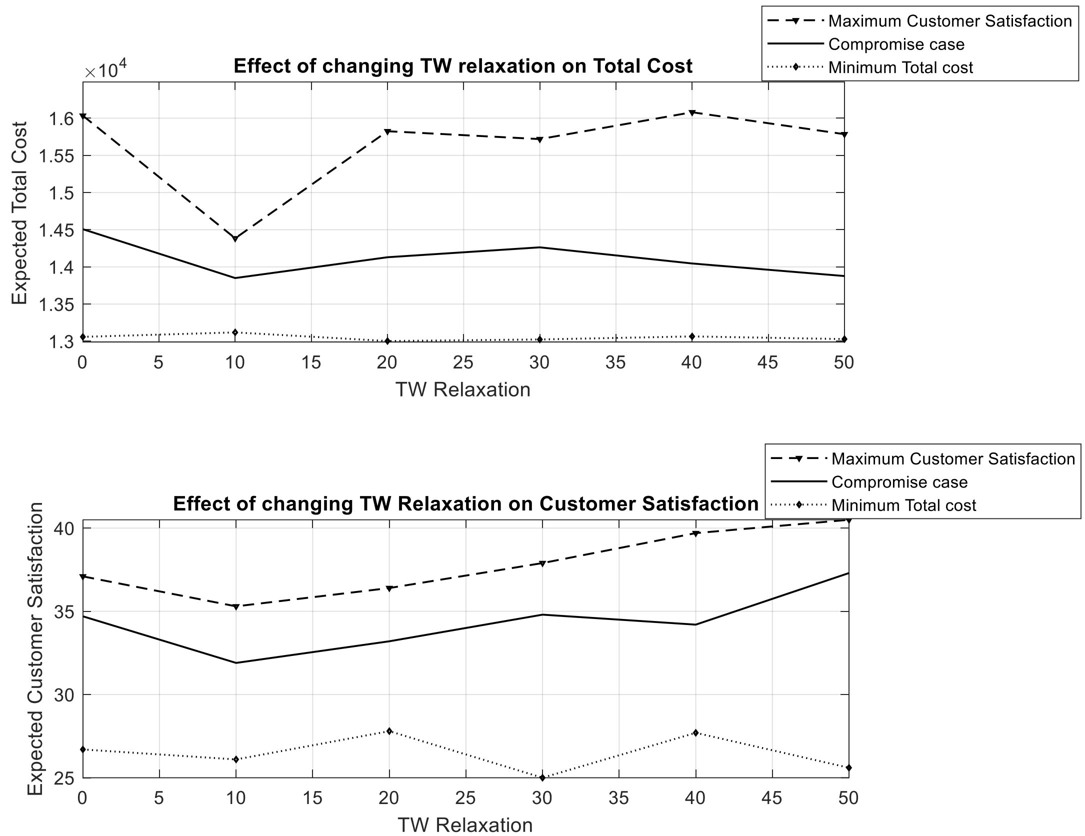


Figure 4-10: Effect of TW relaxation on the total cost and customer satisfaction, Problem 3

Figure 4-11 shows the effect of TW relaxation for the comprise case of problem 3 on the economic, environmental, and social aspects considered in this study. The expected total costs decrease with TW relaxation when compared to the hard TW case with 0% relaxation. The minimum expected total travel and environmental costs are achieved at 10% TW relaxation. On the other hand, TW relaxation does not achieve a significant improvement in terms of the expected customer satisfaction except for 50% TW relaxation.

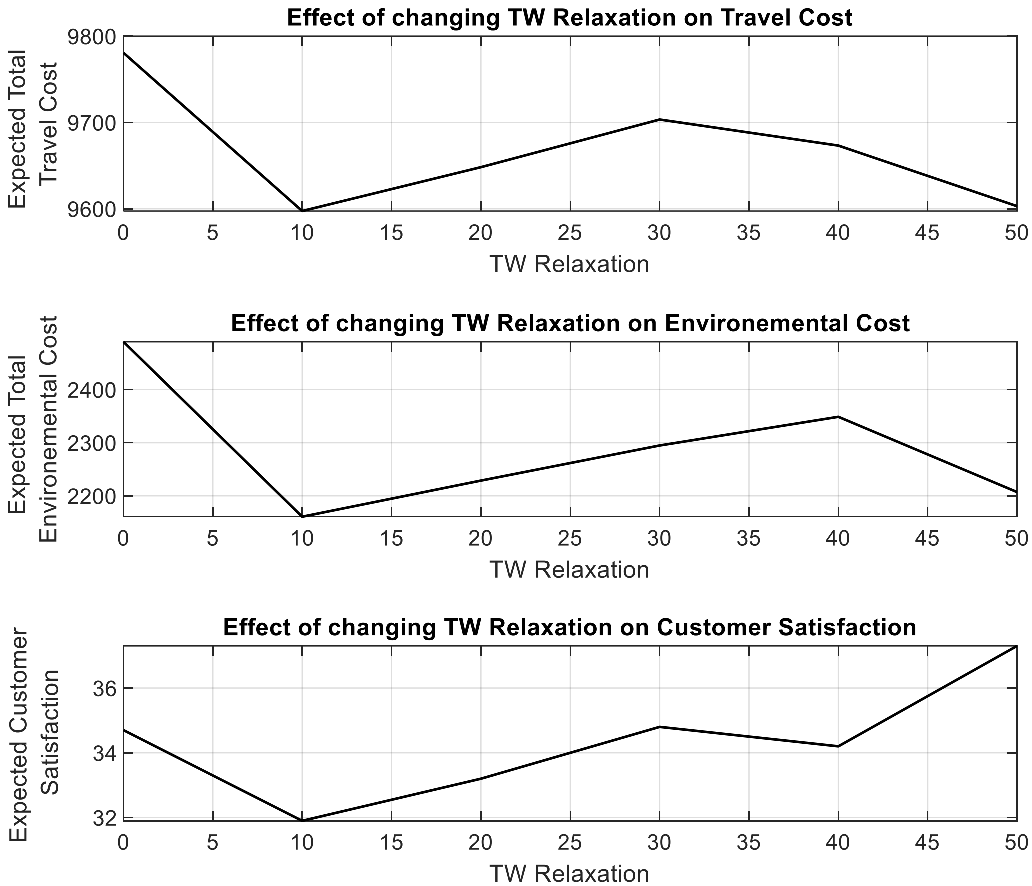


Figure 4-11: Effect of TW relaxation on economic, environmental, and social aspects, Problem 3

4.8 Conclusions

This chapter addresses the stochastic VRP in green environment with customer satisfaction. The developed models consider uncertainties in travel time, service time, and demands. Three models are developed. The first model addresses the green vehicle routing problem with uncertain travel times and service times, considering customer satisfaction. The second and third models handle the green vehicle routing problem with customer satisfaction under uncertain demands. The uncertain demands are conducted in the second and third models with two different demand policies; chance constrained, and recourse, respectively. The models incorporate the new hybrid algorithm developed in chapter 2. The hybrid search algorithm combines the evolutionary genetic search with a resultant search that calculates a heuristic resultant based on both the distance traveled or the nodes/customers' location and the demand associated with the given node/customer. A complete set of runs has been performed to illustrate the Pareto fronts of each problem set and to show the effect of TW tightness measured by the overlap index developed and the effect of customer location and dispersion over the grid. Trade-offs between the three objectives are presented allowing the Decision-Maker (DM) to make choices based on the current situation and the DM's own preferences.

The proposed stochastic multi-objective GVRP with customer satisfaction is the first model that tackles the economic, environmental, and social aspects with uncertainty. As a result, there is no comparative data available for comparison. The developed model optimizes three different objectives simultaneously which are: (1) minimizing the expected operational costs that includes both variable and fixed costs of travel, (2) minimizing the expected fuel consumption based on the distance traveled and the load of the vehicle, and (3) maximizing customer satisfaction. The model developed can be adjusted to consider (1) different distributions for demands, service times and travel times, (2) different type of service (pickup or delivery), and (3) flexibility of TW with different percentage of TW relaxation. Finally, a numerical analysis showing the effect of relaxation in time windows is conducted. The analysis shows how each of the three objectives is affected and provides an overall vision of the effect of introducing flexibility to the TW. In problem 2, the change in TW relaxation increases the expected customer satisfaction and decreases the expected costs at 30 and 40% when compared to the case with no relaxation of the TW. On the other hand, the change of TW relaxation in problem 3 affects both the expected total travel and environmental costs with no improvement in the expected customer satisfaction with the exception of 50% TW relaxation, where a slight improvement is achieved in customer satisfaction.

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Chapter 5

5 Summary, Conclusions, and Future Research

5.1 Summary

The research conducted in this thesis consists of four parts. In the first part, a transportation framework that integrates the performance measures and decision variables relevant to green supply chain management is developed. The framework adopts Beamon's performance measures (resources, output, and flexibility) and incorporates a transportation optimization module and a supply chain module for routing decisions. The optimization module includes not only transportation cost, but also other relevant performance measures. It integrates various performance measures and the trade-offs among them using a decision support system.

In the second part of the thesis, a new hybrid search algorithm that combines the evolutionary genetic search with a new local search heuristic is developed to solve the capacitated vehicle routing problem. The algorithm calculates a heuristic resultant based on both the distance travelled and the demand associated with the given customer, not only distances as previously considered in the literature. The developed algorithm is considered a fundamental tool for the development of a multi-objective Green VRP that considers demand quantities in the calculation of fuel consumption rates. The proposed algorithm was validated, and the results are found to be satisfactory as the algorithm was capable of converging to the optimum solution of the tested benchmark instance.

In the third part of the thesis, a multi-objective green vehicle routing model that handles economic, environmental, and social aspects is developed. The model takes into consideration: (1) operational costs that includes both variable and fixed costs of travel, (2) fuel consumption rate based on the distance traveled and the load of the vehicle, and (3) customer satisfaction measured as the deviation from the desired time window provided by the customer to accept the service, while all customer demands are fulfilled. Problem instances from both benchmark problems of Solomon (1987) and the new benchmarks by Uchoa *et al.* (2017) are used. A new overlap index is developed to measure the amount of overlap between customers' time windows that provides an indication of how tight/constrained the problem is. The multi-objective GVRP studied is solved in MATLAB and evolutionary algorithms are used. The Strength Pareto Evolutionary Algorithm (SPEA) developed by Zitzler and Thiele is combined with the new resultant local search heuristic developed in Chapter 2 to obtain the Pareto fronts of the model. Furthermore, the effect of changing the vehicle capacity is investigated. The analysis shows how each of the three objectives is affected and provides an overall vision of the effect of choosing a different vehicle with a different load capacity.

In the fourth part of the thesis, the stochastic VRP in green environment with customer satisfaction criteria is studied. The multi-objective models proposed take into consideration three main objectives: (1) minimizing the total operational cost, (2) minimizing the environmental cost, and (3) maximizing customer satisfaction, simultaneously, without converting one of the objectives to a constraint with a given threshold. The developed models consider uncertainties in travel time, service time, and demands. Three models are developed. The first model addresses the GVRP with uncertain travel times and service times taking into consideration customer satisfaction. The second and third models handle the green vehicle routing problem with customer satisfaction under uncertain demands. The uncertain demands are conducted in the second and third models with two different demand policies; chance constrained, and recourse, respectively. Pareto fronts between costs and customer satisfaction are obtained and tradeoffs between the three objectives are presented. In addition, the effect of TW tightness measured by the developed overlap index and the effect of customer location and dispersion over the grid are presented. Moreover, a numerical analysis showing the effect of relaxation in time windows is conducted. The analysis shows how each of the three objectives are affected and provides an overall vision of the effect of introducing flexibility to the TW. The study was performed on problem 2 and problem 3 as both problems have the same customers' locations but different overlap index of the time windows. In problem 2, the change in TW relaxation increased the expected customer satisfaction and decreased the expected costs (30% and 40% TW relaxation) when compared to the hard TW case with zero relaxation of the TW. On the other hand, the change of TW relaxation in problem 3, affected both the expected total travel and environmental costs with no improvement in the expected customer satisfaction with the exception of 50% TW relaxation, where a slight improvement was achieved in customer satisfaction.

In the multi-objective optimization models developed, the customer satisfaction value (SV_i) is measured in terms of the deviation from the customers' time windows in which a customer can accept a service. A negative value of customer satisfaction indicates that a deviation from the time windows has occurred. While a zero value means there was no deviation from the time windows indicating a complete customer satisfaction. However, for each of the developed models, the satisfaction criteria is modified to account for the model objectives. For the deterministic multi-objective GVRP model, the customer satisfaction value (SV_i) is used as the satisfaction objective function to be maximized (Chapter 3). In the Stochastic multi-objective GVRP model, the satisfaction objective function is modified to measure the expected number of satisfied customers, showing the number of customers that has been serviced within their given time windows with no deviation reflecting complete satisfaction. In cases of route failure as in the chance constrained stochastic multi-objective GVRP model (Section 4.6.2), two aspects of customer satisfaction criteria are considered: (1) fulfillment of demand, and (2) time window satisfaction. The first aspect measures the fulfillment of demand determining whether the customer demand is fulfilled or not, while the second aspect measures the deviation from the customers' time windows in case of being serviced. The expected number of satisfied customers reflects the number of customers who received their demand and at the same time were serviced within the specified time window.

The developed stochastic multi-objective GVRP with customer satisfaction is the first model that tackles the economic, environmental, and social aspects with uncertainty. As a result, there is no comparative data available for comparison. The stochastic multi-objective GVRP model presented in this thesis adopted Beamon's performance measure framework for supply chains that includes measures for the resources, desired output, and flexibility. In the model, the utilization of resources is measured through the number of vehicles used and the fuel consumption rate. In terms of output measures, customer satisfaction is considered. Finally, accounting for uncertainty and recourse action considered measuring the flexibility of the system to respond to customer requests in uncertain environment.

5.2 Conclusions

The main conclusions drawn from this work are:

1. The developed new hybrid search algorithm is considered a fundamental tool for the development of a multi-objective green VRP that considers demand quantities in the calculation of fuel consumption rates.

2. The green vehicle routing problem developed in chapter three is the first model that takes into consideration: (1) operational costs that includes both variable and fixed costs of travel, (2) fuel consumption rate, and (3) customer satisfaction. It solves them simultaneously without using utility functions or converting one of the objectives to a constraint by setting a threshold while solving the problem.

3. The developed stochastic multi-objective GVRP with customer satisfaction is the first model that tackles the economic, environmental, and social aspects simultaneously under uncertainty.

4. The study of the effect of changing the capacity of the vehicles shows that the vehicle capacity is inversely proportional with the total costs of constructing the routes and the customer satisfaction objectives. The total cost of serving customers decreases with the increase of vehicle capacity, while the decrease in vehicle capacity results in an increase in customer satisfaction.

5. The study of Time Window relaxation shows that:

    - Customer satisfaction increases with the change in TW relaxation for problems with high overlap index, while no significant improvement is shown in problems with low overlap index.

- The expected total operational and environmental costs can be decreased with the change of the TW relaxation for problems with either high or low overlap index.

6. The developed new overlap index shows how tight or relaxed the time windows of customers are and is found to be a great indicator for explaining the performance of the supply chain and its trade-offs.

5.3 Future Work

The current study discussed the stochastic multi-objective GVRP with customer satisfaction that handles economic, environmental, and social aspects. For future research, the following investigations are suggested:

1. Implementation of risk management to minimize supply chain disruptions and uncertainties and propose risk mitigation strategies. Both operational and disruption risks to be considered. Operational risks only influence the operational factors of the supply chain that are known to be uncertain, while disruption risks affect the functionality of the elements of the supply chain such as nature/disaster risks, economic risks, or even events of machine breakdown.

2. Develop a decision support system interface that integrates the various elements of the model. The decision support system will use the multi-objective transportation optimization model of the GVRP taking risks into account and present the set of Pareto optimal solutions that will enable the user to make decisions and trade-offs between the total transportation operations costs, total environmental impact and customer satisfaction level achieved.

Appendices

Appendix A: Sample Vehicle Routing Problem

A problem is created for the purpose of illustration of applying the genetic algorithm operators. The problem consists of a depot and (n) number of customers which is 18, then the number of nodes ($n+1$) in the problem is 19. The vehicle capacity is assumed to be 25 units.

Node	Demand
1	Depot
2	7
3	7
4	6
5	3
6	4
7	2
8	6
9	6
10	5
11	5
12	5
13	8
14	3
15	2
16	12
17	6
18	2
19	3

Appendix B: Uchoa *et al.* (2017) Benchmark Problem: Instance X-n101-k25

Customer No.	Co-ordinates X	Co-ordinates Y	Demand	Customer No.	Co-ordinates X	Co-ordinates Y	Demand	Customer No.	Co-ordinates X	Co-ordinates Y	Demand
1	365	689	0	35	584	572	5	69	254	135	52
2	146	180	38	36	134	554	53	70	346	29	28
3	792	5	51	37	912	173	97	71	75	79	96
4	658	510	73	38	827	233	70	72	893	987	18
5	461	270	70	39	851	677	32	73	729	372	16
6	299	531	58	40	598	322	27	74	29	910	7
7	812	228	54	41	627	472	42	75	356	39	73
8	643	90	1	42	94	442	67	76	274	943	76
9	615	630	98	43	688	274	76	77	322	96	6
10	258	42	62	44	977	176	15	78	664	396	64
11	616	299	98	45	597	461	39	79	704	236	39
12	475	957	25	46	931	23	14	80	415	837	86
13	425	473	86	47	170	640	43	81	576	587	70
14	406	64	46	48	941	601	11	82	750	977	14
15	656	369	27	49	873	487	93	83	726	363	83
16	202	467	17	50	797	95	53	84	861	948	96
17	318	21	97	51	451	816	44	85	302	129	43
18	579	587	74	52	866	970	80	86	415	989	12
19	458	354	81	53	833	912	87	87	199	135	73
20	575	871	62	54	106	913	97	88	801	405	2
21	47	512	59	55	260	107	67	89	679	426	21
22	568	742	23	56	332	45	72	90	994	804	18
23	128	436	62	57	685	613	50	91	311	116	55
24	546	806	66	58	728	372	8	92	739	898	75
25	197	696	35	59	487	497	58	93	268	97	68
26	615	300	53	60	702	440	55	94	176	991	100
27	852	563	18	61	717	412	67	95	688	588	61
28	772	803	87	62	635	794	89	96	107	836	24
29	678	342	32	63	927	972	38	97	708	522	40
30	916	176	4	64	635	356	65	98	679	864	48
31	390	949	61	65	634	540	3	99	985	877	51
32	113	782	95	66	658	261	5	100	954	950	78
33	226	736	23	67	303	168	46	101	615	750	35
34	119	923	15	68	707	410	100				

Appendix C: Solomon Benchmark Problems: Problem R101

Customer No.	Co-ordinates		Demand	Time Windows		Service time
	X	Y		Ready Time	Due time	
1	35.00	35.00	0.00	0.00	230.00	0
2	41.00	49.00	10.00	161.00	171.00	10
3	35.00	17.00	7.00	50.00	60.00	10
4	55.00	45.00	13.00	116.00	126.00	10
5	55.00	20.00	19.00	149.00	159.00	10
6	15.00	30.00	26.00	34.00	44.00	10
7	25.00	30.00	3.00	99.00	109.00	10
8	20.00	50.00	5.00	81.00	91.00	10
9	10.00	43.00	9.00	95.00	105.00	10
10	55.00	60.00	16.00	97.00	107.00	10
11	30.00	60.00	16.00	124.00	134.00	10
12	20.00	65.00	12.00	67.00	77.00	10
13	50.00	35.00	19.00	63.00	73.00	10
14	30.00	25.00	23.00	159.00	169.00	10
15	15.00	10.00	20.00	32.00	42.00	10
16	30.00	5.00	8.00	61.00	71.00	10
17	10.00	20.00	19.00	75.00	85.00	10
18	5.00	30.00	2.00	157.00	167.00	10
19	20.00	40.00	12.00	87.00	97.00	10
20	15.00	60.00	17.00	76.00	86.00	10
21	45.00	65.00	9.00	126.00	136.00	10
22	45.00	20.00	11.00	62.00	72.00	10
23	45.00	10.00	18.00	97.00	107.00	10
24	55.00	5.00	29.00	68.00	78.00	10
25	65.00	35.00	3.00	153.00	163.00	10
26	65.00	20.00	6.00	172.00	182.00	10
27	45.00	30.00	17.00	132.00	142.00	10
28	35.00	40.00	16.00	37.00	47.00	10
29	41.00	37.00	16.00	39.00	49.00	10
30	64.00	42.00	9.00	63.00	73.00	10
31	40.00	60.00	21.00	71.00	81.00	10
32	31.00	52.00	27.00	50.00	60.00	10
33	35.00	69.00	23.00	141.00	151.00	10
34	53.00	52.00	11.00	37.00	47.00	10
35	65.00	55.00	14.00	117.00	127.00	10
36	63.00	65.00	8.00	143.00	153.00	10
37	2.00	60.00	5.00	41.00	51.00	10
38	20.00	20.00	8.00	134.00	144.00	10
39	5.00	5.00	16.00	83.00	93.00	10

Customer No.	Co-ordinates		Demand	Time Windows		Service time
	X	Y		Ready Time	Due time	
40	60.00	12.00	31.00	44.00	54.00	10
41	40.00	25.00	9.00	85.00	95.00	10
42	42.00	7.00	5.00	97.00	107.00	10
43	24.00	12.00	5.00	31.00	41.00	10
44	23.00	3.00	7.00	132.00	142.00	10
45	11.00	14.00	18.00	69.00	79.00	10
46	6.00	38.00	16.00	32.00	42.00	10
47	2.00	48.00	1.00	117.00	127.00	10
48	8.00	56.00	27.00	51.00	61.00	10
49	13.00	52.00	36.00	165.00	175.00	10
50	6.00	68.00	30.00	108.00	118.00	10
51	47.00	47.00	13.00	124.00	134.00	10
52	49.00	58.00	10.00	88.00	98.00	10
53	27.00	43.00	9.00	52.00	62.00	10
54	37.00	31.00	14.00	95.00	105.00	10
55	57.00	29.00	18.00	140.00	150.00	10
56	63.00	23.00	2.00	136.00	146.00	10
57	53.00	12.00	6.00	130.00	140.00	10
58	32.00	12.00	7.00	101.00	111.00	10
59	36.00	26.00	18.00	200.00	210.00	10
60	21.00	24.00	28.00	18.00	28.00	10
61	17.00	34.00	3.00	162.00	172.00	10
62	12.00	24.00	13.00	76.00	86.00	10
63	24.00	58.00	19.00	58.00	68.00	10
64	27.00	69.00	10.00	34.00	44.00	10
65	15.00	77.00	9.00	73.00	83.00	10
66	62.00	77.00	20.00	51.00	61.00	10
67	49.00	73.00	25.00	127.00	137.00	10
68	67.00	5.00	25.00	83.00	93.00	10
69	56.00	39.00	36.00	142.00	152.00	10
70	37.00	47.00	6.00	50.00	60.00	10
71	37.00	56.00	5.00	182.00	192.00	10
72	57.00	68.00	15.00	77.00	87.00	10
73	47.00	16.00	25.00	35.00	45.00	10
74	44.00	17.00	9.00	78.00	88.00	10
75	46.00	13.00	8.00	149.00	159.00	10
76	49.00	11.00	18.00	69.00	79.00	10
77	49.00	42.00	13.00	73.00	83.00	10
78	53.00	43.00	14.00	179.00	189.00	10
79	61.00	52.00	3.00	96.00	106.00	10
80	57.00	48.00	23.00	92.00	102.00	10

Customer No.	Co-ordinates		Demand	Time Windows		Service time
	X	Y		Ready Time	Due time	
81	56.00	37.00	6.00	182.00	192.00	10
82	55.00	54.00	26.00	94.00	104.00	10
83	15.00	47.00	16.00	55.00	65.00	10
84	14.00	37.00	11.00	44.00	54.00	10
85	11.00	31.00	7.00	101.00	111.00	10
86	16.00	22.00	41.00	91.00	101.00	10
87	4.00	18.00	35.00	94.00	104.00	10
88	28.00	18.00	26.00	93.00	103.00	10
89	26.00	52.00	9.00	74.00	84.00	10
90	26.00	35.00	15.00	176.00	186.00	10
91	31.00	67.00	3.00	95.00	105.00	10
92	15.00	19.00	1.00	160.00	170.00	10
93	22.00	22.00	2.00	18.00	28.00	10
94	18.00	24.00	22.00	188.00	198.00	10
95	26.00	27.00	27.00	100.00	110.00	10
96	25.00	24.00	20.00	39.00	49.00	10
97	22.00	27.00	11.00	135.00	145.00	10
98	25.00	21.00	12.00	133.00	143.00	10
99	19.00	21.00	10.00	58.00	68.00	10
100	20.00	26.00	9.00	83.00	93.00	10
101	18.00	18.00	17.00	185.00	195.00	10

Appendix D: Solomon Benchmark Problems: Problem R102

Customer No.	Co-ordinates		Demand	Time Windows		Service time
	X	Y		Ready Time	Due time	
1	35.00	35.00	0.00	0.00	230.00	0.00
2	41.00	49.00	10.00	0.00	204.00	10.00
3	35.00	17.00	7.00	0.00	202.00	10.00
4	55.00	45.00	13.00	0.00	197.00	10.00
5	55.00	20.00	19.00	149.00	159.00	10.00
6	15.00	30.00	26.00	0.00	199.00	10.00
7	25.00	30.00	3.00	99.00	109.00	10.00
8	20.00	50.00	5.00	0.00	198.00	10.00
9	10.00	43.00	9.00	95.00	105.00	10.00
10	55.00	60.00	16.00	97.00	107.00	10.00
11	30.00	60.00	16.00	124.00	134.00	10.00
12	20.00	65.00	12.00	67.00	77.00	10.00
13	50.00	35.00	19.00	0.00	205.00	10.00
14	30.00	25.00	23.00	159.00	169.00	10.00
15	15.00	10.00	20.00	32.00	42.00	10.00
16	30.00	5.00	8.00	61.00	71.00	10.00
17	10.00	20.00	19.00	75.00	85.00	10.00
18	5.00	30.00	2.00	157.00	167.00	10.00
19	20.00	40.00	12.00	87.00	97.00	10.00
20	15.00	60.00	17.00	76.00	86.00	10.00
21	45.00	65.00	9.00	126.00	136.00	10.00
22	45.00	20.00	11.00	0.00	201.00	10.00
23	45.00	10.00	18.00	97.00	107.00	10.00
24	55.00	5.00	29.00	68.00	78.00	10.00
25	65.00	35.00	3.00	153.00	163.00	10.00
26	65.00	20.00	6.00	172.00	182.00	10.00
27	45.00	30.00	17.00	0.00	208.00	10.00
28	35.00	40.00	16.00	37.00	47.00	10.00
29	41.00	37.00	16.00	39.00	49.00	10.00
30	64.00	42.00	9.00	63.00	73.00	10.00
31	40.00	60.00	21.00	71.00	81.00	10.00
32	31.00	52.00	27.00	0.00	202.00	10.00
33	35.00	69.00	23.00	141.00	151.00	10.00
34	53.00	52.00	11.00	37.00	47.00	10.00
35	65.00	55.00	14.00	0.00	183.00	10.00
36	63.00	65.00	8.00	143.00	153.00	10.00
37	2.00	60.00	5.00	41.00	51.00	10.00
38	20.00	20.00	8.00	0.00	198.00	10.00
39	5.00	5.00	16.00	83.00	93.00	10.00

Customer No.	Co-ordinates		Demand	Time Windows		Service time
	X	Y		Ready Time	Due time	
40	60.00	12.00	31.00	44.00	54.00	10.00
41	40.00	25.00	9.00	85.00	95.00	10.00
42	42.00	7.00	5.00	97.00	107.00	10.00
43	24.00	12.00	5.00	31.00	41.00	10.00
44	23.00	3.00	7.00	132.00	142.00	10.00
45	11.00	14.00	18.00	69.00	79.00	10.00
46	6.00	38.00	16.00	32.00	42.00	10.00
47	2.00	48.00	1.00	117.00	127.00	10.00
48	8.00	56.00	27.00	51.00	61.00	10.00
49	13.00	52.00	36.00	0.00	192.00	10.00
50	6.00	68.00	30.00	108.00	118.00	10.00
51	47.00	47.00	13.00	0.00	203.00	10.00
52	49.00	58.00	10.00	88.00	98.00	10.00
53	27.00	43.00	9.00	0.00	208.00	10.00
54	37.00	31.00	14.00	95.00	105.00	10.00
55	57.00	29.00	18.00	140.00	150.00	10.00
56	63.00	23.00	2.00	136.00	146.00	10.00
57	53.00	12.00	6.00	130.00	140.00	10.00
58	32.00	12.00	7.00	101.00	111.00	10.00
59	36.00	26.00	18.00	200.00	210.00	10.00
60	21.00	24.00	28.00	0.00	202.00	10.00
61	17.00	34.00	3.00	162.00	172.00	10.00
62	12.00	24.00	13.00	76.00	86.00	10.00
63	24.00	58.00	19.00	58.00	68.00	10.00
64	27.00	69.00	10.00	34.00	44.00	10.00
65	15.00	77.00	9.00	73.00	83.00	10.00
66	62.00	77.00	20.00	51.00	61.00	10.00
67	49.00	73.00	25.00	127.00	137.00	10.00
68	67.00	5.00	25.00	83.00	93.00	10.00
69	56.00	39.00	36.00	142.00	152.00	10.00
70	37.00	47.00	6.00	50.00	60.00	10.00
71	37.00	56.00	5.00	182.00	192.00	10.00
72	57.00	68.00	15.00	77.00	87.00	10.00
73	47.00	16.00	25.00	0.00	197.00	10.00
74	44.00	17.00	9.00	78.00	88.00	10.00
75	46.00	13.00	8.00	149.00	159.00	10.00
76	49.00	11.00	18.00	0.00	192.00	10.00
77	49.00	42.00	13.00	73.00	83.00	10.00
78	53.00	43.00	14.00	179.00	189.00	10.00
79	61.00	52.00	3.00	96.00	106.00	10.00
80	57.00	48.00	23.00	92.00	102.00	10.00

Customer No.	Co-ordinates		Demand	Time Windows		Service time
	X	Y		Ready Time	Due time	
81	56.00	37.00	6.00	182.00	192.00	10.00
82	55.00	54.00	26.00	94.00	104.00	10.00
83	15.00	47.00	16.00	0.00	196.00	10.00
84	14.00	37.00	11.00	0.00	198.00	10.00
85	11.00	31.00	7.00	101.00	111.00	10.00
86	16.00	22.00	41.00	0.00	196.00	10.00
87	4.00	18.00	35.00	94.00	104.00	10.00
88	28.00	18.00	26.00	93.00	103.00	10.00
89	26.00	52.00	9.00	74.00	84.00	10.00
90	26.00	35.00	15.00	176.00	186.00	10.00
91	31.00	67.00	3.00	95.00	105.00	10.00
92	15.00	19.00	1.00	0.00	194.00	10.00
93	22.00	22.00	2.00	18.00	28.00	10.00
94	18.00	24.00	22.00	188.00	198.00	10.00
95	26.00	27.00	27.00	0.00	207.00	10.00
96	25.00	24.00	20.00	0.00	205.00	10.00
97	22.00	27.00	11.00	0.00	204.00	10.00
98	25.00	21.00	12.00	133.00	143.00	10.00
99	19.00	21.00	10.00	0.00	198.00	10.00
100	20.00	26.00	9.00	83.00	93.00	10.00
101	18.00	18.00	17.00	185.00	195.00	10.00

Curriculum Vitae

Name:	Nayera Elgharably
Post-secondary Education and	Arab Academy for Science, Technology and Maritime Transport Alexandria, Egypt
Degrees:	2005-2010 B.A. Arab Academy for Science, Technology and Maritime Transport Alexandria, Egypt 2010-2013 M.Sc. Western University London, Ontario, Canada 2015-2021 Ph.D.
Honours and Awards:	Western Graduate Research Scholarship (WGRS) 2015-2019 Queen Elizabeth II Graduate Scholarship in Science and Technology Government of Ontario, Canada 2015/2016, 2017/2018 Full Graduate Scholarship, Master of Science in Engineering Arab Academy for Science, Technology, and Maritime Transport Alexandria, Egypt 2010-2013 Full undergraduate Scholarship, Bachelor of Engineering Arab Academy for Science, Technology, and Maritime Transport Alexandria, Egypt 2010-2013
Related Work Experience	Teaching Assistant Western University 2016-2019 Teaching Assistant Arab Academy for Science, Technology and Maritime Transport 2010-2015

Publications:

Elgharably, N., S. Easa, and A. El Damatty. “Implementing Performance-Based Analysis in Supply Chain Management: Review and Extension,” CSCE 2017, Vancouver, British Columbia, Canada.

Elgharably, Nayera, Khaled S. El-Kilany, and Aziz E. El-Sayed. “Optimization Using Simulation of the Vehicle Routing Problem,” World Academy of Science, Engineering and Technology International Journal of Industrial and Manufacturing Engineering 7, no. 6, (2013): 1236-1242.