A multi-objective vehicle routing problem with simultaneous pickup and delivery and ecological considerations

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ABSTRACT

Reducing CO_2 emissions in transport and logistics is currently a critical goal in the field of vehicle routing as organisations are now more willing to make strategic decisions in pursuit of sustainability. However, these strategic decisions are often taken without a clear understanding of the relevant operational costs. This thesis aims to bridge the gap between strategic decisions on CO_2 emissions reduction and operational decisions on the optimal routes with respect to distance travelled. Multi-objective optimisation - which provides a framework for simultaneously pursuing the best outcomes in these disparate objectives - is the most appropriate methodology to tackle this problem.

This thesis focuses on the vehicle routing problem (VRP) with simultaneous pickup and delivery (VRPSPD). Although CO_2 emissions have been considered in previous VRP research, the corresponding objectives in those cases were combined with other objectives in a single-objective function. In this study, the VRPSPD is modelled as a multi-objective optimisation problem - where the objectives are distance, and fuel consumption which is equivalent to CO_2 emissions. The development of the model is influenced by a real-world problem from an industrial collaborator. A multi-objective Genetic Algorithm (GA) for VRPSPD, based on an established method (NSGA-II), is developed. A novel constructive algorithm is proposed which uses both the multi-criteria decision-making methods, TOPSIS and greedy randomisation, to generate initial solutions of better quality. The

output of the NSGA-II is a Pareto front, which contains solutions that represent a trade-off between travel distance and fuel consumption which is equivalent to CO_2 emission. The Pareto front visually shows the trade-off between objectives in multiple solutions. It helps the logistics manager to express their a-posteriori preferences towards the importance of particular objectives - and to choose the solution which best meets those objectives. The results from the aforementioned real-world problem demonstrate that the shortest routes do not necessarily incur the lowest fuel consumption or CO_2 emissions. In the majority of problem instances, NSGA-II solutions outperform the solutions generated by the collaborator company's commercial vehicle routing software. It is also shown that the use of the TOPSIS method to generate initial solutions does help NSGA-II to produce a better final Pareto front. In order to further assess the performance of the developed NSGA-II, its performance is compared with the state-of-the-art single-objective algorithm on a set of artificially generated problem instances. It leads to conclusions that for a smaller size problem, NSGA-II produces better result in terms of fuel consumption while results for travel distance is comparable to the benchmark instances.

The cost impact is also investigated in outsourcing decision strategy scenarios that compare asset-specific and asset-sharing outsourcing of transportation logistics from the perspective of the collaborator company. The company's decision was based purely on strategic considerations, without any visibility of the cost impact on VRP performance. Experiments with both similar and different demand

patterns and close and far customer locations concluded that asset sharing for transportation logistics could be beneficial - but any decision in this regard depends on whether the collaborator company wishes to prioritise either minimising fuel consumption or travel distance.

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VRP	Vehicle Routing Problem
RL	Reverse Logistics
GHG	Greenhouse Gas
PRP	Pollution Routing Problem
OEM	Original Equipment Manufacturer
PLC	Product Life Cycle
MVT	Marginal Value of Time
TS	Tabu Search
GA	Genetic Algorithm
PSO	Particle Swarm Optimisation
SA	Simulated Annealing
NSGA-II	Non-dominated Sorting Genetic Algorithm
VRPSPD	Vehicle Routing Problem with Simultaneous Pickup and Delivery
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solutions
TCT	Transaction Cost Theory
TSP	Travelling Salesman Problem
MILP	Mixed Integer Linear Program
ACO	Ant Colony Optimisation
SVRPDSP	Single Vehicle Routing Problem with Deliveries and Selective Pickups
ELV	End-of-Life Vehicle
GVRP	Green Vehicle Routing Problem
VRPRL	Vehicle Routing Problem in Reverse Logistics
EMVRP	Energy Minimising Vehicle Routing Problem
VRPTW	Vehicle Routing Problem with Time Windows
EVRP	Emissions Vehicle Routing Problem
MMPRP-TW	Multi-Objective Multi-Vehicle Pollution Routing Problem with Time Windows
SLPSO	Self-learning Particle Swarm Optimisation
MCDM	Multi Criteria Decision Making
T80	80% solutions generated by TOPSIS
3PRLP	Third-Party Reverse Logistics Provider

RBT	Resource Based Theory
RCL	Restricted Candidate List
MODM	Multi-Objective Decision Making
MADM	Multi-Attribute Decision Making
AEX	Alternating Edge Crossover
MRS	Marginal Rate of Substitution

1. INTRODUCTION

In light of continuously growing environmental awareness, industries are facing the challenge of reducing or even eliminating the detrimental impact on the environment resulting from their operations. One of the key initiatives undertaken in this regard is the introduction of the low carbon emissions concept into vehicle routing problems (VRPs). The VRP is a well-known combinatorial problem that was first introduced in the research of Dantzig and Ramser (1959). Since its inception, the initial formulation of the problem has gradually expanded to consider more "features" or characteristics - including VRPs with capacity limitations, VRPs with time windows, VRPs with multiple depots, and VRPs with pickup and delivery. One of the most recent significant achievements in this area is the incorporation of environmental aspects into the objective functions of the VRP.

In supply chain management, responding to environmental concern has been generally perceived as an additional cost-incurring activity devoid of any direct benefit to an organisation and this perception has acted as a disincentive for investment in environment protection activities. However, in recent times, concern has grown regarding environmental degradation at national and international levels and this has exerted constant pressure on organisations throughout the world. Legislation in different countries, along with resolutions and declarations at various international forums, is increasingly compelling the polluters - both legally and morally - to increase the proportion of funds allocated to tackling pollution within their total investment packages. This trade-off between increased investment in addressing environmental problems and consequent concerns regarding rising costs has compelled firms to investigate optimal ways to resolve pollution concerns within their production activity, and seek a production-pollution nexus that ensures the most efficient solutions. In this regard, the transportation sector ranks significantly highly as a contributor to air pollution through its emissions of CO_2 and other greenhouse gases (GHGs). This has been a motivating factor in directing this research towards minimising pollution through optimisation of vehicle routing.

1.1. Research context and motivation

VRPs currently being considered by researchers and industries are typically governed by a range of new ideas and fast progressing solution methodologies involving distance and cost. In the last few decades, the tremendous expansion of both material production and the share of transportation in the value chain has encouraged these studies to include environmental degradation. Around 2011, a series of research papers published in journals and conference proceedings explicitly stated their concerns regarding environmental degradation, and focused on the benefits of an efficient transportation system (Bektaş and Laporte, 2011; Demir, 2012; Demir et al., 2011, 2012). The concerns voiced by Bektaş and Laporte (2011) were centred around an argument that current literature on VRPs did little to address environmental concerns in a comprehensive way and was inadequate for ensuring the minimisation of GHG emissions. These researchers proposed a move away from the simple optimisation of either travel distance or cost, and suggested the incorporation of reducing GHG emissions into these problem statements. The pollution routing problem (PRP), proposed by Bektaş and Laporte (2011), included a standard VRP with a GHG emissions calculation model - redirecting Green VRP (GVRP) research focusing on minimising pollution and GHG emissions. Many earlier studies had focused on a standard solution technique of optimising a single objective - either travel distance or cost. However, it was suggested by the researchers that the decision maker should have the opportunity of selecting from a plethora of solutions as this approach would provide insights into trade-offs that could not be achieved by considering only a single objective.

Multi-objective optimisation is thus a promising tool that comprehensively examines the domain of VRPs by not merely providing a solution for one specific objective, but more broadly offering an opportunity to explore the complexity of contributions from multiple co-dependent attributes. Previous literature suggests that while some multi-objective optimisation has been conducted for VRPs with the forward supply chain, there is a lack of research pertaining to the reverse supply chain. Discussion of multi-objective optimisation and its applicability to this particular problem is presented in the later chapters of this thesis. The goal of this research, however, is not to debate whether a single-objective or multi-objective optimisation approach is best but rather to demonstrate that multi-objective optimisation provides another valid way of approaching VRPs.

Consequently, this thesis should assist a holistic decision-making approach in future research.

The concept of supply chain management has been developed to allow for different interpretations since the introduction of reverse logistics (RL), or the reverse supply chain. Instead of only seeing a one-way flow from producer to customer - the forward supply chain - some products now also exhibit a reverse flow, from customer to producer. These returns are accelerating gradually. The literature suggests that the U.S. alone handled more than $10 billion of returned products in 2001 (Tedeschi, 2002). One of the major challenges faced in any RL problem is the acquisition of returned products, and the requirement to operate the process in such a way that it minimises operational costs particularly in relation to problems with both pickup and delivery of products that present greater challenges. The question arises whether the pickups and deliveries should be carried out either simultaneously, or individually - along with many other complex operations. Recent studies show that many researchers - for example, Koç et al. (2014), Ombuki et al. (2006), Wang and Chen (2012) and Xu et al. (2008) - are also considering other attributes such as GHG emissions and numbers of drivers that might also require optimisation, as opposed to solely focusing on cost. Drawing on their work, this thesis aims to offer mathematical model that will facilitate the optimisation of vehicle routing for simultaneous pickup and delivery, with an objective of rationalising GHG emissions.

One of the key cost determinants in RL is routing cost, which in turn could be linked to the optimisation of vehicle routing. This factor has captured the attention of practitioners and researchers alike (Das and Chowdhury, 2012; Diabat et al., 2013; Karlaftis et al., 2009). This, consequently, raises another question: who should take responsibility for forward and/or backward delivery - the original equipment manufacturer (OEM), or a third party (Mantel et al., 2006; McIvor, 2000; Yang et al., 2005)? To answer this question, the consideration of outsourcing has come into play. Researchers are trying to justify whether (and in what circumstances) it is preferable to undertake this process in-house or to outsource the process so that the OEM or retailer can concentrate on their core competency, while a third party takes responsibility for these more specific tasks. Previous studies have mainly considered the topic of how to select the third-party logistics provider, rather than investigating when it becomes beneficial to outsource (Azadi and Saen, 2011; Göl and Çatay, 2007; Guarnieri et al., 2014). Although vehicle routing and third-party logistics are prima facie mutually exclusive events from the perspective of their implementation, these two aspects could be linked in the decision-making process - keeping their relative independence intact. In addition to its primary focus on the VRP, this research will explore the scope of such a linkage and suggest a new direction for the outsourcing decision-making process.

This research will examine, critically evaluate, analyse and investigate the VRP for simultaneous pickup and delivery in the context of environmental considerations and will link the solution with the decision on outsourcing to a third-party logistics provider.

1.2. Research description

This research consists of two parts. The first part focuses on solving a multi-objective VRP for RL considering GHG emissions. The second part will discuss outsourcing strategy, focusing on VRPs considering RL.

Product life cycle (PLC), marginal value of time (MVT), return type and types of supply chain will be discussed to identify the desired product and return type in RL that would fill the research gap in the literature. Identification of these characteristics will help shape future research and further investigation of the VRP. Determining the product type will allow a link with the VRP to be established. A classification scheme for the pickup and delivery problem will be analysed to justify the collection policy. Once the final product, return type and classification of VRP are decided, the key objectives to be optimised will be identified. The research will extend from traditional objectives of distance and time to the inclusion of measures for reducing pollution as one of the objectives. The problem will also be linked to the Pollution Routing Problem (PRP), as described by Bektaş and Laporte (2011).

The VRP with the additional factor of environmental degradation - or PRP - could be solved using a range of methodologies, such as Tabu Search (TS), a Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), or Simulated Annealing (SA). Advantages and disadvantages for each of these algorithms are considered in Section 2.2 to identify an appropriate methodology tailored to solve this problem. This research is supported by real-world problem instances, which were made available through a collaborator company who agreed to share their data. The model will be evaluated using computational experimentation involving both real-world data and artificially generated data.

The second part of the research revolves around exploring the decision-making process for outsourcing a logistics service: whether forward, reverse or both. Since the options of outsourcing or in-house logistics could be considered mutually exclusive, opting for either of them automatically excludes the other. (It should be noted that - for simplicity - it was assumed in this research that the process would be either 100% outsourced or 100% completed in-house.) In the case of the outsourcing decision, the cost impact will be investigated for outsourcing the collaborator company's transport logistics operations - both in an asset-specific scenario (where the vehicles are only used by the collaborator company) and an asset-sharing scenario (where the vehicles are shared by two or more companies). Previous academic research in the area of outsourcing has addressed some of these issues. The purpose of this research is to strengthen this field of study with the help of a mathematical model. The main goal is to define boundary conditions and objectives to describe the problem of outsourcing, and to propose a new method for evaluating the conditions for outsourcing decision making or, in other words, for deciding whether or not to share outsourced transportation logistics.

Most previous research has introduced different versions of RL, VRPs and outsourcing separately but only a few papers have tried to combine these practically related issues (Karakayali et al., 2007; Krumwiede and Sheu, 2002). The aim of this research is to address this gap and provide solutions which combine all three areas.

1.3. Research questions and objectives

This research will incorporate:

1) the development of a solution methodology for optimising multiple objectives simultaneously;

2) a discussion about environmental degradation factors; and

3) the development of an outsourcing decision-making technique in the context of a VRP with RL.

The research questions to be addressed are set out below.

1) Whether multi-objective optimisation methods can be used to provide a better tool for generating routes for simultaneous pickup and delivery that will consider not only the distance to be travelled, but also environmental factors. This dissertation will also consider the extent to which incorporating knowledge of multiple objectives can help in the search for a good trade-off solution with respect to all objectives.

2) Whether multi-objective optimisation can help logistics managers to assess the trade-off between different objectives, and specifically between distance and GHG emissions. What is the impact of reducing GHG emissions in route generation on the total distance to travel? How can strategic and operational decision-making tools be incorporated together for outsourcing?

3) When does outsourcing become an economically advantageous option for a VRP in the RL chain?

Reflecting on the research questions, this research proposes a mathematical model that can advise the original equipment manufacturer (OEM) - or the decision maker - on the best possible routing solutions for the simultaneous delivery and pickup of products, taking GHG emissions into account. One point to be further discussed is whether the OEM should operate the routing in-house, or whether it would be beneficial to pass on this task to a third-party logistics provider.

The aim of the thesis is thus to formulate and solve a multi-objective optimisation problem for simultaneous pickup and delivery of products, and to include environmental considerations. This task will be accomplished through the following objectives.

1) To study the existing RL research to find a link between RL and VRPs.

2) To study the use of GAs for multi-objective optimisation, and investigate the impact of initial population generation on final solutions.

3) To evaluate the proposed algorithm by applying it to a real-world problem.

4) To investigate the trade-off solution selection from the Pareto front.

5) To identify a new area of research linking RL, VRPs and outsourcing.

6) To include environmental considerations in an asset-sharing outsourcing decision.

1.4. Research methods

Exploratory methods and methodical reviews have been undertaken to summarise earlier contributions made by other researchers in the field.

To handle the multi-objective optimisation, an elitist non-dominated sorting GA (NSGA-II) will be employed. NSGA-II is one of the best-known population-based metaheuristics used for multi-objective evolutionary optimisation. NSGA-II has three distinctive features that make this approach ideal for tackling multi-objective problems (Deb et al., 2002) - its use of elitist principle, its diversity preserving mechanism, and its emphasis on non-dominated solutions.

This paper will also propose a new constructive heuristic that follows the three rules specified by Talbi (2009) - choice of initial starting point, selection criteria for the next customer to be added to the route, and insertion criteria to decide where the customer should be placed in the route. The heuristic uses a multi-criteria decision-making method - Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) - to identify the customer to be added to the route. Fuel consumption and distance are employed to choose the "best" customer to be added to the route.

The heuristic uses knowledge-based Alternating Edge Crossover (AEX) and Swap Mutation to generate offspring from the initial solution. The tour-splitting algorithm described by Prins et al. (2009) will be adopted for the current problem. Experimental results obtained from real-world problems in the context of a collaborator company have been used to evaluate the proposed model and algorithm. Some benchmark instances taken from the literature have also been used in the evaluation of the proposed algorithm.

1.5. Contributions of the research

This research makes the following contributions to the field.

- A new multi-objective elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) for VRPs with simultaneous pickup and delivery (VRPSPD) is developed. A new approach to initial population generation based on TOPSIS is proposed, and it is shown that the proposed method produces good final solutions - in other words, reaching a Pareto front. The proposed algorithm is evaluated against real-world problem instances received from the collaborator company. The final solutions generated by the algorithm are of better quality than the solutions which were provided by the collaborator company.
- The research proposes a new perspective for simultaneous pickup and delivery problems - moving from a single-objective optimisation problem to a multi-objective optimisation problem.
- The solution method reveals that when compared to the approach of minimising only one objective (in this case, distance) - if there are instead multiple objectives, the route may change. This finding represents a departure from the more traditional approach where the same route would have been used over and over again, as the objective was solely to minimise distance but

when also considering other objectives such as CO_2 emissions or equivalent fuel cosnumption, the route becomes dependant on the load as well as distance, and can change even if the customers remain the same.

- This research considers products with a low marginal value of time and long life cycle. The customers are assumed to be located in a wide and dispersed region which removes the problem of congestion that is faced in a VRP where customers are generally located in urban areas.

- The introduction of minimisation of carbon emissions in the form of fuel consumption as one of the objectives for the multi-objective optimisation problem.

- The solutions are presented in the form of a Pareto front that allows the decision maker to take control of prioritising their preferences among the objectives.

- Research is also conducted to compare asset-specific and asset-sharing approaches to transportation logistics. The goal of this aspect of the research is to provide a comparative study for line managers to use in making an outsourcing decision.

1.6. Dissemination of research

The main results of this thesis were presented at the following conferences.

- A multi criteria decision making model for vehicle routing problem in reverse logistics. In the proceedings of New Perspectives in Scheduling Theory, 29 March - 2 April 2016, Aussois, France.

- A multi criteria decision making model for vehicle routing problem considering simultaneous pickups and deliveries. In the proceedings of Student Conference on Operational Research (SCOR) 2016, 8-10 April 2016, Nottingham, UK.

- Optimising vehicle routing problem for reverse logistics considering CO_2 emission. In the proceedings of European Logistics Association (ELA) Doctorate Workshop, 22-25 June 2016, Vienna, Austria.

- CO_2 emission costs in a multi-objective vehicle routing problem with simultaneous pickup and delivery. In the proceedings of Twentieth International Working Seminar on Production Economics, 19-23 February 2018, Innsbruck, Austria.

1.7. Outline of the thesis

This thesis is divided into seven chapters. A reference list and appendix are presented at the end of the thesis.

Chapter 2 provides a review of literature, an overview of the RL and environmental considerations in the context of VRPs, and shows how these are linked. Different solution methods are discussed, with a view to understanding which methods would be appropriate for the problem at hand. A short study is conducted on the outsourcing decision in the context of RL in vehicle routing to identify a research gap.

Chapter 3 sets out the problem formulation and mathematical model for the multi-objective VRP. A mathematical formulation of the problem, which includes descriptions of its decision variables, objective functions and constraints, is presented in this chapter. Calculation of CO_2 emissions which is equivalent to fuel consumption is described at length, together with an example that justifies why it is necessary to have fuel consumption and distance as two objectives for the multi-objective VRP.

In Chapter 4, the developed NSGA-II for VRPs is presented. Various heuristic methods for VRPs including the Savings Algorithm, Sweep Algorithm and random generation are discussed, in addition to the proposed constructive heuristics. TOPSIS and its use is explained in detail in this chapter. The developed algorithm and its components including Alternating Edge Crossover, Swap Mutation and the Split Algorithm are also explained here.

Chapter 5 introduces problem instances, and explains the experimental setup that will be used to evaluate the algorithm. The developed algorithm is then tested against the collaborator company and benchmark instances.

Chapter 6 puts forward the transaction cost theory (TCT) to explain the making of outsourcing decisions and shared outsourcing strategy.

Experiments with similar and different demand patterns and close and far customer locations are carried out to validate the viability of both the proposed algorithm and the shared outsourcing strategy.

Finally - the conclusion of this thesis, and proposals for future work, are presented in Chapter 7.

2. REVIEW OF LITERATURE

This chapter presents a review of the existing research into vehicle routing problems (VRP) with pickup and delivery and reverse logistics (RL) (Section 2.1), environmental impacts in VRP and RL (Section 2.2), multi-objective optimisation (MOO) in VRP (Section 2.3), and solution methods for VRP (Section 2.4). Debates over the decision-making process for outsourcing vehicle routing activities in RL - along with the relevant environmental impact factors are reviewed in Section 2.5. The chapter concludes with a discussion that summarises its findings.

2.1. Vehicle Routing Problem

Vehicle Routing Problem (VRP) is a common term given to a class of problems where a set of customers are serviced by a set of vehicles (Dantzig and Ramser, 1959). The VRP is a generalisation of the travelling salesman problem (TSP). The difference between the VRP and TSP is that in the TSP, a single traveller visits all the cities whereas in the VRP, multiple vehicles may be required to service all the customers. Various versions of the VRP have been researched over time - the most significant being capacitated VRP (CVRP), the VRP with time windows (VRPTW) and the VRP with pickup and delivery (VRPPD). Researchers such as Golden et al. (1984), Kulkarni and Bhave (1985) and Min (1989) have stated that conventional VRP dealt with a set of customers where the requirement was to deliver a certain volume of products from a single depot to the customers using a fleet of homogeneous vehicles. The product to be delivered was typically a single type of commodity. The problem was to route vehicles from the depot in such a way that all the customers were served and their demands were met. The vehicles were to be returned to the same depot. The routing process generally aimed to minimise the total travel distance, subject to the constraint of vehicle capacity. This suggested that generally there was only one directional flow of material in VRPs. However, with the introduction and spread of the Reverse Logistics (RL) concept, there is now also a need to return products through the supply chain. VRPs acquired a new dimension after RL started to gain momentum in the industry with new capacity constraints and new pickup and delivery policies, which has led to an increase in investment on different fronts. An efficiently designed value chain for RL would ensure that the logistics system does not result in any monetary losses and could also potentially reduce any adverse impact on the environment.

RL was the outcome of a paradigm shift within the industrial sector. According to the researchers, producers' responsibility was no longer limited to manufacturing but rather extended to proper disposal or efficient material recovery systems with minimal impact to the environment. In line with growing environmental concerns and rapid depletion of resources, new and stricter legislation led to the increase in attention to RL (Dekker et al., 2004; Stock and Lambert, 2000). Each value-adding activity of RL may generate an opportunity for large revenue generating businesses. Consequently, this area is continuously attracting the interest of both researchers and practitioners. Among the various research opportunities, the problem of acquisition or collection remains a critically vital segment of the process. None of the other activities of RL can even begin before the products are properly collected. Achieving an efficient collection system for the return of products is the key to ensuring that RL remains profitable.

The VRP is therefore just as crucial a component of RL as it is of forward logistics. However, when both forward logistics and RL are intermingled in a single transportation problem, a new dimension for both theoretical and practical research is created. A recent body of literature on this topic has therefore emerged within the field.

Min (1989) mentioned that the aim of a typical multiple VRP (M-VRP) is either to minimise the travel distance or time for a set of known customer locations - generally for a fleet of vehicles with limited capacity or alternatively to minimise the number of vehicles required. The M-VRP is usually limited to a pure delivery or pickup problem that overlooks the presence of both deliveries and pickups. Nevertheless, many practical situations dictate that each customer will require both delivery and pickup services that cannot be provided independently. Examples where such circumstances occur in designing optimal routes include public transit systems, airlines, library material distributors, and grocery distributors. The VRPPD thus arises logically in the planning of reverse logistics operations that involve, for example, the delivery of full bottles and the collection of empty ones (Dethloff, 2001; Montané and Galvão, 2006). Real-world applications faced in the beverage industry were described in Privé et al. (2006). Mosheiov (1994) provided another application - this time relating to the transportation of children in a community program. Applications encountered in mail transportation were described by Wasner and Zäpfel (2004) and Gribkovskaia et al. (2007). Min (1989) suggested that the extended M-VRP implicitly involved the "mixed loading" problem, as the task of picking up items cannot be performed without enough vehicle space to accommodate pickup loads.

From a practical point of view, the VRPPD can be very helpful in RL - a research area of increasing importance. From a mathematical point of view, the VRPPD is a combinatorial optimisation problem; it is an NP-hard problem, as it is a generalisation of the classical VRP. While it has been shown that VRPPD can be formulated using mixed integer linear programming (MILP) and solved by exact methods for small problems (Nagy and Salhi, 2005; Wassan et al., 2008), it becomes difficult to obtain an optimum solution with exact methods when the number of customers increases. Different heuristics and metaheuristics are therefore employed to solve these types of problems.

In any VRPPD problem, it is usually assumed that all goods either are originated from the depot (for a delivery problem), or end up at a depot (for a collection problem). Thus, the so-called "dial-a-ride" problems which consist of generating routes and schedules between origins and destinations for customers are omitted from consideration. However, in some instances, these are described as being pickup and delivery problems.

It is often presumed that the vehicle fleet is homogeneous, and that its size is not fixed in advance. The objective function of the VRPPD is generally to minimise the total distance travelled by the vehicles, conditional to the maximum time (or maximum distance) and maximum capacity constraints on the vehicles. However, time windows will not be considered in this thesis, as the requirements are usually more limiting than the constraints arising from the presence of pickups and deliveries and including such constraints would therefore weaken the focus of the research.

Berbeglia et al. (2007) classified pickup and delivery problems into three main categories: many-to-many, one-to-one, and one-to-many-to-one problems. Many-to-many problems are characterised by the presence of several origins and destinations for each commodity. Conversely, one-to-one problems have only one pickup location and one delivery location for each commodity. Finally, one-to-many-to-one problems generally arise in the context of RL. The solution for a one-to-many-to-one problem is usually a Hamiltonian tour, where each location that combines both pickup and delivery is visited exactly once.

Wassan et al. (2008), on the other hand, pointed out that there are generally three types of VRPPD: delivery-first and pickup-second, mixed pickup and deliveries, and simultaneous pickup and deliveries.

<u>Delivery-first and pickup-second</u>: Many previous researchers have presumed that the customers could be divided generally into linehauls (customers receiving goods, or in other words requiring delivery) and backhauls (customers sending goods, or in other words requiring pickups). Furthermore, the researchers in these cases also assume

that the vehicles can only pick up goods after they have finished delivering their entire load. This type of problem arises from the difficulty of re-arranging the delivery and pickup goods within the vehicles. A typical approach to solving such problems would be to generate open vehicle routes for delivery and pickup, and match them. This problem class is often described as the VRP with backhauling (VRPB).

<u>Mixed pickup and deliveries</u>: A VRPPD where linehauls and backhauls can occur in any sequence on a vehicle route is referred to as a mixed pickup and delivery problem. This is theoretically a relatively difficult problem class, as the vehicle load may increase or decrease at a customer location depending on whether the customer is a linehaul or a backhaul. In the CVRP or linehaul problems, the vehicle load is always decreasing while in the VRPB, it decreases to zero and then starts to increase again. A common way to solve this type of problem is to create routes for linehauls only, and then insert the backhauls.

<u>Simultaneous pickups and deliveries</u>: In this model, customers may simultaneously receive and return products. It could be argued that the mixed and simultaneous VRPPD problems could be modelled in the same framework. Mixed problems could be designed as a simultaneous pickup and delivery problem with either the pickup or the delivery load being zero. On the other hand, for the simultaneous pickup and delivery problems, the customers could be divided into separate pickup and delivery entities - which would then turn the problem into a mixed pickup and delivery problem. Wassan et al. (2008) suggested that the nature of this problem class requires an integrated solution approach.

It could be argued that the serving of the pickup and delivery demand either in a mixed order or simultaneously causes difficulties due to the need for reorganisation of goods on-board. However, such reorganisation is not an impossible task especially if the vehicle is close to being empty. Some vehicles also have an improved design (with features such as both rear and side loading), which would make the reorganisations of goods a more practical option.

The first two types of VRP mentioned above - delivery-first and pickup-second and mixed pickup and delivery problems - will not be discussed further in this thesis. This thesis will solely focus on vehicle routing problems with simultaneous pickup and delivery (VRPSPD).

Min (1989) defined the VRPSPD as a problem where a set of customers requires a delivery or pickup of some products or both operations, and must be visited by the vehicles once for both operations. In that paper, VRPSPD was investigated in the context of a book distribution and collection problem. The problem presented a central library and 22 remote libraries in Ohio that were to be served using two vehicles. In the tour, vehicles were not allowed to carry more than their capacity. A three-phase heuristic for the VRPSPD was developed in that work. In the first phase, clusters of customers were formed using the average linkage method proposed by Anderberg (1973). The assignment to clusters was performed in the second phase. In the third phase, a routing problem was solved by means of a TSP algorithm.

After Min's work, there was a gap of more than 10 years with very scarce work on this problem being published. However, a number of researchers have revisited the problem in recent years. One of the reasons for this resurgence is the growing interest in RL in combination with environmental issues.

Dethloff (2001) studied the problem from the point of view of RL. He developed an insertion-based heuristic that used four different criteria to solve VRPSPD. Two local search heuristics were developed by Montané and Galvão (2002). The first of these was an adaptation of a tour partitioning heuristic defined by Beasley (1983), and the second used the Sweep Algorithm of Gillett and Miller (1974). Both were originally developed for the classical VRP. The procedures developed by Montané and Galvão (2002) solved travelling salesman problems with simultaneous pickup and delivery (TSPSPD) for each individual route, by adjusting methods originally proposed for the non-simultaneous case.

Anily (1996) proposed an $O(n3 \log n)$ heuristic algorithm for the VRPSPD that converged to the optimal solution under some probabilistic conditions. Another local search heuristic that considered solutions with a certain degree of infeasibility was developed by Nagy and Salhi (2005) for the VRPSPD with a maximum route length. It consisted of constructing an initial solution which was often infeasible and then applying a series of improvements and procedures to restore feasibility. They also applied their heuristics to the multi-depot version of the problem and these proved capable of solving instances of up to 249 customers within a few seconds. Heuristics in Hoff and Løkketangen (2006) and Nagy and Salhi (2005) allowed two visits to the same customer. Chen and Wu (2006) proposed an insertion-based procedure and a hybrid heuristic for the VRPSPD. This hybrid heuristic was based on the record-to-record travel principle proposed in Dueck (1993), Tabu lists, and several improvement procedures. The algorithms were tested on instances with up to 199 customers and 19 vehicles. Bianchessi and Righini (2007) developed and compared several constructive, local search and Tabu Search (TS) algorithms for the VRPSPD using five neighbourhoods. Several experiments allowed the authors to conclude that local search algorithms were robust, and could yield good solutions when applied to complex and variable neighbourhoods. A TS algorithm for the VRPSPD was presented by Montané and Galvão (2006). The neighbourhood was defined by three inter-route movements and a 2-opt intra-route operator. At each iteration, the best feasible neighbour was selected. The metaheuristic included intensification and diversification strategies with a frequency penalty scheme. The algorithm yielded good quality solutions on test instances with up to 400 clients within a maximum computing time of six minutes (Berbeglia et al., 2007).

There exists an extensive literature on pickup and delivery routing problems, but these problems are generally ‘‘many-to-many’’ problems that involve deliveries between customer locations. Such problems are beyond the scope of the present study but they can be reviewed in Cordeau et al. (2001). VRPSPD combines ‘‘one-to-many’’ and ‘‘many-to-one’’ structures: all customer deliveries originate at a unique depot, and all collections are destined to the depot. Most published pickup and delivery models (see, for example, Angelelli and Mansini (2002), or Nagy and Salhi (2005)) have assumed that each customer was visited only once. They also considered the possibility of splitting customer visits into two, or merging the two visits during the solution process. Nagy and Salhi (1998) developed a large scale model allowing two visits per customer, to provide a more general many-to-many pickup and delivery location routing problem.

VRPSPDs are mainly concerned with RL. Savaskan and Van Wassenhove (2006) studied both the direct product collection system where a manufacturer collects used products directly from the customers and indirect collection, where different retailers acted as collecting agents. Deciding on whether the use of either direct or indirect collection is important for the design of RL is crucial as this would also dictate the routing policy for vehicles. As a general rule of thumb, direct collection would be considered for products that are bulky and may require less handling from the customers themselves. Indirect collection may take place when products are small enough that customers would not encounter any additional hassle in returning the products. Examples of direct collection include products such as print and copy cartridges - while examples of indirect collection include single-use cameras and cellular phones. As part of this study, factors that would influence the decision of a manufacturer as to when to collect used products directly from the consumer and when they would prefer to collect via retailers were investigated. The collection strategy affects the structure of the RL system and it can therefore be stated that the process of return is a key component of the reverse supply chain network. The diverse ways in which the returned products could be handled are of major concern for the logistics chain. It could be argued that returns of products are closely associated with VRPs - more specifically, how they are collected, where they are stored after collection (collection points), and what needs to be done with the returned products. The design of RL is thus essential but forward logistics cannot be excluded when trying to optimise the overall network.

Salema et al. (2005) designed a RL solution by simultaneously optimising the forward and reverse network. They developed a MILP model for the problem with a single product and unlimited capacity of vehicles. It must be noted that unlimited capacity - whether of the warehouse or the vehicles - always simplifies the problem. It is thus imperative that the appropriate constraints be acknowledged for any problem that wishes to address the various real life issues of the VRP. Nonetheless, their work provided a good example of the problem formulation.

There are other examples among the research which considered VRP and RL, but had been oversimplified - by assuming either unlimited supply of vehicles, or unlimited capacity. This issue was raised by Bodin (1990), who mentioned that to justify the selection of easy solution techniques, and to generate standardised problems - researchers were neglecting some important constraints present in real-world problems. Xu et al. (2003) tried to avoid this oversimplification in solving their pickup and delivery VRP. The additional factors they considered for determining the cost of a journey included the total waiting time, fixed charges and total layover time for the drivers. Other researchers have worked with different variations of objective functions and constraints.

Bettac et al. (1999) studied ten large take-back schemes - including printer cartridge recycling in Great Britain, power tool recycling in Germany, worldwide take-back and reuse of single use cameras, and worldwide collection and refurbishing of IT equipment. In all these cases, the collection of used products was combined with delivery of new products. The number of recovered products - when taken together with the cost - provided an indication of the effectiveness of the collection process. The chosen collection policy thus has an immense influence on system design, and dictates whether it should have centralised or decentralised collection centres and also whether it should be efficient or responsive in nature.

Moon et al. (2012) studied a different version of the VRP with time windows in the context of the forward supply chain. They extended their research from the classical VRP and included both overtime, and the option of outsourcing vehicles from a third-party logistics provider. The problem was formulated as a mixed integer programming model, and solved using a GA. Although this study suggested that the option of outsourcing the vehicle routing to a third party could be profitable, it did not elaborate on precisely when it would become beneficial to outsource.

Das and Chowdhury (2012) investigated modular product design by adding multiple echelons into the RL chain. Their study included detailed discussion of stock selection, centralised collection, transportation, data collection, refurbishing and remanufacturing. The objective of their research was to develop a network for RL to minimise total cost - comprising inventory carrying cost, material handling and shipping cost. A mixed integer non-linear programming model was proposed for the problem that was solved by two algorithms: a GA, and an artificial immune system. The artificial immune system provided better results than the previously defined solution techniques and the proposed GA.

Bing et al. (2014a) designed a sustainable RL network for household plastic waste. They introduced an idea of source separation or post separation that was implemented in the Netherlands. A MILP model, which minimised both transportation cost and environmental impact, was developed for the network design and TS was used to find a solution. The strategy of differentiating urban and rural municipalities, and assigning source separation to rural municipalities and post separation to urban ones, produced the best results. One of the limitations of the model was that only emissions from transportation were considered and the model could also have been improved by incorporating the quality of returned material. Bing et al. (2014b) subsequently extended their previous work (Bing et al., 2014a) on RL by formulating the vehicle routing for household plastic waste. This research was aimed at redesigning the collection routes and comparing the collection options of plastic waste using eco-efficiency as a performance indicator. The problem was also formulated using MILP, along the same lines as their previous work. A TS heuristic was used to find the routes.

Demirel et al. (2014) also proposed a MILP model to optimise RL activities of end-of-life vehicles (ELV) in Turkey. They reported that an estimated 30 million vehicles would reach the end of their service lives throughout the world in 2019. Their main objective was to minimise the transportation, recovery, disposal, and fixed opening costs in a multi-stage RL network. Revenue that was generated from selling the reused or remanufactured parts and scrap metals was also included in the proposed model. An optimised routing policy for the ELVs was obtained through their computational modelling from ELV sources to landfill passing through dismantlers, shredders and recycling facilities. A general algebraic modelling system was used to solve the problem. Eskandarpour et al. (2014) also studied the RL network for recovery systems, and proposed a metaheuristics solution approach. A comprehensive seven-layer recovery network was designed including primary customers, collection and redistribution centres, recovery, recycling and disposal centres, and secondary customers. They modelled the problem as a MILP and solved using TS.

Ghezavati and Nia (2014) developed a mixed integer non-linear programming model for product returns, and proposed a solution using both a GA and SA. The model optimised the number and location of collection and inspection centres and recovery centres, as well as collection frequency with the objective of minimising total costs, including RL shipping costs and the fixed costs of opening facilities. Küçükoğlu et al. (2015) recommended a memory structure that adapted an SA algorithm for a green VRP (GVRP). The study included three different stages: the construction of a non-linear fuel consumption calculation algorithm, the development of a MILP model, and the development of solution methodology using an SA metaheuristic algorithm.

Vehicle routing is a complex decision-making problem that draws upon many parameters related to the products that are to be delivered and/or collected. The life cycle of a given product, its marginal value of time and some other characteristics will determine the optimal RL type in each case - for instance, whether it will primarily require an efficient or a responsive supply chain.

Product life cycle (PLC) acts as an important factor in the design of RL, as it allows forecasts to be made accurately - enabling the establishment of the appropriate supply chain. Products that have usage and storage life from one to three years are considered to have a short PLC (Hanafi et al., 2007). Products such as microwave ovens, toasters, televisions and steam irons have a medium usage and storage life from three to eight years. The third category in this list contains products that have a life span from eight to fifteen years or more. The goal of the supply chain is to accommodate these products while allowing for varying importance of cost, placement of depot and so on (Hanafi et al., 2007).

Blackburn et al. (2004) suggested that whether a supply chain is responsive or efficient can be determined by marginal value of time (MVT), which has a profound effect on the nature of the collection system - meaning, in this case, whether it should be centralised or decentralised. A product losing its value quickly (such as a product with a short life cycle) has to be returned to the OEM as soon as possible - making high flexibility a paramount requirement for the system, so that it can accommodate any urgency. On the other hand, a product losing its value more slowly has less urgency. So its supply chain can focus on being more cost efficient by comparison. This categorisation is important, as the type of supply chain that will be required is decided by these factors.

Blackburn et al. (2004) also suggested that products could be classified as either innovative or functional - stating that this would determine whether the supply chain should be responsive or efficient. An efficient supply chain is generally associated with functional products, meaning those with a predictable demand and long life cycle. An efficient supply chain is designed in such a manner that service is provided for a low cost. A responsive supply chain, on the other hand, is associated with innovative products which would typically have variable demand, a short life cycle and require a speedy response. Table 2.1 shows how the products considered in different studies could be categorised according to their MVT, PLC, return type and types of supply chain.

Table 2.1: Research work categorised based on MVT, PLC, return type and types of supply chain

Researchers	MVT	PLC	Return type	Supply chain
Min (1989)	Low	Short	End-of-use	Efficient
Bettac et al. (1999)	Low	Short	End-of-life	Efficient
Xu et al. (2003)	---	---	General return type	Efficient
Salema et al. (2005)	Low	Medium	End-of-life, end-of-use	Efficient
Savaskan and Van Wassenhove (2006)	Low	Short	End-of-life	Efficient
Gajpal and Abad (2009)	Low	High	End-of use	Efficient
Castro-Gutierrez (2012)	High	Short	End-of-life	Efficient
Yin et al. (2013)	Low	Medium	End-of-use	Efficient
Liu et al. (2013)	High	Medium	End-of-use	Responsive
Soysal et al. (2015)	High	Short	End-of-use	Efficient

This table shows that the VRPs in the existing studies do not include one specific product type, although having a specific product type can significantly affect the supply chain. Different varieties of VRPs have been researched where these product types have made their mark.

Various other extensions of the VRP relevant to our VRPSPD problems were analysed in the literature. Some examples of these variants are listed below.

- The multiple depot VRP - where a vehicle could start and end up in a variety of depots (Brandão, 2004; Cordeau et al., 2001).
- The Split delivery VRP - where customers could be serviced by multiple vehicles if necessary (Archetti and Speranza, 2012; Archetti et al., 2006).
- The VRP with satellite facilities - where vehicles could replenish goods at any satellite facilities if required (Bard et al., 1998).
- The periodic VRP - with a defined horizon for customer demand (Baptista et al., 2002; Cordeau et al., 2001).
- The VRP with backhauls, with collection being possible after all the deliveries are carried out - where customers could have both delivery and pickup demand (Ropke and Pisinger, 2006).
- The heterogeneous fleet VRP - including vehicles with differences in capacity and other characteristics (Gendreau et al., 1999).
- Green logistics (GVRP) (Erdoğan and Miller-Hooks, 2012).

Green logistics, or GVRP, is the latest contribution in the research field of supply chain management. According to Lin et al. (2014), in GVRP traditional objectives are replaced with costs related to economic and environmental issues, such as CO_2 and other greenhouse gas (GHG) emissions. Studies authored by Bektaş and Laporte (2011), Demir et al. (2012), Franceschetti et al. (2013), Koç et al. (2014), Soysal et al. (2015a), Zhang et al. (2015) and Qian and Eglese (2016) all investigated CO_2 emissions within the VRP framework. An extensive study was conducted to better understand their effect on optimal routing and to formulate mathematical models that would better address the connected real-world issues (Lin et al., 2014). Subdivisions of GVRP are presented in Figure 2.1.

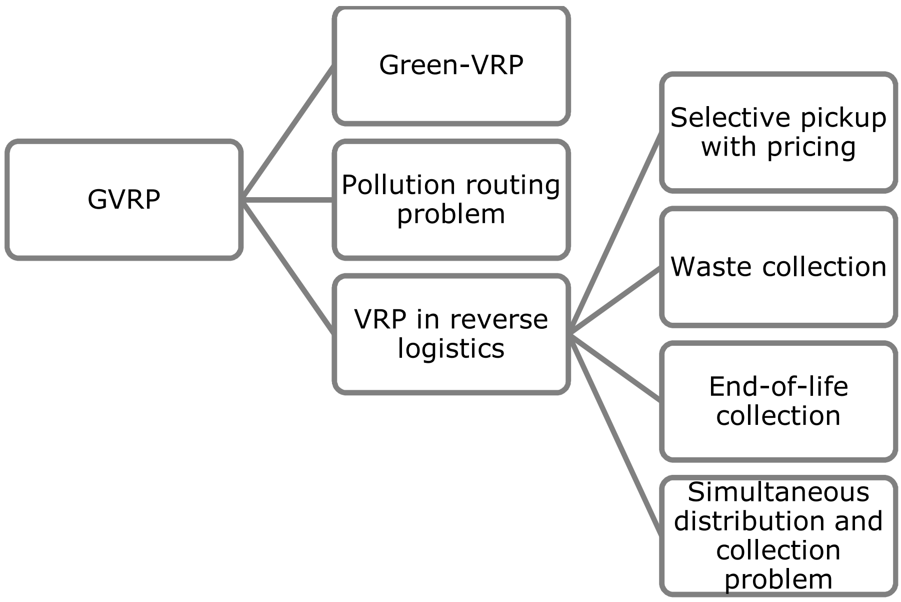


Figure 2.1: Classification of GVRP
Source: (Lin et al., 2014)

The field of GVRP can be subdivided into three major categories: Green-VRP, the pollution routing problem (PRP), and the VRP in RL. All three types of problem look at energy consumption in transportation logistics - especially CO_2 emissions. In Green-VRP, the main aim is to optimise the energy consumption of transportation. Reducing fuel consumption while improving the efficiency of transportation is the goal of Green-VRP. The PRP optimises the reduction of carbon emissions by including the relevant social and environmental impact. The VRP in RL (VRPRL) is mainly concerned with the distribution aspect of the logistics system. A research gap regarding the vehicle routing solution approaches was identified by Beullens et al. (2004), who extended the study of VRPRL by dividing it further into four subcategories: selective pickups with pricing, waste collection, end-of-life goods collection, and simultaneous distribution and collection problems. Each of these types of problem has its unique merits that contribute to the formulation and solution of the problem. Selective pickups with pricing identifies the most profitable pickup points to visit. In this scenario, the companies do not have to visit all the customers, and can choose only the ones that are more profitable. The aim is to make the collection operation as profitable as possible. Waste collection is a key component for protecting the environment and conserving resources and it includes waste avoidance, reuse and recycling. End-of-life goods collection has the potential to benefit the original equipment manufacturer (OEM), as some of the components remain functional after disposal or remanufacturing.

Research work dealing with the recovery model is presented in the literature. The first generalised recovery model for RL was proposed by Fleischmann et al. (2001), who mentioned that the recovery model formed a link between a “disposer market” - where products were returned by the user and a “reuse market”, with a demand for the recovered products. Simultaneous pickup and delivery problems deal with environmental pollution and various ways to minimise its effects (Lin et al., 2014). Environmental degradation is thus an important criterion to be taken into consideration, and this is discussed in terms of VRP in the next section.

2.2. Environmental impacts in VRP and RL

It is widely acknowledged that environmental awareness has grown in recent years and through the concepts of RL, manufacturing companies now have an opportunity to positively affect the environment. It would also create a positive perception among their customers if these companies could maintain an environmentally friendly process of production and supply. Many customers are now more vigilant of what they purchase and may would not prefer to buy products that are unnecessarily harmful to the environment. It can be predicted that an implementation of RL that is considerate of environmental degradation would make a positive impression on customers. Another important aspect to consider is that depletion of natural resources is likely to encourage increased competition among businesses to use their resources as efficiently as possible. Any company that is capable of reusing the returned products more efficiently will have a greater chance of minimising loss.

Reduction of CO_2 emissions via transportation is one way for a business to demonstrate its green credentials. Vehicles used for the collection and delivery of products in supply chain logistics can be utilised in a manner which is designed to lead to a reduction in emissions of CO_2

and other GHGs. The use of efficient modes of vehicle transportation is the key to this issue, and this aspect therefore represents a major part of the research in the field of VRP.

The global climate summit held in Copenhagen in 2009 proposed a policy for countries around the world (Zhang et al., 2015). Their main goal was to take counter-measures with the aim of addressing global climate change. They proposed the low-carbon concept of "low energy consumption, low pollution, and low emissions" that attracted public attention. China especially appreciated this proposal and promised to reduce its CO_2 emissions intensity by 40-50% below 2005 levels by 2020.

Zhang et al. (2015) also mentioned that in order to reduce carbon emissions, a carbon emissions tax was widely used in the relevant industries. For example, the EU imposed a carbon emissions tax in early 2012. As CO_2 emissions created by transportation are high, these new policies pose challenges for this sector. Thus, operations policies in the transportation sector will need to consider this new cost. At the same time, energy consumption remains a major concern for the transportation industry. It is estimated that the transportation industry alone consumes about 9% of society's total energy consumption. Accordingly, fuel consumption cost should be considered whenever operations strategies have to be developed.

Carbon dioxide equivalent (CO_{2e}) is a measure used to calculate the amount of global warming that may be caused by a certain type of GHG. It is measured using the functionally equivalent amount or concentration of CO_2. The selection of GHGs to include in the carbon footprint is an important issue. Wright et al. (2011) suggested that a significant proportion of emissions could be captured through measurement of the two most prominent anthropogenic GHGs: CO_2 and CH_4. Emissions of CO_2 are directly proportional to the amount of fuel consumed by a vehicle. This amount is dependent on the type of vehicle, environment and traffic-related parameters such as vehicle speed, load and acceleration (Demir et al., 2011). On the other hand, the emission of CH_4 is a function of many complex aspects of combustion dynamics and of the type of emission control systems in use (Demir et al., 2014a).

Freight transportation in the United Kingdom (UK) is responsible for 22% of the CO_2 emissions from the transportation sector which accounts for 33.7 million tonnes, or 6% of the CO_2 emissions in the country (McKinnon 2007). He also reported that 92% of those emissions could be attributed to road transport. The 2008 Climate Change Act committed the UK to an ambitious and legally binding 80% reduction in GHG emissions by 2050, from a 1990 baseline. The situation in Europe is very similar. According to the TERM 2011 report published by the European Environment Agency, transport (including international maritime) contributed 24% of overall GHG emissions in the 27 countries that were EU member states in 2009 with road transport accounting for 17% of total GHG emissions (Vicente, 2011). The transportation sector therefore has an important role to play, as one of the largest contributors to GHG emissions, in achieving these reduction targets.

Statistics show that fuel cost represents a significant proportion of total transportation cost. Xiao et al. (2012) pointed out that for a road transportation company in Shanghai, China - fuel cost (amounting to about US$1,550,000 per year) accounts for 67.41% of total transportation cost. If fuel cost could be reduced by 5%, a saving of approximately US$75,500 could be achieved per year which suggests that over 3% of total transportation cost could be saved. An empirical analysis by Sahin et al. (2009) indicated that for a truck with a capacity of 20 tons, when fully loaded, the fuel cost for 1000km travelled accounts for 60% the total cost. It is therefore important to reduce fuel consumption by improving operational efficiency. A reduction in fuel consumption also benefits society at large, since the emission of carbon dioxide which is reported to be a major factor in the greenhouse effect can be correspondingly reduced.

The following literature has considered various strategies that researchers have observed being employed with the aim of reducing these emissions. These strategies include optimising vehicle speed, reducing the number of vehicles used, and improving the understanding of CO_2 emissions calculation.

Bektaş and Laporte (2011) considered minimisation of both fuel cost and the costs of drivers. To estimate total pollution, the authors analysed factors such as speed of vehicles, load, and time windows of delivery - employing the emissions functions that were proposed by Barth et al. (2005). Their model differs from other models in this field, as it allows for simultaneous optimisation of speed and load. Using the functions proposed by Barth et al. (2005) and Bektaş and Laporte

(2011), it was established that the engine out emission rate was directly related to the rate of fuel use.

Bektaş and Laporte (2011) also advised that all the parameters should remain fixed on a given tour for a vehicle but suggested that load and speed might change from one tour to another. They developed a model to calculate the total consumed energy on the tour that was directly converted into fuel consumption and GHG emissions. However, they only considered a vehicle speed of 40km/h as the free-flow speed. This speed would suggest that the routes covered by the vehicles had to be within the city peripherals as the speed limit on the highway was much higher. Although no further explanation was provided by the authors. Consideration of the highway speed limit would change the solutions, as a wider area could be covered and deployment of heavy vehicles would become possible. The authors did consider a single objective that related to the emissions minimisation problems, but did not offer any trade-off solutions that would be important for decision makers.

Demir et al. (2014a) proposed a bi-objective PRP incorporating different cost characteristics. The advantage of using different cost characteristics is that decision makers could input cost figures relevant to their organisation to generate custom-made trade-off curves for their use. They also proposed a solution method that utilised both an enhanced adaptive large neighbourhood search and a specialised speed optimisation algorithm which had previously been introduced in Demir et al. (2012).

Jabali et al. (2012) studied the VRP considering both free-flow traffic and congestion. They experimented with a trade-off between CO_2 emissions and total travel distance. The authors solved the problem using TS, and proposed a procedure to calculate the lower bound of the objective function. Franceschetti et al. (2013) examined the time-dependent PRP along similar lines to the work of Jabali et al. (2012) and also suggested a two-stage planning boundary. They divided the planning horizon that allowed for a categorical modelling of congestion in extension to the PRP objectives. The authors defined an integer linear programming model, where optimal vehicle speeds were selected from a set of discrete values. The studies of both Jabali et al. (2012) and Franceschetti et al. (2013) were conducted on a homogeneous vehicle fleet. Kopfer and Kopfer (2013), on the other hand, examined the VRP with a fleet of heterogeneous vehicles and aimed to minimise CO_2 emissions. They defined a mathematical formulation of the problem, and calculated CO_2 emissions based on the vehicle's payload and travel distance. They were, however, able to present results of computational experiments on small problem instances including up to 10 customers. Expanding on their previous work, Kopfer et al. (2014) analysed the possibility of reducing CO_2 emissions arising from the use of an unlimited heterogeneous fleet of vehicles of different sizes. Kwon et al. (2013) examined a limited number of heterogeneous vehicles, with the intention of minimising carbon emissions. They formulated a mathematical model which allowed them to produce a cost-benefit assessment of the value of purchasing or selling carbon emission rights. This research indicated that CO_2 emissions could be calculated by considering fuel consumption based on the travel distance of the vehicles. For other relevant references and a state-of-the-art coverage on green road freight transportation, the reader is referred to a survey study by Demir et al. (2014b).

The work of Demir et al. (2011, 2014b) and Koç et al. (2016) showed that, as had been found to be the case with the speed of a vehicle, using different types of vehicle also had a considerable effect on fuel consumption and CO_2 emissions. Demir et al. (2011) mentioned that, in a goods distribution context, using smaller capacity vehicles was likely to increase the total travel distance and might therefore also increase CO_2 emissions. Campbell (1995) also suggested that replacing larger vehicles with smaller ones was likely to cause an increase in CO_2 emissions despite the fact that a heavy-duty vehicle would have a larger engine resulting in increased fuel consumption per kilometre compared to a smaller vehicle. However, Kopfer et al. (2014) had a different opinion arguing that replacing a large vehicle with several vehicles of different types might sometimes result in a reduction of CO_2 emissions. These contradicting claims have yet to be fully justified, and need to be tested thoroughly. It could still be claimed that vehicle type does affect CO_2 emissions as vehicles have different engine friction factors, engine speeds, engine displacements, aerodynamic drag, frontal surface areas and vehicle drive train efficiency, all of which would directly impact CO_2 emissions and fuel consumption calculations. Vehicle curb-weight and payload also play an important role.

Kramer et al. (2015) found that higher speeds lead to routes with shorter durations. However, they argued that this might result in a copious emissions and viceversa at lower speeds. Hence, to curtail pollution, they advised that the speed on arcs should be reduced as far as possible towards the speed which corresponds to the minimum level of emissions. On the other hand, at lower speeds, the set of feasible routes might be completely empty or might at least be extremely small. The authors therefore implied that, a consequence of optimally reducing speed could be that fuel consumption would be adversely affected, potentially leading to longer travel distances and even greater emissions in some cases.

Earlier studies which considered GVRP included Apaydin and Gonullu (2008), Kuo (2010), Suzuki (2011), Tavares et al. (2009), Xiao et al. (2012). Generally, in calculating fuel consumption calculation, these studies either overlooked the acceleration rate or did not directly contemplate the vehicle load. Other researchers examined the effect of traffic lights and road congestion or detailed vehicle specifications in the fuel consumption calculation. However, in these cases, the size of the problems which were considered tended to be rather small. Küçükoğlu et al. (2015) aimed to measure fuel consumption and CO_2 emissions of the vehicles in each route by allowing the integration of each vehicle's technical data, speed, weight, acceleration, and travelled distance.

In a recent study, Kumar et al. (2016) proposed a multi-objective multi-vehicle PRP with time windows (MMPRP-TW) that was developed acknowledging two objectives: minimisation of total operational cost, and minimisation of total emissions (which was equivalent in this case to minimisation of fuel consumption). A hybrid self-learning particle swarm optimisation (SLPSO) algorithm in a multi-objective framework was also proposed to solve the MMPRP-TW. To establish which algorithm was more effective, results obtained by the hybrid SLPSO algorithm were compared against a well-known non-dominated sorting Genetic Algorithm (NSGA-II). It was found that for this specific problem, SLPSO provided better results.

Kara et al. (2007) proposed an energy minimisation VRP (EMVRP), and suggested that both load and distance should be considered in the calculation of the emissions. Based on their computational experiments on various realistic problem instances, they reached the following important conclusions.

- The conventional objective of distance minimisation did not always lead to minimal values for either fuel or driver cost. Similarly, a solution incurring minimal cost did not automatically correspond to a solution incurring minimal energy.
- Minimising the load did not automatically translate into minimisation of energy consumption. Reduction in energy consumption could be achieved while there was demand variation among the customers and especially when a few customers exhibited higher demand than the others.
- When smaller vehicles were used, fuel consumption could be significantly lower and the utilisation rate would be much higher.

There are different ways to calculate fuel consumption. Qian and Eglese (2016) divided the research on minimising emissions in vehicle routing models into two main categories, in terms of their approach to fuel consumption calculation.

- Time-independent models.
- Time-dependent models - where road conditions are subject to traffic congestion, with the effect that the length of time needed to travel along a particular road segment is dependent on the time of day.

Among the various time-independent models, Palmer (2007) was the first to incorporate environmental issues into the VRP. The author reflected on issues such as road topography, congestion and vehicle speeds to generate a CO_2 emissions matrix. He was able to find CO_2 reductions of 5.2% and 5.02% when minimising distance and travel duration respectively. However, his model did not explicitly take vehicle loads into account. Suzuki (2011), on the other hand, used a model where load was taken into account. He found that delivering relatively heavy items early in a tour could be useful in reducing fuel consumption. He also reported several case studies that used time-independent approaches with the objective of minimising fuel consumption and hence emissions. For example, Ubeda et al. (2011) considered emissions factors in planning routes for a food delivery operation. They showed savings of around 25.5% in CO_2 emissions but this was primarily achieved by reducing the number of routes needed compared to the original plan. Nevertheless, they showed in their research how logistics managers could lead the initiative in this area by incorporating environmental management principles into their daily decisionmaking process.

Sbihi and Eglese (2007) suggested that social and environmental factors should be incorporated into vehicle routing arrangements to reduce carbon emissions effectively. They particularly considered the topics of reverse logistics, waste management and vehicle routing and scheduling. Hsu et al. (2007) studied the delivery problem of frozen foods by considering transportation, storage, fuel consumption and time windows. In their study, fuel consumption was expressed as a function of both the running and service time, which was based on the load of the vehicles.

Figliozzi (2010) carried out research on an emissions VRP (EVRP), which was an extension of the time-dependent VRP. He produced a new formulation and solution technique for the problem. The main goal of the EVRP was to minimise the emissions cost that was directly proportional to the emitted GHGs, which was expressed as a function of speed and travel distance. In his solution technique, a partial EVRP was first solved to minimise the number of vehicles used - with the second stage being to optimise emissions while keeping the fleet size fixed. Urquhart et al. (2010) studied the VRPTW to generate solutions with low CO_2 emissions. They developed an evolutionary algorithm that employed an instantaneous fuel consumption model, which had first been proposed by Akcelik and Biggs (1985). The authors investigated the trade-off between CO_2 savings, travel distance and total number of vehicles. Fagerholt et al. (2010), on the other hand, studied emissions reductions attributable to differences in navigation routes, and demonstrated that energy consumption by ships depended on both their sizes and voyage distances. Kuo (2010) studied the time dependence of oil consumption reduction within the VRP framework - paying significant attention to the impact of travel time on fuel consumption, and the corresponding simulated annealing algorithm. Bauer et al. (2010) proposed an emissions reduction model under multi-modal transport, and applied it to Eastern Europe’s transportation network. Maden et al. (2010) investigated a vehicle routing and scheduling problem with time windows, where speed depended on travel time. Bektaş and Laporte (2011) proposed a pollution routing problem in which the objective function accounted for the travel distance, the amount of GHG emissions, fuel, travel times and their costs.

Jabali et al. (2012) examined a problem where they approximated total emissions using a nonlinear function of speed arguing that speed could not be calculated properly with a linear function. However, many other researchers did not follow the example of Jabali et al. (2012) believing that a linear function was comprehensive enough to calculate emissions based on speed.

Erdoğan and Miller-Hooks (2012) conceptualised and formulated a green vehicle routing problem. Xiao et al. (2012) analytically characterised the fuel consumption rate using a mathematical model. They proposed a Simulated Annealing (SA) algorithm with a hybrid exchange rule and showed that for their green vehicle routing problem, their model could reduce fuel consumption by 5% on average, as compared with the CVRP model.

However, most of these existing models neglected two important aspects. First, they did not consider the environmental pollution costs, especially costs attributable to carbon emissions, and the vehicle's usage. Second, they did not consider the distance, speed, load, or other relevant factors that had significant impacts on fuel consumption calculation. Demir et al. (2012) acknowledged that the calculation of fuel consumption was too complex. A hybrid ant colony system for a green capacitated vehicle routing problem in sustainable transport was proposed by Adiba et al. (2013), and they developed a technique that estimated CO_2 emissions. Soysal et al. (2014) proposed a method for modelling a food logistics network taking emissions into consideration, for an international company specialising in beef supply.

Figliozzi (2011) analysed CO_2 emissions considering different stages of congestion and time-dependent demands from the customer. Results from computational analysis led to the conclusion that congestion had a significant impact on emissions from commercial vehicles. He also mentioned that travel speed could be set to an optimal level with the effect that travel distance or fleet size could be reduced without causing any significant changes.

From the literature, it can be argued that the speed of vehicles is an important factor in the calculation of CO_2 emissions which in turn initiates a new avenue for pollution routing research.

This section reviews macroscopic (average speed) emissions models which are important tools in wide-area emissions assessment. These models can be used to calculate and develop a national or regional emissions inventory. Generally, macroscopic emissions models are used to measure emissions rates for different routes where the routes are designated for different average speeds. Note that the emissions of CO_{2e} are directly related to fuel consumption, and can therefore be easily calculated if the amount of fuel consumption is known. The best-known macroscopic emissions models include the methodology for calculating transportation emissions and energy consumption (MEET), the network for transport and environment (NTM), computer programme to calculate emissions from road transportation (COPERT), the ecological transport information tool (ECOTRANSIT), the national atmospheric emissions inventory (NAEI), and the motor vehicle emissions simulator (MOVES) (Demir et al., 2014b).

This section reviews microscopic models for the estimation of hot-stabilised vehicle emissions. Microscopic models are necessary to predict traffic emissions more accurately. These models are based on instantaneous vehicle kinematic variables. Variables include speed and acceleration, time spent in each traffic mode, cruise and acceleration. The best-known microscopic emissions models include the instantaneous fuel consumption model (IFCM), the four mode elemental fuel consumption model (FMEFCM), the average speed fuel consumption model (ASFCM), the comprehensive power-based fuel consumption models (CPFMs), and the comprehensive modal emissions model (CMEM) (Demir et al., 2014b).

The first application of the CMEM within the vehicle routing context came in the study conducted by Bektaş and Laporte (2011). The authors introduced PRP, which was an extension of the classical VRPTW. They defined that the problem of PRP consisted of routing a number of vehicles to serve a set of customers, and determining their speed on each route segment with the objective of minimising a function comprising fuel, emissions and driver costs. In estimating pollution, the authors considered factors such as speed, load, and time windows. They assumed that, in one vehicle route all parameters would remain constant on a given arc, but load and speed may change from one arc to another. Their model approximated the total amount of energy consumed on the arc, which directly translated into fuel consumption and further into GHG emissions.

Demir et al. (2012) also applied the CMEM to the PRP. The authors proposed a heuristic to solve the PRP, where the algorithm iterated between the solution of the VRPTW and of a speed optimisation problem. The authors introduced new removal and insertion operators aimed at improving solution quality in terms of CO_2 emissions. In order to analyse fuel consumption more accurately, the authors generated benchmark instances by randomly selecting cities from the United Kingdom which allowed them to incorporate real geographical distances. In a related study, Demir et al. (2014) investigated the trade-off between fuel consumption and driving time using CMEM. They showed that trucking companies could achieve significant reductions in CO_2 emissions without greatly compromising on driving time. They also suggested that the converse of this insight also holds

- so considerable reductions in driving time are achievable if one is willing to increase fuel consumption only slightly. Demir et al. (2014b) proposed a three-point scale to analyse both macroscopic and microscopic models and they concluded that HBEFA and CMEM outperformed the other models. However, they pointed out that CMEM was more suitable for use in optimisation than the HBEFA model.

Using CMEM, Ramos et al. (2012) investigated the service areas and routes that minimised the CO_2 emissions of a transportation system with multiple products and depots. The authors proposed a decomposition solution, and applied it to a case study in order to reshape the current system and create more environmentally friendly routes.

Franceschetti et al. (2013) investigated fuel consumption, CO_2 emissions and driver costs under conditions of traffic congestion. The authors identified the conditions under which it would be optimal to wait idly at certain locations in order to avoid congestion, and to reduce the cost of emissions.

Table 2.2 lists frequently cited research works with different emissions models, together with their corresponding objective functions.

Table 2.2: Literature on green logistics (selection)

Author	Emissions model	Objective function	Objective type
(Urquhart et al., 2010)	Power-based instantaneous fuel consumption model	Fleet size and CO_2	Multiple objectives combined to one
(Figliozzi, 2011)	Function developed by Transport Research Laboratory	Fleet size, distance	Multi-objective
(Jabali et al., 2012)	Methodology for calculating transportation emissions and energy consumption (MEET)	Travel time cost, fuel and emissions cost	Multiple objectives combined to one
(Demir et al., 2012)	A comprehensive modal emissions model (CMEM) (speed of 40km/h or lower was considered for the model)	CO_2 emissions cost, driver wages	Multiple objectives combined to one
(Kopfer and Kopfer, 2013)	Spritmonitor 2012 and Eurotransport 2012	Fuel consumption	Single-objective
(Kwon et al., 2013)	Carbon emissions from all sources of combustion are estimated on the basis of fuel burned and average emissions factors (Eggleston et al., 2006)	Operation cost and carbon emissions cost	Single-objective
(Pradenas et al., 2013)	Environmental impact factor proposed by Bektas and Laporte (2011)	Energy requirement in a route	Single-objective
(Zhang et al., 2014)	Total fuel consumption = fuel consumption of on loaded vehicle * percentage increase of fuel consumption by load	Fuel consumption and carbon emissions, vehicle usage cost	Single-objective
(Demir et al., 2014b)	A comprehensive modal emissions model (CMEM)	Fuel consumption, driving time	Multiple objectives combined to one
(Molina et al., 2014)	A comprehensive modal emissions model (CMEM) (modified)	Internal cost, CO_2 emissions, NO_x emissions	Multi-objective
(Kramer et al., 2015)	A comprehensive modal emissions model (CMEM)	CO_2 emissions cost	Single-objective
(Tiwari and Chang, 2015)	CO_2 emissions = vehicle load*average distance*CO_2 emissions factor	CO_2 emissions (gm equivalent)	Single-objective
(Jabir et al., 2015)	Emissions = distance*avg. price/unit wt of CO_2*wt of CO_2 emission/lt consumption of fuel * volume of fuel consumption*load of vehicle	CO_2 emissions cost, economic cost (travel, routing, fixed)	Multi-objective
(Zhang et al., 2015)	Total fuel consumption = fuel consumption of on loaded vehicle * percentage increase of fuel consumption by load	Fuel consumption and carbon emissions, vehicle usage cost	Single-objective
(Qian and Eglese, 2016)	Methodology for calculating transportation emissions and energy consumption (MEET)	Amount of GHG (equivalent weight of CO_2)	Single-objective

For a basic GVRP, it was assumed that the amount of CO_2 emissions depended both on the distances to be travelled and on the degree to which the used vehicles were loaded. Kopfer and Kopfer (2013) argued that the goal of minimising total travel distance contradicts with the goal of minimising the total amount of emissions. Jemai et al. (2012) suggested that a number of factors actually affect vehicle fuel consumption in the real world, and these are set out below.

Vehicle weight: A vehicle carrying more weight requires more energy to run, which directly impacts its fuel economy (Boriboonsomsin et al., 2010).

Vehicle speed and acceleration: Fuel consumption and the rate of CO_2 emission per mile travelled both decrease as vehicle operating speed increases up to approximately 55 to 65mph and then begin to increase again (Aronsson and Huge Brodin, 2006). Moreover, the CO_2 emission rate doubles on a per mile basis when speed drops from 30mph to 12.5mph, or when speed drops from 12.5mph to 5mph (Bickel et al., 2006). The relationships between these factors and fuel economy are not simple. For example, the effect of vehicle operating speed on fuel consumption is not linear, and depends on vehicle type and size. It also varies depending on the model and age of the vehicle. For instance, studies of vehicle fuel economy carried out during the 1990s show less of a drop off in vehicle fuel economy above 55mph than similar studies undertaken during the 1970s and 1980s due to vehicle design changes, and improvements in engine operating efficiency.

The measure of fuel efficiency per unit of travelled distance was proposed by Qian and Eglese (2016), and is shown below in Figure 2.2. This tool makes it easier to estimate the optimum speed at which emissions can be minimised.

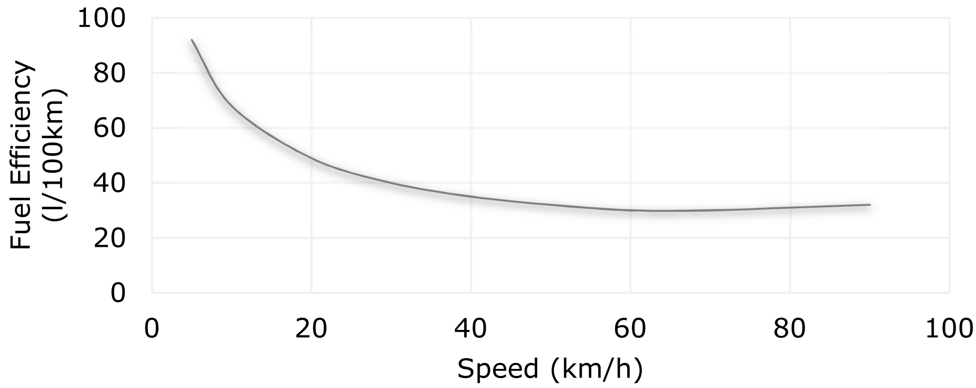


Figure 2.2: Speed-fuel consumption curve
source: (Qian and Eglese, 2016)

Kramer et al. (2015) pointed out that, at higher speeds, one may achieve a shorter time duration but end up with higher emissions. It follows that, to reduce pollution, speed on arcs may be decreased to be closer to the speed that minimises emissions. However, at lower speeds, the set of feasible VRP routes may be empty, or at least drastically smaller. Consequently, an optimal solution for the reduced speed VRP can mean longer distance and even higher emissions in some cases. The results of Zhang et al. (2014) showed that the shortest distance solution differed from the lowest emissions solution which suggests that one may not generally find a single solution that minimises both of these objectives simultaneously. Instead, it would be more convenient to find a Pareto front (Demir et al., 2014a; Zhang et al., 2014).

Many of the problems discussed here suggested that minimisation of CO_2 emissions or fuel consumption did not necessarily also lead to minimised distance or cost. It can therefore be seen that the application of multi-objective optimisation (MOO) to this field could be hugely beneficial. The following section therefore discusses the multi-objective optimisation approach.

2.3. Multi-objective optimisation

Solutions to real problems are often evaluated from several points of view that may be described by different objectives. Solving such a problem often necessitates a choice of the best solution from among a finite but large set of feasible solutions. In this vein, there are significant research efforts in the fields of combinatorial optimisation (CO) and multi-objective decision-making (MODM) (Czyzżak and Jaszkiewicz, 1998).

The objectives underlying real problems often affect one another in complex, nonlinear ways. MOO requires the identification of values for a set of decision variables that satisfy a set of constraints and that optimise a vector function whose elements represent the objectives. These objective functions are a mathematical representation of performance criteria that are usually in conflict with each other. Given that it is often not possible to obtain a single solution by optimising all the objectives simultaneously, a common way to address these problems is to obtain a set of efficient solutions called the non-dominated frontier. An optimum solution is the one that has the objective function values that would be most acceptable to a decision maker (Pacheco and Martí, 2006).

It can be argued that optimisation of a single objective is not an appropriate reflection of the required level of managerial insight. Instead, most real-world VRPs are typically governed by multiple factors that require simultaneous optimisation of multiple objectives. In practice, a single-objective optimisation problem generally produces a single final solution that presents a severe limitation on the final decision-making process. In order to enable logistics managers to better understand the trade-off between the classical VRP objectives and environmental ones, multi-objective optimisation - producing a Pareto front - enables a good trade-off between the identified objectives. This problem is visualised in Figure 2.3, which shows an example of a bi-objective optimisation (minimisation) problem.

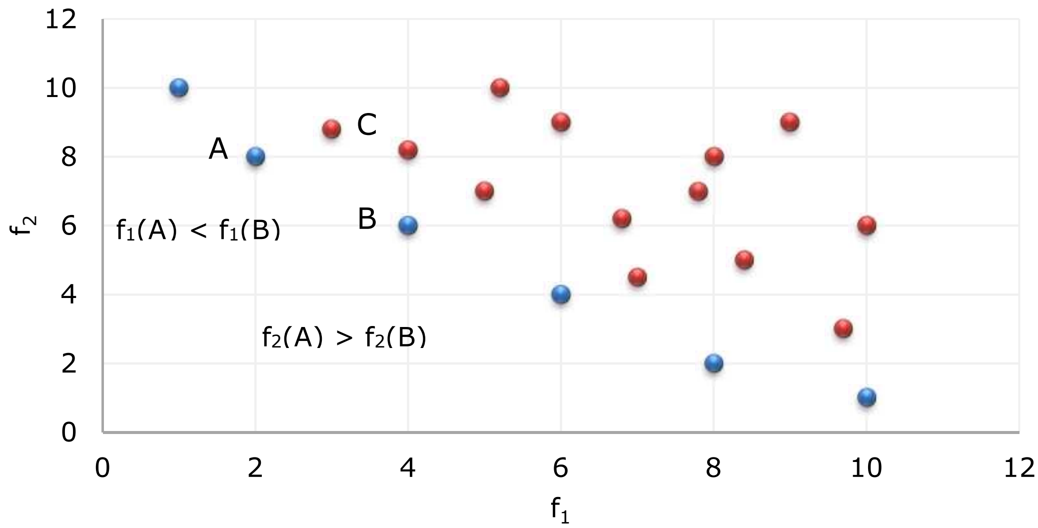


Figure 2.3: An example of a Pareto front for a bi-objective minimisation problem

The dominated solutions are shown as red circles in the figure. Each solution on the Pareto front has values that cannot be improved for one objective without worsening the value for the other objective (represented by blue circles in the figure). In Figure 2.3, it can be seen that $f_1(A)$ is smaller than $f_1(B)$ - while on the other hand, $f_2(A)$ is greater than $f_2(B)$. This implies that neither could be improved without degrading the other objective function. Point C is not on the Pareto front, as it is dominated by both points A and B.

Pareto optimisation methods establish relationships between solutions according to Pareto dominance relations in the following manner. A solution dominates (or is preferred to) another solution if and only if the first solution is better in at least one objective, and not worse in the others. Two solutions are regarded as indifferent if neither of them dominates the other. Since all the objectives are considered as equally important, the aim of Pareto-based multi-objective optimisation is to identify a set of non-dominated solutions as a representation for the true Pareto-optimal front, which in complex problems will remain unknown. The practical advantage of Pareto-based multi-objective algorithms is that they provide a set of trade-off solutions that can be used by the decision maker to select one of the solutions according to specific criteria (Baños et al., 2013a).

Bai et al. (2012) stated that multi-objective optimisation techniques could be classified into preference-based methods where preferences of decision makers are incorporated into the optimisation process and non-preference-based methods, where such preferences are not incorporated.

Hwang and Masud (1982) discussed the following three preference-based techniques.

- A priori preference articulation: This method converts the multi-objective optimisation problem into a single-objective problem by integrating the decision maker’s choices. This method is well accepted within the research community. However, it fails to provide the decision maker with the opportunity for any subsequent analysis, as only one solution is left available.
- Progressive preference articulation: The decision maker’s preferences and the optimisation process are intertwined. Based on the outcome at each iteration, the decision maker has the opportunity to change their preferences.
- A posteriori preference articulation: A set of efficient candidate solutions is first generated, and a final decision can then be taken based on the Pareto front. This provides the decision maker with a good insight into the trade-off between the objective function values of alternative solutions.

In multi-objective problems, heuristics generally have two aims, according to Zitzler et al. (2004) - first, to minimise the distance of the generated solutions, called the Pareto approximation, from the true Pareto front; and second, to maximise the diversity of these solutions, or in other words the coverage of the Pareto front. In the literature, there are a number of evolutionary algorithms that have been successfully implemented including NSGA-II (Deb et al., 2002), the strength Pareto evolutionary algorithm (SPEA2), the Pareto archived evolution strategy (PAES) (Knowles and Corne, 2000), and the indicator based evolutionary algorithm (IBEA). However, comparing the performance of multi-objective optimisers is not straightforward. In contrast to single-objective optimisers, where one can compare the best solution or averages of them while multi-objective problems have to compare whole sets of solutions, with at least the two aims mentioned at the start of this paragraph. For this reason, the definition and use of appropriate performance metrics are crucial. This issue has already been widely studied and among the many proposed metrics, hypervolume, proposed by Zitzler and Thiele (1998a), is most frequently used.

Ehrgott and Gandibleux (2002) offer a good source for general definitions and references for the introduction of multi-objective optimisation. In addition, reviews of multi-objective genetic algorithms (MOGAs), are provided by Coello et al. (2002) and Deb (2001).

As discussed throughout this chapter - to represent a real-world scenario, multiple objectives need to be optimised simultaneously. In the case of VRPs, optimising multiple objectives simultaneously requires special methods to solve these problems. In the next section, various methods are discussed in the context of the problems ranging from smaller numbers of customers to larger numbers, and from single objectives to multiple objectives.

2.4. Solution methods for VRPs

VRPs are generally complex, and a variety of different methods - both exact and heuristic in nature - have been developed to solve them. As the size and complexity of the VRP increases, the computation time increases considerably. It is impossible to solve large problem instances optimally in polynomial time with exact methods. VRP problems and their subcategories are NP-hard as confirmed by the work of Avci and Topaloglu (2015), Çatay (2010), Subramanian et al. (2008), and Wang et al. (2015).

Two of the best-known exact methods for solving VRPs are Branch and Bound where all possible solutions are investigated, while eliminating non-promising solutions (Mayer and Wagner, 2002) and Branch and Cut, where the solutions space is curtailed by adding new cuts (constraints) that push the solutions towards optimisation (Bektaş et al., 2011; Subramanian et al., 2011; Toth and Vigo, 2002).

Some constructive algorithms for heuristics have also been developed to generate solutions, starting from the empty solution, and iteratively extending the solution until the full solution is constructed. Common constructive algorithms for solving VRPs include:

- the Savings Algorithm (to be explained in more detail in Section 4.3.2);
- the route-first cluster-second algorithm;
- the cluster-first route-second algorithm; and
- insertion heuristics.

In the route-first cluster-second approach proposed by Beasley (1983), a giant TSP tour is generated in the first phase, disregarding the side constraints. In the second phase, the TSP is disassembled into smaller, more feasible vehicle routes. This approach generally assumes that there is an unlimited number of vehicles (Laporte et al., 2000; Vidal et al., 2013).

By contrast, the cluster-first route-second approach requires that the nodes should first be added to a cluster, with routes then being optimised within each cluster. The Sweep Algorithm proposed by Gillett and Miller (1974) is one of the best-known cluster-first route-second approaches, and this will be described in more detail in Section 4.3.3.

The approach of using an insertion heuristic was first introduced for a TSP, and it belongs to a group of route construction algorithms (Campbell and Savelsbergh, 2004; Rosenkrantz et al., 1977). The insertion heuristic starts an initial route from the depot with a single node commonly known as a seed node. The selection of the seed tour is generally a matter of choice (Bräysy and Gendreau, 2005). Other nodes are injected one after another by using certain functions. Different approaches to the node selection include random insertion, the nearest insertion, the farthest insertion and the cheapest insertion. Each of the insertion techniques has its own advantages and limitations.

Recent trends suggest that metaheuristics are a popular approach to solving a complex VRP that may be too difficult or even impossible to solve by using exact techniques. Some of the metaheuristics that have been applied to VRPs are set out below.

- Simulated Annealing (SA): SA was first introduced by Metropolis et al. (1953) in thermodynamics, and later used in the context of optimisation by Kirkpatrick et al. (1983). SA was initially motivated by the process of physical annealing in solids. This has since been used in many combinatorial optimisation problems, including many variations of VRPs. In order to ensure that the algorithm can escape the local optima, some deteriorated solutions are accepted with a probability. The probability of approving a degraded move as the solution revolves around the so-called "temperature". A higher temperature implies a higher probability of accepting a deteriorated solution. The cooling of temperature is kept relatively slow, with the aim of ensuring that the solution does not converge to any local optimum. Küçükoğlu et al. (2015), Kuo (2010), Osman (1993), Tavakkoli-Moghaddam et al. (2006), Thangiah et al. (1994) and Wang et al. (2015) have all studied VRP with SA.

- Tabu Search (TS): TS was first introduced by Glover (1986). The TS approach avoids local optimality by forbidding certain moves. It prevents a search from selecting a solution that was already considered during a specified number of preceding iterations. The discarded solutions are stored in a memory bank that is called the "Tabu list". In this way, TS prevents cycling in the search, and allows the search to be manoeuvred into unexplored search space. Archetti et al. (2006), Barbarosoglu and Ozgur (1999), Brandão (2004, 2009), Cordeau et al. (2001), Gendreau et al. (1999), Ho and Haugland (2004) and Montané and Galvão (2006) are among the researchers who have used TS in solving VRPs.

- Ant Colony Optimisation (ACO): ACO was first introduced by Colorni et al. (1991). This approach was inspired by the behaviour of ants. It has been observed that, in nature, each ant strolls randomly until food is available, at which point it will return to the colony by establishing a pheromone trail. The other ants will then follow the pheromone trail path, so they have a higher probability of finding the path compared to when they were moving at random pattern. Longer paths would evaporate more easily than shorter ones, as the time required to travel the path and return back again would be longer. Various evaporation techniques of the pheromone trails are used to minimise the path length. ACO has been applied successfully to solve various VRPs by Gajpal and Abad (2009), Reed et al. (2014), Rizzoli et al. (2007), Sayyah et al. (2016), Yu et al. (2009) and Zhang et al. (2007).

The metaheuristics presented above follow a single solution-based approach. The alternative to this is referred to as population-based metaheuristics, and the most common technique of this type is the Genetic Algorithm (GA).

The GA was first introduced by Holland (1975). The GA is a popular metaheuristic that belongs to the class of Evolutionary Algorithms. It is a population-based algorithm that follows the idea of biological evolution and natural selection, where the fittest individuals survive. GAs are inherently adaptive, and they are capable of converging to near optimal solutions. The GA maintains a pool of solutions from where, through crossover and mutation operations, new and better solutions are produced. GAs have been successfully implemented in various VRPs by Liu et al. (2009), Oliveira et al. (2017), Tasan and Gen (2012) and Vidal et al. (2012). One widely used GA is the elitist non-dominated sorted genetic algorithm (NSGA-II).

NSGA-II was first proposed by Deb et al. (2002), and it is frequently used in solving a variety of multi-objective optimisation problems including VRPs. Jozefowiez et al. (2009) formulated an NSGA-II algorithm to solve a bi-objective VRP in which both the length of the route and load balance between different routes had to be minimised. Hamdi-Dhaoui et al. (2014) introduced an NSGA-II algorithm to minimise both the total cost of transportation (instead of the length of the route) and load balance between different routes. Jemai et al. (2012) developed an NSGA-II algorithm to minimise the travel distance and CO_2 emissions cost, but considered only delivery of products whereas Chiang and Hsu (2014) proposed a knowledge-based multi-objective evolutionary algorithm for a bi-objective VRP with time windows in which customers need to be serviced within given time periods. Further details of NSGA-II are given in Section 4.1.

The following literature sheds light on different models and methods for a VRP with simultaneous pickup and delivery.

Angelelli and Speranza (2002) studied a periodic VRP incorporating the possibility of replenishing the vehicle's capacity at an intermediate facility. This type of problem may arise in cases of waste collection, as well as various RL and distribution scenarios. In these problems, although the vehicles start and end at the depot, the products can be stored at any of the warehouses that are distributed around the wider geographical area. The possibility of replenishing the vehicle's capacity increases the load the vehicle can carry within the scheduled routes. This changes the routing optimisation technique and number of vehicles required, and therefore also affects the time windows. They modelled the problem using integer programming, and solved it with a TS algorithm.

Gribkovskaia et al. (2007) developed a problem using the framework of a single VRP with both pickups and deliveries. The assumption they made was that each customer was visited once for both pickup and delivery, or twice if the two operations were performed separately. A MILP model was proposed for the problem, and a TS algorithm was developed to solve it. Computational results showed that best solutions generated were non-Hamiltonian and allowed up to two customers to be visited twice.

Gribkovskaia et al. (2008) studied a single VRP with deliveries and selective pickups (SVRPDSP). The difference between an SVRPDSP and a single VRP with pickup and deliveries is that in the former there is no requirement to satisfy all the pickup demands. A MILP model was also proposed for this problem. It showed that TS produced near optimal results. Their results also indicated that the best solutions were often non-Hamiltonian, which meant that some of the customers were being visited more than once.

One of the main aims in solving VRPs is to find the set of routes with the shortest distance to deliver goods, using a fleet of identical vehicles with restricted capacity. However, there are other objectives and having a range of solutions representing the trade-offs between objectives is crucial for many VRP applications (Jozefowiez et al., 2008). Jozefowiez et al. (2008) argued that, although most research papers in the field of VRPs concentrate on the optimisation of a single objective - the use of multi-objective optimisation is attracting increasing research attention, because it offers new opportunities for tackling VRPs. Therefore, methods that provide a range of solutions representing the trade-offs between objectives are crucial for many real-world applications, and Pareto-based strategies are well-suited for this purpose (Baños et al., 2013; Goldberg, 1989). Although previous research has used evolutionary methods for solving VRPs, it has rarely concentrated on the optimisation of more than one objective and hardly ever explicitly considered the diversity of solutions (Garcia-Najera and Bullinaria, 2011).

However, so far, the majority of research papers in the field of VRPs has concentrated on simplifying these problems - either by establishing a hierarchy between the objectives to be optimised, or by using aggregating approaches where all these objectives are included in an objective function using a combination of mathematical operations. The drawback in the former case is that it intrinsically necessitates the consideration of one objective as more important than others. On the other hand, the main disadvantage of using an objective reduction approach is that weights to be attributed to different objectives are difficult to determine precisely, particularly when there is often insufficient information or knowledge concerning larger real-world vehicle routing problems (Tan et al., 2006).

Arguably the most studied multi-objective formulation is the use of a hierarchical approach to minimise both the number of vehicles used and travel distance where the optimisation algorithm first finds the solution that minimises the number of tours (as the primary objective), and for the same number of tours then minimises the total travel distance (as the secondary objective) (Nagata et al., 2010; Ombuki et al., 2006). However, several practical aspects would seem to indicate that total travel distance should be preferred as the objective to be optimised instead of using the number of tours as the primary objective. First, the vehicles often belong to the company and as a result their cost is almost independent of their use. The drivers also often either work for the owner of the company of the goods or for the owner of the company of the vehicles which is why they are remunerated in some way even in the case of not driving any vehicles. On the other hand, the travel distance has a higher economic impact, since fuel consumption is the most expensive variable cost of the transportation process. When looking at multi-objective optimisation, it is particularly important to consider that some authors have demonstrated that these two objectives - number of vehicles and travel distance - may be conflicting, or in other words that deploying the minimum number of vehicles will not necessarily minimise travel distance (Tan et al., 2006a).

Molina et al. (2014) studied a multi-objective VRP with cost and emissions functions as objectives to be minimised for a forward supply chain. They formulated the problem as a MILP model. The problem was formulated to minimise three objectives, with two of these being CO_2

and NO_x emissions. The calculation of NO_x was solely dependent on distance. Although the CO_2 emissions calculation depended on both load and distance, Molina et al. (2014) failed to define why having these two separate objectives suited their problem. They also did not elaborate on their inclusion of a fleet of heterogeneous vehicles. Jabir et al. (2015) proposed a multi-depot green vehicle routing problem, where CO_2 emissions and economic cost were optimised simultaneously. They proposed an ACO to solve this multi-objective problem, using a fleet of homogeneous vehicles. They concluded that minimising economic cost did not guarantee environmentally friendly routes, and therefore led to a Pareto front with trade-offs between these two objectives. Table 2.3 presents different approaches to VRPs grouped by objective types and the methods used.

Table 2.3: Approaches to VRPs with objective types

Solution algorithms	Objective type		
	Single-objective	**Multiple objectives formulated as one function**	**Multi-objective**
Exact algorithm	(Bektaş et al., 2011; Dell'Amico et al., 2006; Erdoğan and Miller-Hooks, 2012; Karaoglan et al., 2011; Kopfer and Kopfer, 2013; Toth and Vigo, 2002)		
Population based metaheuristics	(Adiba et al., 2013; Ai and Kachitvichyanukul, 2009; Çatay, 2010; Gajpal and Abad, 2009; Pradenas et al., 2013; Zhang et al., 2014, 2007)	(Wang and Chen, 2013)	(Chiang and Hsu, 2014; Jabir et al., 2015; Molina et al., 2014)
Genetic Algorithm	(Bräysy and Gendreau, 2001; Jun and Jian-yong, 2007; Tasan and Gen, 2012)	(Ombuki et al., 2006)	(Jemai et al., 2012; Xu et al., 2008)
Single solution based metaheuristics	(Avci and Topaloglu, 2015; Dethloff, 2001; Golden et al., 1984; Kramer et al., 2015; Montané and Galvão, 2002; Tiwari and Chang, 2015)	(Baños et al., 2013; Demir et al., 2012, 2014b; Koç et al., 2014; Urquhart et al., 2010; Xiao et al., 2012)	(Demir et al., 2014a; Figliozzi, 2011)
Tabu Search	(Barbarosoglu and Ozgur, 1999; Bianchessi and Righini, 2007; Gendreau et al., 1999; Kwon et al., 2013; Montané and Galvão, 2006; Qian and Eglese, 2016; Zhang et al., 2015)	(Bing et al., 2014b; Jabali et al., 2012)	

It is notable that the majority of approaches to VRPs have been formulated as either a single-objective optimisation problem or a multi-objective optimisation problem in which multiple objectives are combined into a single-objective function. Simultaneous optimisation of multiple objectives in a VRP seems logical, from the perspective that a single objective is rarely able to portray any real-world VRP situations.

2.5. Outsourcing

Once RL is acknowledged by OEMs as an area of the supply chain system which might potentially be suitable for outsourcing, several options for outsourcing the RL operations to a third-party RL provider (3PRLP) can be considered. In this research, the outsourcing of the reverse supply chain and vehicle routing is studied with the aim of understanding "when", "why" and "how" to outsource.

In general, the main operational activity of companies revolves around supplying products to their customers and as such, managing the reverse flow of products from the customer is not necessarily considered a core activity. In this regard, the issue becomes whether the non-core activities should either be dealt with in-house or outsourced. The comparative advantage of a firm has played an important role in popularising outsourcing. In the following section, several key studies are outlined that focus on outsourcing, RL and VRP with the aim of highlighting the existing research gap in the field that this study wishes to fill.

McIvor (2009) demonstrated how both transaction cost theory (TCT) and resource-based theory (RBT) can explain the outsourcing decision of a firm. He advised that TCT and RBT are important and influential theories in understanding the outsourcing decision-making process. However, these theories individually cannot explain all the complexities of the outsourcing process. He argued that including factors such as performance management, operations strategy, business improvement and process design in the study of outsourcing can help to make the firm’s decision more explainable. Yang et al. (2005) studied a production inventory system with Markovian properties (specifically, the memoryless property of a stochastic process) and discussed the point at which the outsourcing option became more viable. The study concluded that, with reasonable cost assumptions outsourcing policy would be cost dependent. Under further cost assumptions, it could also be shown that the firm’s production policy was capacity dependent, with a modified-based stock type. They found that when the capacity process was Markovian and stochastically monotone, the policy parameters decreased at the current capacity level. The research also pointed out that there were some benefits when considering problems with the Markovian properties and the exercise of the outsourcing choice. The outsourcing possibility became beneficial when the option was cheaper, backlogging of inventory was expensive, the firm’s own capacity level was lower than the mean demand, and forecasting accuracy was lower.

Although the concept of outsourcing has changed somewhat from the time it was first introduced, the question of “why” to outsource has remained more or less the same from the very beginning. The possibility of reducing costs due to economies of scale, achieving greater flexibility, the opportunity to improve services, better budget control, faster setup of functions or services, improved risk management, and lower ongoing investment in internal infrastructure are a few of the reasons why OEMs might prefer to involve a third-party logistics provider. Some of the other research works concentrating on outsourcing are Karakayali et al. (2007), Kroes and Ghosh (2010), Mantel et al. (2006) and McIvor (2000) - who investigated the behavioural factors influencing the decision of outsourcing, proposed outsourcing collection activity, and investigated the lack of strategic perspective into outsourcing decisions and strategic alignment of overall competitive strategy respectively. The absence in current literature of any attempt to combine mathematical models and strategic reasoning in outsourcing decision making emphasises that current research on outsourcing decision making is not considering monetary costs and strategic reasoning simultaneously, but rather in separation.

Schittekat and Sörensen (2009) discussed the specific problem of outsourcing in the context of routing optimisation. They developed a tool to solve large scale location routing problems. They studied the choice of third-party logistics provider for Toyota, and generated diverse solutions which would provide Toyota with the negotiating power and flexibility to change their routing as required. Commercial VRP software was incorporated into their model to enable more realistic modelling of the vehicle routing decision. Their research thus focused on the choice of third-party logistics provider in routing optimisation but they left out "when" it is beneficial to outsource, and "how" it should be conducted, choosing instead to focus on the ways to select a third-party logistics provider. Other research on outsourcing in the field of routing optimisation includes Agnetis et al. (2014), Ko and Evans (2007), and Liu et al. (2014).

Ko and Evans (2007) devised a GA-based heuristic to dynamically integrate both forward logistics and RL for the third-party logistics provider. Agnetis et al. (2014) investigated a delivery scheduling problem for a third-party logistics provider. Liu et al. (2014) dealt with a scheduling problem for a fourth party logistics provider. Zäpfel and Bögl (2008) also studied a multi-period vehicle routing problem incorporating the outsourcing option, but added crew scheduling into their scenario.

Lee and Kwon (2010) looked solely at the forward supply chain for distribution centre operation planning, more specifically, at the determination of facility locations and distribution plans. The problem was described as a single sourcing constraint that defined that each customer would be serviced by only a single supplier. Ahmadi-Javid and Seddighi (2013) also considered a location routing problem in the context of a supply chain network. Their goal of the problem was to determine locations, allocation and routing decisions while minimising annual cost. Bashiri et al. (2013) studied the hub and spoke network for distribution systems, with the objective of minimising cost and/or time. In addition to considering quantitative measures (such as cost and time), the authors also considered qualitative parameters in their problem. The design of a distribution system with cost minimisation was formulated by fuzzy VIKOR and MCDM, as the problem was considered to be a hybrid in nature and solved with a GA. Chung et al. (2013) similarly dealt with the problem of distribution centres and their differing processing efficiency, handling reliability and costs. A modified GA was proposed for the problem and new chromosome encoding enabled the algorithm to find better location, allocation and routing solutions, with high handling reliability and recycling ability for the distribution centres.

Pichka et al. (2014) presented an integer linear programming model to formulate the open VRP under realistic assumptions. A SA method was proposed for solving the problem, given the additional complexity of this problem. The open VRP represents the scenario where the supplier does not have a fleet of vehicles, but does have preferences regarding the outsourcing of transportation and distribution projects. Rancourt and Paquette (2014) studied the truck driver scheduling problem. They proposed a multi-criteria optimisation approach for a long haul routing problem. A TS algorithm was used to arrive at a solution, and a heuristic non-dominated solution set was produced to show the trade-off between operating costs and driver inconvenience. Their results showed that a cost increase of just 2.6% could reduce driver inconvenience by up to 10% which would in turn reduce driver turnover. Sadeghi et al. (2014) discussed vendor-managed inventory policy with fuzzy demand, with the intention of decreasing the bullwhip effect. They developed a framework for vendor-managed inventory in a multi-retailer single-vendor supply chain, with the consignment of stock policy. Yu and Lin (2014) discussed an open location routing problem. This differed from the capacitated location routing problem in the sense that the vehicles did not return to the distribution centres after they serviced all the customers: rather, transportation logistics was entirely outsourced. They proposed an SA-based heuristic for the solution of the problem.

Freitas et al. (2014) studied a general problem while Ayvaz and Bolat (2014) studied a very specific problem with both relating to electrical and electronic equipment waste. They also differed in their approach to RL in a way that may provide a general research gap which has still to be resolved. Other researchers who studied specific instances of VRPs in the context of RL are Oliveira et al. (2014), who investigated the recycling of used cooking oil; Demirel et al. (2014), who studied the recycling of ELV; Barrera and Cruz-Mejia (2014) and Huang et al. (2014), who both designed a recovery and recycling system for non-returnable beverage containers; and Bing et al. (2014a), who developed an RL system for the collection of plastic waste, with a trade-off between environmental impacts, social issues and costs.

The following table sets out the relevant literature according to its main research topic. In the table, RL stands for Reverse Logistics, VRP stands for Vehicle Routing Problem, and O stands for Outsourcing.

Table 2.4: Related topics from the literature with respect to the identified research gap

	Authors	Topic
1	(Schittekat and Sörensen, 2009)	VRP O
2	(Agnetis et al., 2014)	VRP O
3	(Moon et al., 2012)	VRP O
4	(Zäpfel and Bögl, 2008)	VRP O
5	(Freitas et al., 2014)	RL VRP
6	(Tasan and Gen, 2012)	RL VRP
7	(Jun and Jian-yong, 2007)	RL VRP
8	(Çatay, 2010)	RL VRP
9	(Avci and Topaloglu, 2015)	RL VRP
10	(Reeves Jr. et al., 2010)	RL O
11	(Hsiao et al., 2010)	RL O
12	(Grabara and Kot, 2010)	RL O
13	(Huang et al., 2014)	RL O
14	(Karakayali et al., 2007)	RL O

Figure 2.4 is a Venn diagram, which has been produced using the information from Table 2.4 to visualise the overlap and also identify the gap between the studies.

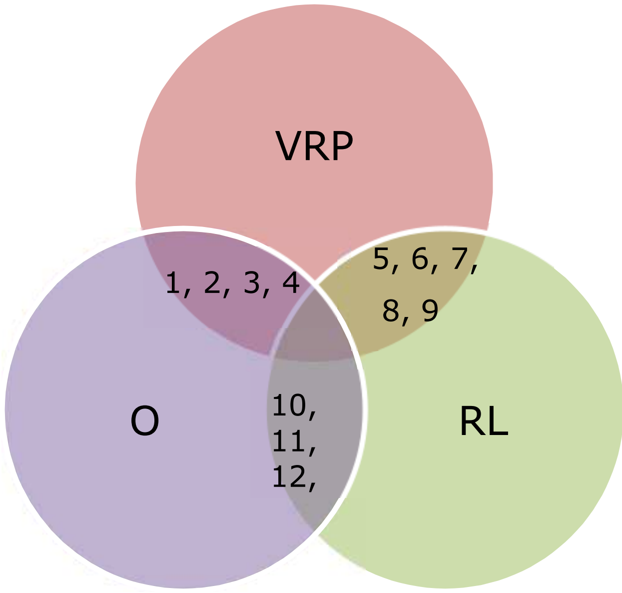


Figure 2.4: Venn diagram identifying research gap

The focus of this study lies in the overlap between outsourcing, RL and VRPs. The above figure shows that these topics have not previously been studied together, rather they have been considered either only in isolation, or combination with other topics. This study will fill this gap by discussing the point at which an RL option (whether asset-sharing or asset-specific) becomes economically advantageous in the context of a VRP with RL and will also investigate how strategic and operational decision-making tools can be incorporated together into the decision-making process. This study will also consider how GHG or CO_2 emissions could be included in the decision-making process for outsourcing.

2.6. Review of the chapter

Reducing CO_2 emissions in transportation logistics is currently a major focus in the field of VRPs, as organisations try to align their (potentially competing) strategic and operational objectives to make themselves more sustainable. Study of the classical VRP and its variants has shown that a simultaneous pickup and delivery problem can align with both RL and green VRP. A follow-up study also revealed that the choice of product and its return state dominate the choice of supply chain system. It was found that many researchers have generalised the VRP without proper regard to choice of product and it is the assertion of this paper that therein lies the potential research gap. The following chapter discusses the focus of the research, and the choice of VRP to suit the type of product and RL under the current study.

Integration strategies such as backhaul, mixing and partial mixing dictated the delivery and collection prioritisation that led to routes being either double path or Hamiltonian. In many real-world problems that dealt with simultaneous pickup and delivery, double path was not taken into consideration, because the vehicle would have to travel twice. The current study will therefore focus on Hamiltonian routes in considering its pickup and delivery problem.

Exploring RL has led to an enhanced understanding of the importance of CO_2 emissions and fuel consumptions. It has also led to the creation of a new variant of VRP - VRPSPD - which also deals with RL and environmental impacts. The literature review revealed the importance of environmental factors in VRPs showing that the transportation sector is responsible for 21% of CO_2 emissions in UK, and therefore highlighting that measures should be taken to reduce its impact. The effect of load and speed in the CO_2 emissions calculation was also discussed.

It was established through the examination of literature that optimisation of a single objective such as minimising CO_2 emissions cannot fulfil the requirements of real-world problems alone. Multi-objective optimisation considering not only travelled distance but also CO_2 emissions or fuel consumption was found to be a suitable methodology to address the current shortcomings in the field.

Comparing several solution methods revealed the preference of other researchers for using population-based metaheuristics over single solution-based metaheuristics as single solution-based metaheuristics cannot incorporate trade-off solutions that are often desired by the end user. The non-dominated sorting GA (NSGA-II) was identified as one of the potential methodologies to be used, and this is discussed in detail in Chapter 4.

The study of outsourcing in the context of RL and VRPs has showed that there is scope to identify new research opportunities in these fields by combining these three topics. For example, by considering the outsourcing of asset-specific or asset-sharing transportation logistics within the framework of a VRP, one can understand the complex relationship between simultaneous pickup and delivery problems (incorporating RL), with minimisation of environmental impact also being one of the objectives in a multi-objective optimisation problem.

3. PROBLEM FORMULATION AND MATHEMATICAL MODEL FOR MULTI-OBJECTIVE VRP

In this chapter, a description of the VRPSPD which is motivated by a real-world problem provided by the industrial collaborator will be presented, followed by the corresponding multi-objective model. The formulation of the problem is presented in Section 3.1. The calculation of fuel consumption which is directly equivalent to CO_2 emissions is explained in Section 3.2. The mathematical formulation is described in Section 3.3, which will cover the definitions of the decision variables (3.3.1), objective functions (3.3.2) and relevant constraints (3.3.3). Section 3.4 will provide an example that justifies the consideration of CO_2 emissions / fuel consumption and distance as two objectives in a multi-objective VRP. Finally, Section 3.5 concludes the chapter with a discussion.

3.1. Problem formulation

This research aims to combine RL and the VRP to obtain an optimised solution with respect to distance and fuel consumption simultaneously. Most research has been undertaken to optimise distance, but very few studies have aimed to take a holistic approach in combining this with CO_2 emissions or fuel consumption. The aim of this research is to develop a mathematical model and propose a methodology that incorporates combined contributions from multiple objectives, with the aim of arriving at an optimal vehicle routing solution which would be suitable for a real-world company which delivers and collects products simultaneously.

In the previous chapter, Table 2.1 highlighted some noteworthy research works in the field of VRPs. Based on these findings, one can design a corresponding supply chain for a particular product type. For example, when a product is chosen that has a high marginal value of time (MVT), its supply chain needs to be more responsive than would be the case for a low MVT product. For a low MVT product, on the other hand its supply chain could be less responsive, but then again could equally be more efficient. The type of return could also affect certain aspects of the ideal supply chain. A subsequent question may arise as to whether a centralised or de-centralised depots should be used for different product types.

Although similar studies have been conducted with re-usable containers, to the best of my knowledge, none have been integrated in the study of simultaneous pickup and delivery vehicle routing problems for a multi-objective optimisation problem with ecological considerations. In this research, a gas cylinder has been selected as the product. This choice was based on the characteristics of its life cycle and marginal value - together with the fact that it was possible to collect information from a collaborating company that deals with the delivery and return of gas cylinders. To build a mathematical model, it was first necessary to define the VRP conditions and boundaries which governed the direction of the research.

The specific vehicle routing problem with simultaneous pickup and delivery (VRPSPD) for a homogeneous vehicle fleet which is investigated in this research is defined as follows. Let $G = (V, A)$ be a complete and directed graph, with vertex set $V = \{V_0, V_1, V_2, \ldots., V_n\}$ and an arc set A, $A = \{(i,j): i,j \in V, i \neq j\}$. Vertex V_0 denotes the depot at which m homogeneous vehicles are stationed, and set $V\backslash\{V_0\}$ describes the customers. Associated with A is a distance matrix $[y_{ij}]$ of size $(n+1 \times n+1)$. The notations used in this model are defined below.

V	Set of nodes denote customers, $V = \{V_0, V_1, \ldots \ldots, V_n\}$, V_0 denotes a depot, V_i denotes customers $V_i, i = 1, \ldots, n$
M	Set of vehicles
m	Index for vehicles, $m \in M$
L	Set of capacity measures used to measure the load of vehicle and customer demand
C^l	The capacity of vehicle given in units of capacity measure $l \in L$
y_{ij}	Distance between nodes i and j, $i,j \in V$
p_i^l	Demand for pickup from customer i, $i \in V\backslash V_0$, l denotes capacity measure, $l \in L$
d_i^l	Demand for delivery from customer i, $i \in V\backslash V_0$, l denotes capacity measure, $l \in L$
T	Maximum driving time for each vehicle
v	Speed of vehicle
N	Sufficiently large number

The aim was to create a set of routes - each starting and ending at the depot - with simultaneous pickup and delivery for the customers. Each customer is visited only once by exactly one vehicle. When a customer is visited, their complete demand for pickup and delivery is met by the vehicle. The total load of a vehicle must not exceed its capacity at any time in the allocated route (C^l). The total time that a vehicle spends on the route must not exceed a pre-defined maximum driving time (T). It was also assumed that no transshipments are made at the locations of any of the customers. A fleet of homogeneous vehicles, $m \in M$, is available to service the customers and each vehicle has a fixed capacity in terms of various capacity measures, expressed as l.

The most common objective of a typical VRP is either to minimise the number of vehicles or to minimise total driving distance. However, in a real-world problem, investigating only one criterion would rarely allow an end user to adequately assess the quality of the generated solution. So it is preferable to include multiple criteria (or objectives) which should be optimised simultaneously. In real-world problems, there is a simultaneous contribution from multiple objectives while single-objective methods focus solely on one factor that may not fully represent the true nature of a problem.

This paper defines a multi-objective VRP that considers both driving distance as well as CO_2 emissions which is equivalent to fuel consumption. Distance has simply been measured in kilometres or miles. Fuel consumption, on the other hand, requires a complex approach. Many theories have been identified and tested in real life to precisely calculate CO_2 emissions or fuel consumption. Section 3.2 explains these approaches, leading to the selection of one which will be used further in this thesis.

3.2. Calculation of fuel consumption

Barth et al. (2005) offered an accurate model to calculate CO_2 emissions that considered more vehicle characteristics. This model was subsequently used in many studies in the field of VRPs - including the work of Franceschetti et al. (2013), Huang et al. (2012), Koç et al. (2014) and Soysal et al. (2015a). This model will also be adopted here for the calculation of CO_2 emissions - which is directly related and equivalent to fuel consumption. In the remaining part of the thesis, the term “fuel consumption” will be used instead of “CO_2 emissions”.

The parameters that are used in the objective function to calculate fuel consumption are presented in Table 3.1. For a detailed explanation of the notations, please refer to the Appendix.

Table 3.1: Parameter values for calculating fuel consumption

Notation	Description	Typical values
ξ	Fuel to air mass ratio	1
η	Efficiency parameter for diesel engine	0.45
κ	Heating value of a typical diesel fuel (kJ/g)	44
Ψ	Conversion factor (g/s to l/s)	737
w	Curb weight (kg)	14000
k	Engine fraction factor $(kJ/rev/l)$	0.15
N	Engine speed (rev/s)	30.0
V_e	Engine displacement (l)	10.5
C_d	Coefficient of aerodynamics drag	0.9
C_r	Coefficient of rolling resistance	0.01
A_f	Frontal surface area (m^2)	10
n_{tf}	Vehicle drive train efficiency	0.45

Source: (Koç et al., 2016)

Modelling of emissions follows the same approach as was proposed in Barth et al. (2005). To calculate fuel consumption, the comprehensive emissions model of Barth et al. (2005) and Barth and Boriboonsomsin (2008) was used. The instantaneous fuel use rate, denoted FR (l/s) when travelling at a constant speed v (m/s) with load (kg), is estimated as:

$$FR = \frac{\xi}{\kappa\psi}\left(kNV_e + \frac{0.5C_d\rho A_f v^3 + (w+f)v(gsin\phi + gC_r cos\phi)}{1000n_{tf}\eta}\right) \quad (3.1)$$

where ξ is fuel-to-air mass ratio, κ is the heating value of a typical diesel fuel (kJ/g), ψ is a conversion factor from grams to litres (from g/s to l/s), k is the engine friction factor $(kJ/rev/l)$, N is the engine speed (rev/s), V_e is the engine displacement (l), ρ is the air density (kg/m^3), A_f is the frontal surface area (m^2), w is the vehicle curb weight (kg), g is the gravitational constant (equal to 9.81 m/s^2), ϕ is the road angle, C_d and C_r are the coefficients of aerodynamic drag and rolling resistance, n_{tf} is vehicle drive train efficiency, and η is an efficiency parameter for diesel engines. Using $\alpha = gsin\phi + gC_r cos\phi$, $\beta = 0.5C_d A_f \rho$, $\gamma = 1/(1000n_{tf}\eta)$ and $\lambda = {}^{\xi}/_{\kappa\psi}$, (3.1) can be simplified as

$$FR = \lambda\big(kNV_e + \gamma(\beta v^3 + \alpha(w+f)v)\big) \tag{3.2}$$

The total fuel consumption denoted by F, for traversing a distance y (m) at constant speed v (m/s) with load f (kg), is equal to the fuel rate multiplied by the travel time ${}^{y}/_{v}$ - which can be expressed as:

$$F = \lambda\left(kNV_e\frac{y}{v} + \gamma\beta y v^2 + \gamma\alpha(w+f)y\right) \tag{3.3}$$

Expression (3.3) contains three terms in the parentheses. We refer to the first term, $kNV_e\frac{y}{v}$, as the engine module which is linear in the travel time. The second term, $\gamma\beta y v^2$, is called the speed module which is quadratic in the speed. The last term, $\gamma\alpha(w+f)y$, is the weight module which is independent of travel time and speed.

In our study, the distance y_{ij} is the actual driving distance calculated with the help of Google Maps API. The expression for the distance measurement is given at the below URL.

https://maps.googleapis.com/maps/api/distancematrix/json?origins=&destinations=&key

3.3. Mathematical formulation

The mathematical formulation of the problem is presented in this section with a clear description of the decision variables, objective functions and constraints.

3.3.1 Decision variables

The decision variables are set out below.

$Z_j^{m,l}$: Load of vehicle m at customer j, $j \in V$, $l \in L$ is the capacity measure (number of cylinders, weight, or number of pallets)

S_j: Variable used to avoid sub-tours, which can be interpreted as position of node $j \in V$ in the route

x_{ij}^m = Binary decision variable that indicates whether vehicle m travels from i to j

3.3.2 Objective functions

The objectives in this model are as follows.

1. To minimise total fuel consumption.

$$minimise \sum_{i,j\in V}\sum_{m\in M}\lambda kNV_e\frac{y_{ij}}{v}x_{ij}^m+\sum_{i,j\in V}\sum_{m\in M}\lambda\gamma\beta v^2\,x_{ij}^m + \sum_{i,j\in V}\sum_{m\in M}\lambda\gamma\alpha\left(w+Z_j^{m,w}\right)y_{ij}x_{ij}^m$$

Using the typical values of the parameter given in Table 3.1 implies:

$$minimise \sum_{i,j\in V}\sum_{m\in M}0.00145*\frac{y_{ij}}{v}x_{ij}^m+\sum_{i,j\in V}\sum_{m\in M}7.35^{-7}*v^2x_{ij}^m + \sum_{i,j\in V}\sum_{m\in M}1.33^{-8}*\left(w+Z_j^{m,w}\right)*y_{ij}x_{ij}^m \qquad (3.4)$$

y_{ij} = travelled distance between point i and j

$Z_j^{m,w}$ = load of vehicle m = $P_j^w - d_j^w$, weight is considered in fuel consumption calculation

The objective function given in equation (3.4) is an adaptation of the function proposed by Koç et al. (2014) that presents fuel consumption. The first term of equation (3.4) is based on the engine of the vehicle, the second term is based on the speed of the vehicle, and the third term considers the load of the vehicle. It should be noted here that there is a non-linear term $(Z*x)$. Koç et al. (2014) proposed a model that calculated the cost of the fuel consumption and of CO_2 emissions which also included the total driver wage and sum of all vehicle fixed costs. These two have been omitted from our objective function as it is the goal to calculate the CO_2 emission in the form of fuel consumption only.

2. To minimise the total travel distance by all the vehicles (in kilometres).

$$\text{minimise} \sum_{i,j \in V} \sum_{m \in M} y_{ij} x_{ij}^m \tag{3.5}$$

3.3.3 Constraints

The following constraints are defined.

$$\sum_{i \in V} \sum_{m \in M} x_{ij}^m = 1, \qquad \forall\, j \in V \backslash \{V_0\} \tag{3.6}$$

$$\sum_{i \in V} x_{ik}^m - \sum_{j \in V} x_{kj}^m = 0, \qquad \forall\, k \in V \backslash \{V_0\}, m \in M \tag{3.7}$$

$$x_{ii}^m = 0, \qquad \forall i \in V, m \in M \tag{3.8}$$

$$Z_0{}^{m,l} = \sum_{i \in V} \sum_{j \in V \backslash (V_0)} d_j\, x_{ij}^m\,, \qquad \forall\, m \in M, l \in L \tag{3.9}$$

$$Z_j^{m,l} \geq Z_0{}^{m,l} - d_j + p_j - N\left(1 - x_{0j}^m\right),\ \ \forall j \in V \backslash (V_0), m \in M, l \in L \tag{3.10}$$

$$Z_j^{m,l} \geq Z_i^{m,l} - d_j + p_j - N\left(1 - \sum_{m \in M} x_{ij}^m\right),\ \ \forall i,j \in V \backslash (V_0), i \neq j, m \in M, l \in L \tag{3.11}$$

$$Z_j^{m,l} \leq C^l, \qquad \forall\, j \in V, m \in M, l \in L \tag{3.12}$$

$$\sum_{i \in V} \sum_{j \in V} \frac{y_{ij}}{v} x_{ij}^m \leq T, \qquad \forall\ m \in M \tag{3.13}$$

$$S_j \geq S_i + 1 - n\left(1 - \sum_{m \in M} x_{ij}^m\right) \qquad \forall i,j \in V \backslash \{V_0\}, j \neq i \tag{3.14}$$

$$S_j \geq 0 \quad \forall j \in V \backslash \{V_0\} \tag{3.15}$$

$$x_{ij}^m \in \{1,0\}, \qquad \forall\, i,j \in V, m \in M \tag{3.16}$$

Constraint (3.6) ensures that each customer node is served exactly once. Equation (3.7) guarantees that, for each customer node, the same vehicle arrives at and leaves from this node. Constraint (3.8) confirms that the vehicles do not return to the same node creating a small loop. Initial vehicle loads are calculated as in (3.9), with each vehicle's initial load being the sum of demands of all customer nodes assigned to this vehicle. Inequality (3.10) calculates the load of vehicles after vehicles visit the first customer node on their respective routes. For other customer nodes, the loads of vehicles are calculated as in equation (3.11) similarly through their routes. Constraint (3.12) impose limits on capacity. Drivers are not allowed to drive for more than a specific duration, and the corresponding constraint is given at (3.13). Constraint (3.14) ensures sub-tour elimination, and is taken from Tasan and Gen (2012). Equation (3.15) maintains the non-negativity of S_j and the status of x_{ij}^{m} as a binary decision variable is ensured by (3.16).

It is well-known that VRP is NP hard and there are papers which investigate the complexity of different variants of VRP (see for example Archetti and Speranza (2012), Toth and Vigo (2002)).

3.4. Justification of multi-objective optimisation for fuel consumption and distance

Two objectives that are considered in the thesis are distance and fuel consumption (or equivalent CO_{2e} emission). The fuel consumption depends not only on the travelled distance but also on the load of vehicle. These two objectives are incommensurable, i.e. they are measured in different measurement units (km and litres). The mapping of the objective's values to one measurement unit, say cost, is not straightforward. By using a simple example it is illustrated that minimising distance does not automatically lead to minimisation of fuel consumption. That is the reason why a multi-objective optimisation is used in this research. An example is presented here to demonstrate that optimisation of distance and fuel consumption result in two different solutions with the same minimum distance, but with different fuel consumption. In this example, let us suppose there are three customers, who are to be served by one vehicle that departs from and return to the same depot. The customer location, delivery and pickup demand are presented in Table 3.2.

Table 3.2: Coordinates of the customers and their delivery and pickup demands

	ID	**Coordinates**		**Delivery demand**	**Pickup demand**
Depot	0	100	100	0	0
Customer 1	1	200	300	4300	0
Customer 2	2	400	200	6100	500
Customer 3	3	500	500	2780	2500

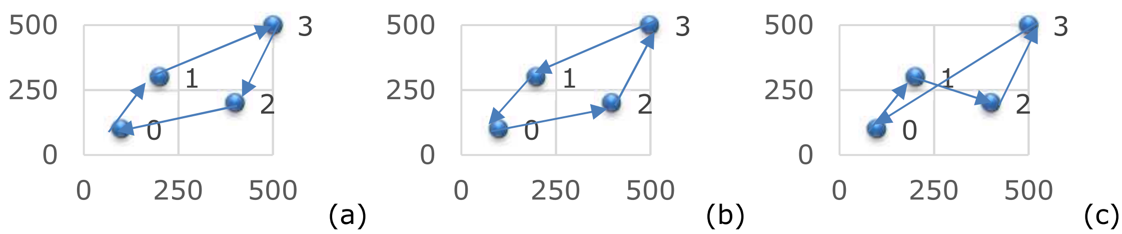


Figure 3.1: Routes with shortest distance and lowest fuel consumption

Figure 3.1 presents three routes for the VRP. The routes initiate and end at the depot (0). Out of six possible combinations, the three presented here are those with the shortest distance and lowest fuel consumption. Fuel consumption is calculated using the formula quoted in Section 3.3.

$$\sum_{i,j\in V} 0.00145 * \frac{y_{ij}}{v} x_{ij} + \sum_{i,j\in V} 7.35^{-7} * v^2 x_{ij} + \sum_{i,j\in V} 1.33^{-8} * \left(w + Z_j^{m,w}\right) * y_{ij} x_{ij}$$

Where,

$$x_{ij} = \begin{cases} 1, \text{if vehicle traverses arc } (i,j), \forall\, i,j \in \{V\}, \\ 0, \qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases}$$

Step by step break-down of the calculation is shown in Table 3.3.

Table 3.3: Detailed calculation of distance and fuel consumption for three routes

Route in Figure 1(a)				Route in Figure 1(b)				Route in Figure 1(c)			
$\boldsymbol{i,j}$	distance	Load	Fuel	i,j	distance	Load	Fuel	i,j	distance	Load	Fuel
0,1	223.61	13180	95.57	0,2	316.23	13180	135.16	0,1	223.61	13180	95.57
1,3	360.56	8880	133.48	2,3	316.23	7580	111.61	1,2	223.61	8880	82.78
3,2	316.23	8600	115.89	3,1	360.56	7300	125.91	2,3	316.23	3280	93.51
2,0	316.23	3000	92.34	1,0	223.61	3000	65.30	3,0	565.69	3000	165.19
Distance = 1216.63 ($\boldsymbol{km}$) Fuel consumption = 437.28 ($\boldsymbol{l}$)				Distance = 1216.63 (km) Fuel consumption = 437.98 (l)				Distance = 1329.14 (km) Fuel consumption = 437.05 (l)			

Fuel consumption on each of the route are 437.28 litres, 437.98 litres and 437.05 litres respectively. The route depicted at Figure 3.1(c) thus produces the lowest fuel consumption. However, the distance travelled in Figure 3.1(c) is longer than the other two routes. This example shows that distance and fuel consumption have to be considered as two different objectives in a multi-objective VRP.

In addition, there are views that a single objective optimisation is not appropriate in many real-world optimisation problems in the sense that it operates with a single artificially made function which does not have a meaning for a decision maker. Opposite to this, multi-objective optimisation deals with objectives which have real meaning in the problem under study.

3.5. Review of the chapter

In this chapter, the formulation of a problem was introduced, together with an introduction to the VRP nomenclature. A multi-objective optimisation model for a VRPSPD was defined. Single-objective problems are limited to considering one particular angle while real-life problems are usually more complex, and require simultaneous optimisation of multiple objectives. In this research, both distance and fuel consumption (which is directly proportional to CO_2 emissions) are optimised simultaneously. This is an original contribution to the body of research looking at VRPSPDs. It is not straightforward to combine the two objectives in a weighted sum because they are expressed in different units of measure. In addition, defining the problem as a multi-objective optimisation problem gives opportunities for the decision-maker to select a solution from a pool of solutions that represent a trade-off between the two objectives. An example was presented which demonstrated that two routes with the same distance can have different fuel consupmtion due to the different load of vehicles between customers on their routes. This fact introduces asymmetry into the problem as a tour might be feasible in terms of capacity in one direction, but not necessarily in another. It was also shown that a tour exhibiting minimum fuel consumption would not necessarily also have the lowest travel distance.

The calculation of fuel consumption is a complex process, as demonstrated in the existing literature. Many researchers have produced different methods to calculate fuel consumption for vehicles (or more specifically trucks). The model proposed by Barth et al. (2005) has been widely used in the research, as it covers typical as well as specific parameters for calculation of fuel consumpiton that are directly proportional to CO_2 emission.

4. A MULTI-OBJECTIVE GENETIC ALGORITHM FOR VRPS

This chapter presents the NSGA-II. While it was developed specifically for the VRPSPD, this algorithm can also work for a general VRP. A description of the NSGA-II and its general components are given in Section 4.1. Components of the algorithm that are tailored to a VRPSPD including the representation of a chromosome, selection, crossover, mutation, Split Algorithm, and a new approach to initialisation are presented in Section 4.2. The design of the components follows the findings in the literature. The main focus of the design in this study is on the generation of the initial population, and investigation of the effect of different initialisation on the final Pareto front. A discussion on various initial population generation methods including the Savings Algorithm, Sweep Algorithm and random generation is given in Section 4.3. A novel initial population generation method, using a multi-criteria decision-making method TOPSIS, is then introduced. First, TOPSIS is presented in Section 4.4, followed by a description of the proposed TOPSIS-based constructive heuristic to be used in the initialisation of the NSGA-II. The chapter concludes with a review at Section 4.6.

4.1. NSGA-II for a multi-objective VRP

A number of metaheuristics have been developed over the years to solve multi-objective optimisation problems. One of the best-known population-based metaheuristics used for multi-objective evolutionary optimisation is elitist NSGA-II, as proposed by Deb et al. (2002). The NSGA-II has been used by many researchers in a variety of multi-objective optimisation problems. The NSGA-II has two main distinctive features that makes it appropriate for solving multi-objective problems.

1. It uses an elitist principle that emphasises non-dominated solutions.
2. It defines a mechanism for preserving diversity.

Various experiments were conducted to compare the Pareto Archived Evolution Strategy developed by Knowles and Corne (2000), the Strength Pareto EA developed by Zitzler and Thiele (1998a), and the NSGA-II. A conclusion was reached that the NSGA-II performed better against both algorithms in a 0/1 knapsack problem (Zitzler and Thiele, 1998b).

The block diagram of the NSGA-II is presented in Figure 4.1. The NSGA-II starts with the set of initial population, P_0. The initial population is generated using various methods, and has size $population_{size}$. In this algorithm, P_t has been used to denote the current population in iteration t - and Q_t represents the offspring population created using the GA operators, crossover, mutation and Split algorithm. The selection algorithm, which is described in Section 4.2, chooses solutions to be used in the crossover. The offspring, Q_t, are added into the parental population P_t to create the population R_t of size $2 * population_{size}$. The solutions in the population R_t are grouped into Pareto fronts of different levels using non-dominated sorting, which is explained in Section 4.2. The size of R_t is $2 * population_{size}$, and we need only a $population_{size}$ number of solutions. The selection of solutions for the next iteration starts with the best non-dominated front, continues with the second non-dominated front, and so on. Each non-dominated front to be included in the next iteration is checked to see whether all of its solutions can be included. If it contains more solutions than required, then Crowding distance sorting is performed to select the required number of solutions. This technique ensures that diverse solutions will be chosen from this front and it is also explained in Section 4.2.

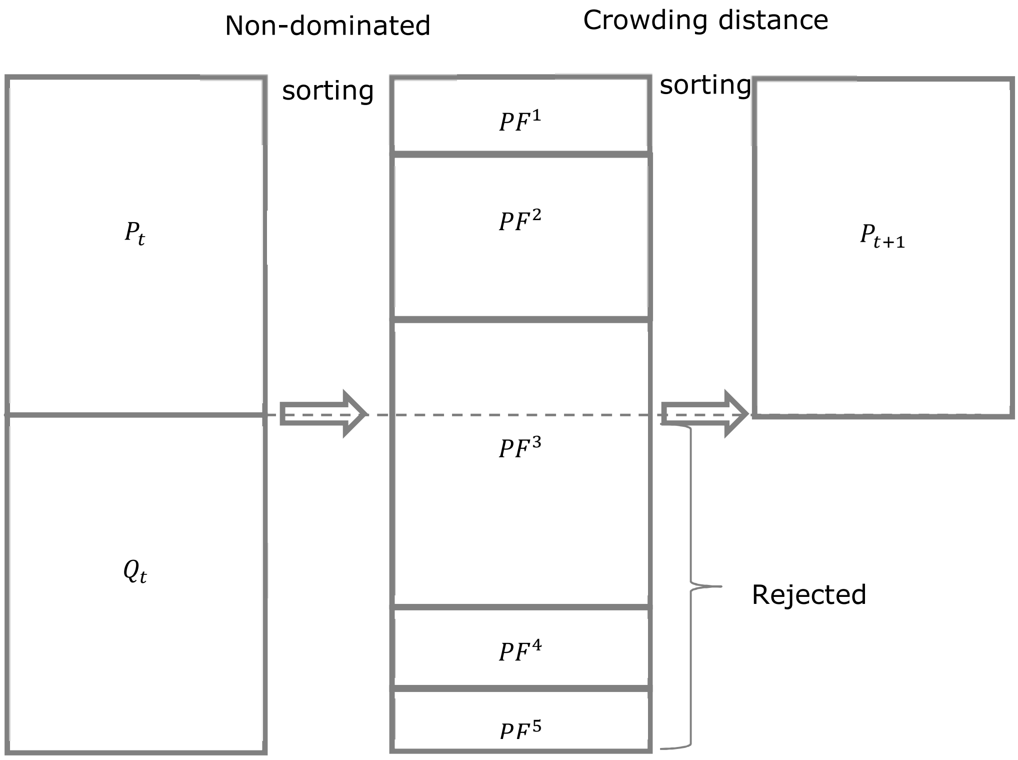


Figure 4.1: A block diagram of the NSGA-II
Source: (Deb et al., 2002)

A pseudocode for the NSGA-II for VRP is presented as Algorithm 4.1.

Algorithm 4.1: NSGA-II for VRPSPD
$\boldsymbol{Output}$: $\boldsymbol{Final\ Pareto\ front}$
$\boldsymbol{Initialisation}$: $\boldsymbol{create\ P_0\ initial\ population\ of\ size\ population_{size}}$
$\boldsymbol{t = 0}$
$\boldsymbol{Repeat\ until\ termination\ condition\ is\ met}$
$\boldsymbol{Create\ offspring\ population\ Q_t\ from\ P_t\ by\ using\ the\ selection, cros}$ $\boldsymbol{and\ mutation}$
$\boldsymbol{R_t = P_t \cup Q_t}$
$\boldsymbol{Non - dominated\ sorting(R_t)}$
$\boldsymbol{Identify\ different\ Pareto\ fronts\ F_i, i = 1, \ldots, I}$
$\boldsymbol{P_{t+1} = \varnothing}$
$\boldsymbol{i = 1}$
$\boldsymbol{While\ \lvert P_{t+1} \rvert + \lvert F_i \rvert < population_{size}}$
$\boldsymbol{P_{t+1} = P_{t+1} \cup F_i}$
$\boldsymbol{i = i + 1}$
$\boldsymbol{Crowding - distance\ sorting\ (Fi, < c)}$
$\boldsymbol{Add\ the\ most\ widely\ spread\ population_{size} - \lvert P_{t+1} \rvert)\ solutions\ to\ P_{t+1}}$
$\boldsymbol{t = t + 1}$

4.1.1 Non-dominating sorting and Crowding distance sorting

Non-dominated sorting classifies solutions into different Pareto fronts in such a way that solutions on each front are dominated only by the previous front. An algorithm for non-dominated sorting is presented at Algorithm 4.2. Two variables are introduced: S_P, which is a set that contains solutions dominated by solution p; and domination count n_P, which stores the number of solutions that dominate the solution p. All solutions in the first non-dominated front will have their domination count $n_P = 0$. Each member of S_P will then have its domination count reduced by 1. Each solution with a domination count equal to 0 at this stage will belong to the second non-dominated front. The algorithm continues to run until all solutions are classified into different levels of fronts.

Algorithm 4.2: Non-dominated sorting (P)	
$\boldsymbol{for\ each\ p \in P}$	
$\quad \boldsymbol{S_p = \emptyset}$	$Set\ of\ solutions\ dominated\ by\ solution\ p$
$\quad \boldsymbol{n_p = \emptyset}$	$Domination\ count{:}\ the\ number\ of\ solutions\ which\ dominate\ the\ solution\ p$
$\quad \boldsymbol{for\ each\ q \in P}$	
$\qquad \boldsymbol{if\ (p \prec q)\ then}$	$If\ p\ dominates\ q$
$\qquad\quad \boldsymbol{S_p = S_p \cup \{q\}}$	$Add\ q\ to\ the\ set\ of\ solutions\ dominated\ by\ p$
$\qquad \boldsymbol{else\ if\ (q \prec p)\ then}$	
$\qquad\quad \boldsymbol{n_p = n_p + 1}$	$Increment\ the\ domination\ counter\ of\ p$
$\qquad \boldsymbol{if\ n_p = 0\ then}$	$p\ belongs\ to\ the\ first\ front\ F1$
$\qquad\quad \boldsymbol{F_1 = F_1 \cup \{p\}}$	
$\boldsymbol{i = 1}$	$Initialise\ the\ first\ counter$
$\boldsymbol{While\ F_i \neq \emptyset}$	
$\quad \boldsymbol{Q = \emptyset}$	$Used\ to\ store\ the\ members\ of\ the\ next\ front$
$\quad \boldsymbol{for\ each\ p \in F_i}$	
$\qquad \boldsymbol{for\ each\ q \in S_p}$	
$\qquad\quad \boldsymbol{n_q = n_q - 1}$	
$\qquad\qquad \boldsymbol{if\ n_q = 0\ then}$	$q\ belongs\ to\ the\ next\ front$
$\qquad\qquad\quad \boldsymbol{Q = Q \cup \{q\}}$	
$\quad \boldsymbol{i = i + 1}$	
$\quad \boldsymbol{F_i = Q}$	

The filling of the new population starts from the Pareto front of level 1 (F_1), continues with level 2 (F_2), and so on. If the size of the considered Pareto front is larger than needed, the diversity of the solutions away from this front is used for selection. To determine the density of solutions of each front, Deb et al. (2002) proposed the Crowding distance, $\rho_{distance}$, which is illustrated in Figure 4.2. In the presented pseudocode and accompanying explanation we refer to two objectives as these are the parameters of our optimisation problem but Crowding distance can be defined for any number of objectives. Crowding distance is a measure of the search space around a solution which is not occupied by any other solution in the population. The process of calculation of the density of solution ρ takes two solutions which are the nearest neighbours of p on either side of p for each objective. Crowding distance for each solution p - denoted by d_ρ - is defined as the perimeter of the rectangle formed by using its nearest neighbours as vertices, divided by the number of objectives. The distances have to be normalised, because the objectives are incommensurable. The larger the Crowding distance of a solution, the more isolated that solution and therefore the more likely it is to be kept. The extreme solutions with the optimal values for the objectives in a Pareto front by definition have infinite Crowding distance.

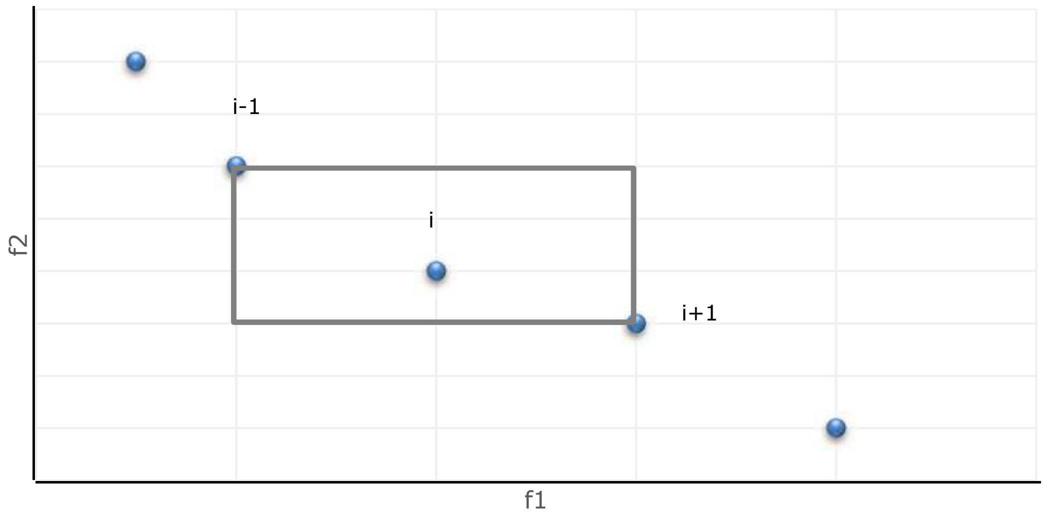


Figure 4.2: An illustration of Crowding distance calculation
Source: (Deb et al., 2002)

An algorithm for calculating Crowding distance is presented at Algorithm 4.3.

Algorithm 4.3: Crowding distance sorting ($F_i <_c$)	
$\boldsymbol{For\ all\ p \in F_i, d_{pi} = 0, i = 1, \ldots, s}$	$There\ are\ s\ solutions\ in\ the\ front\ F_i$
$\boldsymbol{For\ each\ objective\ k, k = 1, 2}$	
$\boldsymbol{I_k = sort(f_k, >)}$	$Sorts\ the\ set\ from\ lowest\ to\ highest\ of\ objective\ f_k, where\ I_k\ is\ the\ list\ of\ indices$
$\boldsymbol{For\ each\ objective\ k = 1, 2}$	
$\boldsymbol{d_{IK1} = d_{IKs} = \infty}$	$The\ distance\ for\ the\ extreme\ solutions\ is\ infinite$
$\boldsymbol{I_{kj}\ is\ the\ index\ of\ the\ jth\ member\ in\ the\ sorted\ list\ I_k}$	
$\boldsymbol{For\ all\ other\ solutions\ j = 2, \ldots, s - 1}$	
$\boldsymbol{d_{Ikj} = \frac{f_k^{(I_{k\,j+1})} - f_k^{(I_{k\,j\_1})}}{f_k^{max} - f_k^{min}}}$	
$\boldsymbol{d_j = d_j + d_{Ik}}$	

4.2. Components of the NSGA-II for the VRPSPD

In this section, the components of the NSGA-II which are specifically designed for the stated VRPSPD are described which includes representation, selection, crossover, mutation and Split Algorithm. However, these components could be also used for a general VRP. The components are presented in more detail in Sections 4.2.1 to 4.2.5.

4.2.1 Representation

Each potential solution - also referred to as a chromosome - takes the form of a string, and generally requires further encoding or decoding steps which are defined by the algorithm. Depending on the problem at hand, these representations can be either binary or literal strings. The choice of chromosome format is of utmost importance and is one of the critical aspects which can determine the success or failure of the Genetic Algorithm. Chromosomes have to be defined in such a way as to cover the whole solution space. In our approach, the chromosome is an integer string that denotes the sequence of customers to be visited in each route. The routes are split by delimiter '0', which represents the depot. An example of a chromosome in which there are 10 customers is given in Figure 4.3. The first vehicle will service customers 1, 5, 10 and 9 before returning back to the depot, and so on.

0	1	5	10	9	0	3	7	6	0	8	2	4	0

Figure 4.3: Chromosome representation for a VRP with 10 customers

4.2.2 Selection

There are many selection procedures for deciding which solutions survive and take part in the reproduction system or to put it another way, which solutions are subject to crossover. Common selection procedures include the roulette wheel, ranking, tournament selection, stochastic universal sampling, and random selection. There are no universal rules that determine which procedure is best. This largely depends on the problem at hand, and also on the overall design of the algorithm.

This study use a combination of random and rank selection. We categorised the population into Pareto fronts, and selected one of the parents randomly from the 1st front. The second parent was then selected randomly from among the other fronts.

4.2.3 Crossover

An interesting debate has been presented in the literature on whether both crossover and mutation are required in a GA. Researchers supporting both views have provided good evidence to establish their arguments. On one hand, Fogel and Atmar (1990) claimed that crossover operators did not necessarily produce better results, but were in fact merely a generalisation of the mutation operator. On the other hand, researchers such as Goldberg and Lingle (1985), Pan (2016), Prins (2004) and Vidal et al. (2012) have successfully argued for the use of crossover operators and also implemented crossover in their proposed research.

In general, GAs search the solution space for better solutions by using crossover and mutation operators. The crossover operator simulates reproduction between two individuals, where the offspring inherit some characteristics of each individual. Crossover operators enable "exploitation", which refers to the search of the vicinity of the known two good solutions. A crossover serves as a convergence operator, with the aim of exploitation.

A crossover operator selects two parents from the mating pool, and recombines them to generate new and potentially better offspring, that will inherit some characteristics from each parent. In most crossover operators, the two selected parents are recombined with a probability p_c, called the crossover rate. If a randomly generated number, r, is less than or equal to p_c, the selected parents undergo crossover operation. The value of p_c can be set either experimentally, or by using the schema theorem principles established by Goldberg (1989). However, it has been suggested that the crossover value should be kept as high as possible. A higher value for the crossover rate ensures that convergence will occur at a steady but quicker rate.

Applying classical crossover operators to a TSP or VRP, in which solutions are represented as permutations, commonly generates infeasible solutions with repeated elements. Many crossover operators are designed for protecting the feasibility of offspring in a TSP or VRP. Some well-known crossover operators are set out below.

- Two-Point Crossover (Baker and Ayechew, 2003)
- Partially Mapped Crossover (PMX) (Goldberg and Lingle, 1985; Mandal et al., 2015; Pan, 2016)
- Ordered Crossover (OX) (Liu et al., 2009; 2013)
- Linear Order Crossover (LOX) (Prins, 2004)
- Periodic Crossover with Insertions (Vidal et al., 2012)
- Insertion Based Crossover (IBX) (Berger and Barkaoui, 2004)
- Alternating Edge Crossover (AEX) (Grefenstette et al., 1985; Larrañaga et al., 1999; Puljić and Manger, 2013; Alinaghian et al., 2017)

Alternating Edge Crossover (AEX) was first introduced by Grefenstette et al. (1985) and then later used again by Larrañaga et al. (1999) for their respective travelling salesman problems. However, this efficient yet simple crossover did not draw much attention from researchers until recently when Alinaghian et al. (2017) and Puljić and Manger (2013) implemented it successfully in their VRPs. Puljić and Manger (2013) studied different evolutionary crossover operators in the context of VRPs, and their findings suggested that AEX and Heuristic Crossover (HGreX) provided better results than other evolutionary crossovers -

such as OX, CX, PMX or Edge Recombination Crossover (ERX). They also found that while TSPs and VRPs have so much in common their relative rankings of best-performing crossover operators were significantly different. They concluded that while OX and ERX performed better than all other crossovers for TSPs, AEX and HGreX outperformed them in the VRP setting.

In the developed NSGA-II, AEX crossover was implemented. An example of AEX crossover is presented in Figure 4.4. It is assumed that there are nine customers. An offspring is generated by selecting arcs from two parents alternately. The two parents chosen for the crossover operation are denoted as P_1 and P_2, with removed delimiters given in the two rows labelled (a).

In the first step, the first two genes (5 and 1) from P_1 are chosen to initialise the offspring - shown at row (b). The arc emanating from 1 in P_2 is chosen for the offspring. The offspring now has the elements described in row (c). The arc from 9 is now chosen from P_1, and is added to the offspring. The process continues, and produces the next offspring - shown in row (d). The next arc emanating from 3 in P_2 is 6 but this leads to infeasibility. To avoid infeasibility, any unvisited vertices are chosen randomly. It is assumed that the next vertex chosen is 7. The offspring is given in row (e). The procedure continues, taking the arc $7 \rightarrow 8$ from P_1 and $8 \rightarrow 4$ is chosen from P_2. The final offspring is presented in row (f).

(a)	P_1	5	1	7	8	4	9	6	2	3
	P_2	3	6	2	5	1	9	8	4	7
(b)	c	5	1	*	*	*	*	*	*	*
(c)	c	5	1	9	*	*	*	*	*	*
(d)	c	5	1	9	6	2	3	*	*	*
(e)	c	5	1	9	6	2	3	7	*	*
(f)	c	5	1	9	6	2	3	7	8	4

Figure 4.4: Alternating edge crossover

4.2.4 Mutation

Mutation operators generate new solutions in the regions of the search space that have not been explored previously. This approach contributes to the exploration of the search space (Hicks, 2006). A mutation operator generally prevents a solution from becoming stuck at a local optimum, and guides the solution towards the global optimum. It may break the local optimum, and lead to the discovery of a better solution. According to Hicks (2006), crossover tries to make the individuals in a population more similar whereas mutation makes them diverse. The value of the mutation rate, p_m, should be set as low as possible - as opposed to the desired high value of p_c - because it is not expected that too many alleles should be changed too randomly. Too many random changes would generate offspring almost randomly, and the genetic search would thereby be degraded to a random search.

Typical mutation operators used in TSP and VRP problems are (Reeves, 1995):

- adjacent pairwise interchange in the sequence;
- Exchange Mutation - the interchange of two randomly chosen elements of the permutation;

- Shift Mutation - the movement of a randomly chosen element a random number of places to the left or right; and
- Scramble Sub-List Mutation - the choice of two random points on the string, and subsequent random permutation of the elements between these two positions.

Some recent applications of mutation operators in permutation-based problems will now be described. Avci and Topaloglu (2015), Baker and Ayechew (2003), Lu et al. (2018), Qi et al. (2015) and Zhang et al. (2014) used Swap Mutation in their respective work with VRPs. Yang et al. (2017) proposed a simple Swap Mutation operator to be used in a GA for a TSP where two selected genes exchange positions under a given probability. Pan (2016) referred to inverse and pairwise interchange mutation in the GA for a steelmaking continuous casting scheduling problem.

Three Swap Mutations proposed by Lee et al. (2015) in their study of the identical parallel machine scheduling problem have been selected for this research. There are three possible mutations, each to be performed with a given probability. Two positions in a chromosome, x and y, are chosen randomly. The first mutation circularly shifts to the left, within those x and y positions, if the generated random value is less than 0.45 (with this value being taken from Lee et al., 2015). The second mutation circularly shifts to the left again - though this time outside x and y - if the generated random value is bigger than 0.45, but less than 0.9. The third mutation swaps the positions of customers in x and y, if the generated random value is between 0.9 and 1.

The pseudocode for three Swap Mutations is presented as Algorithm 4.4.

Algorithm 4.4: Swap Mutation for VRPSPD
Input: ***Chromosome without delimiters***
Output: ***Mutated offspring***
Randomly choose cutoff points x ***and*** y
Generate a random number z
if $z < .45$
Circularly shift left within x ***and*** y
else if $.45 \le z < .9$
Circularly shift left outside x ***and*** y
else
Swap genes of position x ***and*** y
endif

Figure 4.5 depicts examples of three scenarios.

Before mutation	1	2	3	4	5	6	7	8
After mutation	1	3	4	5	2	6	7	8

(a) Scenario 1

Before mutation	1	2	3	4	5	6	7	8
After mutation	2	3	4	5	6	7	8	1

(b) Scenario 2

Before mutation	1	2	3	4	5	6	7	8
After mutation	1	5	3	4	2	6	7	8

(c) Scenario 3

Figure 4.5: An example of Swap Mutation

In Figure 4.5, two cut-off points are chosen as 2, and 5. In scenario 1, the sequence 2, 3, 4 and 5 is shifted circularly - so the new sequence becomes 3, 4, 5 and 2. In scenario 2, the genes outside points 2 and 5 go through the circular shift as can be seen in Figure 4.5(b). Finally, in scenario 3, the two genes 2 and 5 simply switch places.

Both crossover and mutation satisfy the constraints that all customers are visited only once (as elements in the permutations are not repeated) but they cannot guarantee to satisfy all the other constraints present in the VRP, such as vehicle capacity and time constraints. To address this problem, a Split Algorithm is used before the application of the crossover and mutation operators (Prins, 2004). A Split Algorithm converts a chromosome into a solution in the corresponding TSP form by removing the route delimiters and after application of crossover and mutation operators, divides the obtained TSP solution into appropriate routes, so that vehicle capacity and constraints on driving time are not violated. The Split Algorithm is explained in detail in Section 4.2.5.

In each iteration, the NSGA-II starts with a solution set of P_t. Next, crossover and mutation operation Q_t solutions are generated. These sets are combined together to undergo non-dominated sorting, and are grouped into different levels of Pareto fronts. As the number of solutions is limited to the size of P_t, the worst solutions have to be removed from the solution set. Crowding distance sorting is employed here to remove solutions from the same level of Pareto fronts to keep P_t number of solutions. At the end of this process, the NSGA-II presents new solutions that are superior to the original set of solutions that the algorithm started with.

4.2.5 Split Algorithm

Prins (2004) compared performance of Genetic Algorithm (GA) and Tabu Search (TS) that he developed for use with VRPs. He concluded that infeasibility of an offspring produced by a crossover was one of the reasons that GA performed worse in his experiments than the TS. If the crossover violated a constraint, the offspring had to be modified further so that constraint violation was repaired. He thus introduced the Split Algorithm to address this problem.

The Split Algorithm takes a VRP solution represented as a corresponding TSP or a giant tour. It could be viewed as a giant TSP for one vehicle with a sufficiently large capacity. The Split Algorithm divides the giant tour into smaller feasible routes. The goal is to divide the giant tour in such a way that the sequence of the TSP is still respected while the constraints for the VRP are also met.

In (Prins, 2004), the objective was to minimise distance. This algorithm will be used for distance but needs and adaptation for fuel consumption.

Before giving a pseudocode for the Split Algorithm, an example is provided. Let us suppose that there are five customers labelled $a, \dots, e$. For the sake of simplicity it is assumed that customers only need delivery and not pickup services. The example is shown at Figure 4.6. The demands of the customers are given in the brackets. Triangular inequalities between customers' distances hold. Capacity of each vehicle is 10000, while the limit on driving time is 10 hours - so a vehicle can potentially travel 800km if its speed is 80km/h. Let us suppose that the giant tour is $S = [a, b, c, d, e]$.

The Split Algorithm creates an auxiliary graph, $H = (\{0, a, b, \dots, e\}, A, R, F)$. Set V contains $n + 1$ nodes indexed from 0 to n, and A contains arc (i, j), $i < j$, if a route visiting customers i to j is feasible in terms of load and driving time. R is the total distance of the routes, F is the total fuel consumption and both are to be minimised.

A contains arcs $(i, j) \in A$ such that:

$$\sum_{k=i+1}^{j} d_k \leq C \tag{4.1}$$

$$y_{ij} = y_{0,i+1} + \sum_{k=i+1}^{j-i} y_{k,k+1} + y_{j0} \leq TD \tag{4.2}$$

where:

C is the capacity of the vehicle;

y_{ij} is the distance to travel between nodes i and j, $i,j \in V$;

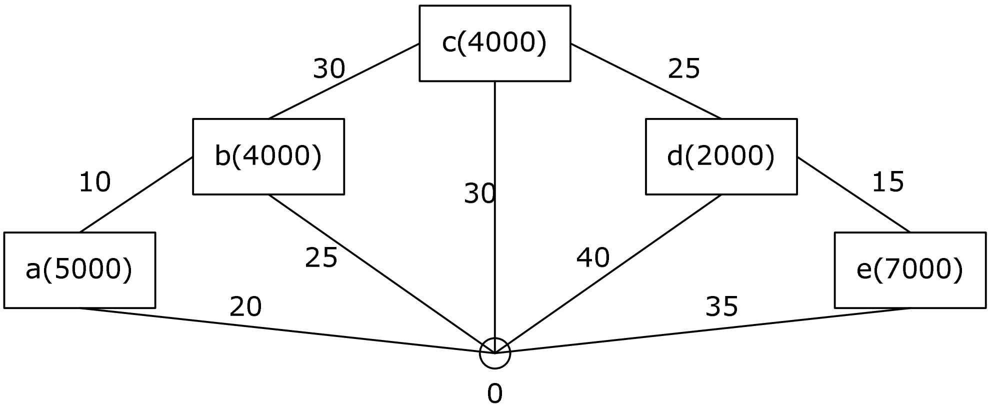
d_i is the demand of customer i (bearing in mind that in this example we do not differentiate between pickup and delivery); and

TD is the maximum distance to travel for each vehicle

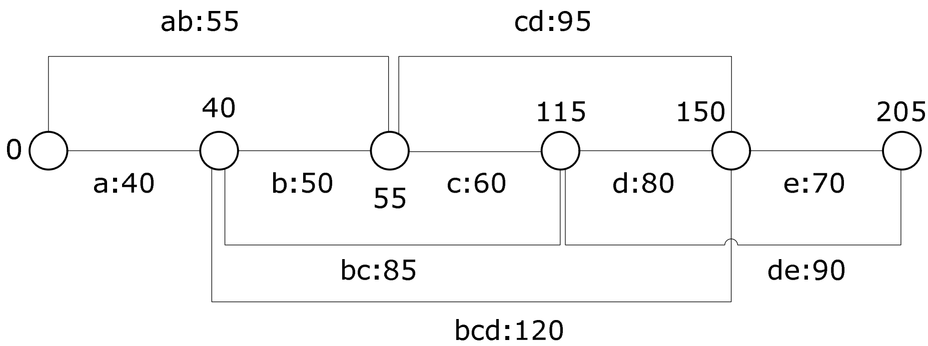
Constraint (4.1) ensures that the load of the vehicle does not exceed its capacity, while constraint (4.2) imposes the limit on the driving time (equivalent to distance to travel). There is no constraint on the maximum fuel consumption.

For instance: $ab \in A$, with distance 55, for the route $(0, a, b, 0)$.

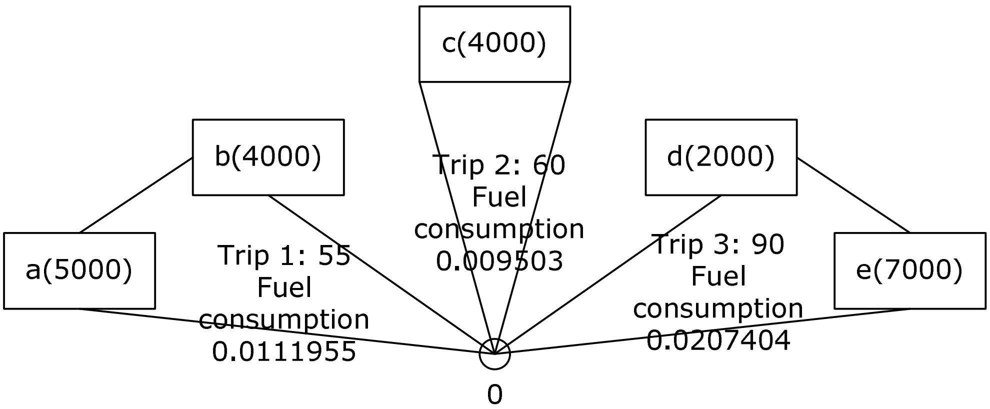
In Figure 4.6 (b) three arcs are shown giving the resulting routes with minimum distance. With three routes, the total distance is 205. However, this solution does not generate the lowest fuel consumption. The solution $(0, a, b, 0, c, 0, d, e, 0)$ requires 0.041438 l while the solution $(0, a, b, 0, c, d, 0, e, 0)$ requires smaller fuel consumption, 0.041233 l, although the distance in this solution is 220.



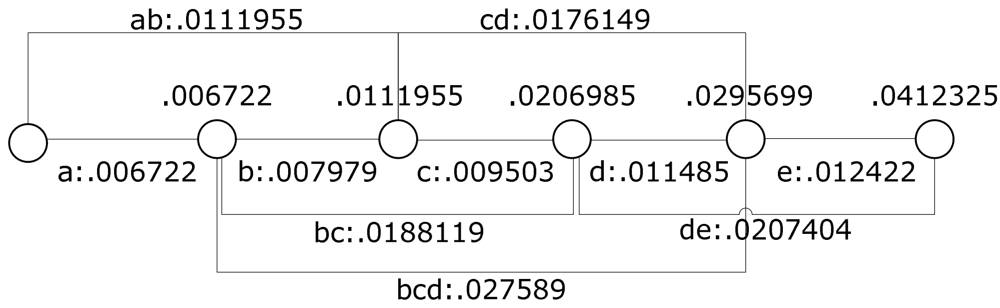
(a) TSP without delimiters S=[a,b,c,d,e]



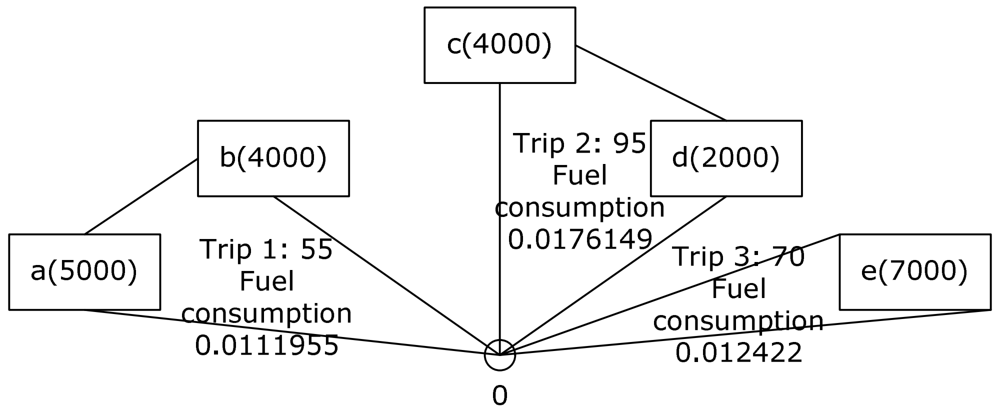
(b) Arcs to be used in the generation of the solution with minimum distance



(c) TSP broken into smaller routes representing a VRP with minimum distance



(d) Arcs to be used in the generation of the solution with minimum fuel consumption



(e) TSP broken into smaller routes representing a VRP with minimum fuel consumption

Figure 4.6: An example of a Split Algorithm

Splitting the giant tour so as to minimise fuel consumption is not as straight forward as the procedure compared to travel distance. For travel distance, an addition of a new customer to a route requires only updating the last leg of the route. However, the fuel consumption depends on load and when a new customer is added to a route, the calculation of fuel consumption needs to update the load starting from the depot, i.e. the delivery load of the new customer needs to be added to the calculation.

The algorithm does not generate H explicitly. It computes four labels for each node $j = 1,2,\dots,n$, where R_j is the shortest path from node 0 to node j in H, $P1_j$ is the predecessor of j in this path (with minimum distance), F_j is the lowest fuel consumption path from node 0 to node j in H, and $P2_{j,}$ is the predecessor of j in this path (with minimum fuel consumption). The while loop enumerates all feasible sub-sequences $S_i, \dots, S_j$, and directly updates R_j, F_j, $P1_j$ and $P2_j$. For a given i, the increment of j stops when the vehicle capacity or driving time (in this case equivalent distance) are exceeded. The value of the objective function is given at the end by R_n. The vector of labels $P1$ and $P2$ are kept with the chromosome to excerpt the final route at the end of the algorithm. The procedure $enqueue$ adds a node at the end of a route. The algorithm is presented in the next page. In the algorithm, for ease of representation, lets name the following equation to calculate the fuel consumption as '$fuel\_consumption$':

$$fuel\_consumption_{ij} = \sum_{i,j \in V} \sum_{m \in M} 0.00145 * \frac{y_{ij}}{v} x_{ij}^m + \sum_{i,j \in V} \sum_{m \in M} 7.35^{-7} * v^2 x_{ij}^m + \sum_{i,j \in V} \sum_{m \in M} 1.33^{-8} * \left(w + Z_j^{m,w}\right) * y_{ij} x_{ij}^m$$

Algorithm 4.5: Split Algorithm for VRPSPD
$\boldsymbol{Input}$: $\boldsymbol{Chromosome\ without\ delimiters}\ [\boldsymbol{x_1}, \boldsymbol{x_2}, \ldots\ldots, \boldsymbol{x_n}]$
$\boldsymbol{Output}$: $\boldsymbol{Chromosome\ with\ delimiters}$
$\boldsymbol{i}$ $= \boldsymbol{index\ for\ first\ customer\ in\ a\ route\ considered\ for\ each\ iteration}$
$\boldsymbol{j = index\ for\ successor\ of\ customer\ i}$
$\boldsymbol{R_i = minimum\ distance\ from\ depot\ to\ i}$
$\boldsymbol{F_i = minimum\ fuel\ consumption\ from\ depot\ to\ i}$
$\boldsymbol{d_i = delivery\ demand\ of\ customer\ i}$
$\boldsymbol{p_i = pickup\ demand\ of\ customer\ i}$
Algorithm for the splitting procedure, split
$\boldsymbol{R_0 = 0}$
$\boldsymbol{F_0 = 0}$
$\boldsymbol{for\ i = 1{:}n}$
$\quad \boldsymbol{R_i} = +\infty$
$\quad \boldsymbol{F_i} = +\infty$
$\boldsymbol{end}$
$\boldsymbol{for\ i = 1{:}n}$
$\quad \boldsymbol{load = 0}; \boldsymbol{distance = 0}, \boldsymbol{consumption = 0}$
$\quad \boldsymbol{j = i}$;
$\quad \boldsymbol{while}\ (\boldsymbol{j \le n})\ \&\&\ (\boldsymbol{load \le C})\ \&\&\ (\boldsymbol{distance \le TD\ km})$
$\quad\quad \boldsymbol{load = load - d_i + p_i}$;
$\quad\quad \boldsymbol{if\ i == j}$
$\quad\quad\quad \boldsymbol{distance = y_{0,j} + y_{j,0}}$;
$\quad\quad\quad \boldsymbol{consumption = fuel\_consumption_{0j}}$
$\quad\quad$ *else*
$\quad\quad\quad \boldsymbol{distance = distance - y_{j-1,0} + y_{j-1,j} + y_{j,0}}$;
$\quad\quad\quad \boldsymbol{consumption = 0}$;
$\quad\quad\quad \boldsymbol{for\ j_2 = 1{:}j}$
$\quad\quad\quad\quad \boldsymbol{consumption = consumption +}$ $\boldsymbol{fuel\_consumption_{ij_2}}$
$\quad\quad\quad \boldsymbol{end}$
$\quad\quad$ *end*
$\quad\quad \boldsymbol{if}\ (\boldsymbol{load \le C})\ \&\&\ (\boldsymbol{distance \le TD})$
$\quad\quad$ // here substring $S_i,\ldots,S_j$ corresponds to arc $(\boldsymbol{i-1}, \boldsymbol{j})$ in $\boldsymbol{H}$
$\quad\quad\quad \boldsymbol{if\ R_{i\_1} + distance < R_j}$
$\quad\quad\quad\quad \boldsymbol{R_j = R_{i-1} + distance}$;
$\quad\quad\quad\quad \boldsymbol{P1_j = i - 1}$;
$\quad\quad\quad \boldsymbol{end}$
$\quad\quad\quad \boldsymbol{if\ F_{i\_1} + consumption < F_j}$
$\quad\quad\quad\quad \boldsymbol{F_j = F_{i-1} + consumption}$;
$\quad\quad\quad\quad \boldsymbol{P2_j = i - 1}$;
$\quad\quad\quad \boldsymbol{end}$
$\quad\quad\quad \boldsymbol{j = j + 1}$;
$\quad\quad \boldsymbol{end}$
$\quad \boldsymbol{end}$
$\boldsymbol{end}$

Algorithm to extract the VRP solution from vector P
$\boldsymbol{for\ i = 1{:}n}$
$\quad \boldsymbol{route(i)} = \emptyset;$
$\boldsymbol{end}$
$\boldsymbol{t = 0};$
$\boldsymbol{j = n};$
$\boldsymbol{while\ i > 0}$
$\quad \boldsymbol{t = t + 1};$
$\quad \boldsymbol{i = P1_j};$
$\quad \boldsymbol{for\ k = i + 1{:}j}$
$\quad\quad \boldsymbol{enqueue(route(t), S_k)}$
$\quad\quad \boldsymbol{j = i};$
$\quad \boldsymbol{end}$
$\boldsymbol{end}$
$\boldsymbol{for\ i = 1{:}n}$
$\quad \boldsymbol{route(i)} = \emptyset;$
$\boldsymbol{end}$
$\boldsymbol{t = 0};$
$\boldsymbol{j = n};$
$\boldsymbol{while\ i > 0}$
$\quad \boldsymbol{t = t + 1};$
$\quad \boldsymbol{i = P2_j};$
$\quad \boldsymbol{for\ k = i + 1{:}j}$
$\quad\quad \boldsymbol{enqueue(route(t), S_k)}$
$\quad\quad \boldsymbol{j = i};$
$\quad \boldsymbol{end}$
$\boldsymbol{end}$

As output, Split algorithm produces two solutions from the giant tour, one which minimises distance and one which minimises fuel consumption.

4.3. Initial population generation

4.3.1 Initialisation

Common initial population generation methods that have been successfully employed in Genetic Algorithms for VRPs are the Savings Algorithm, the Sweep Algorithm and random generation. The use of randomness in generating initial population provides the diversity required to search a broader area of solution space. On the other hand, having some "good" structures in solutions may considerably decrease the time required to solve the problem and may also influence the quality of the final solutions. "Good" structures can be achieved with both the Savings and Sweep Algorithms. However, these tools only consider distance when creating solutions. This thesis therefore proposes a novel initial population generation method based on multiple criteria.

Initial population is an essential element of population-based metaheuristics. In the majority of population-based metaheuristics for VRPs, initial populations are generated using a sequential insertion heuristic in which customers are inserted in a random order at randomly chosen positions within routes (Berger and Barkaoui, 2003a; García-Villoria and Pastor, 2010; Hicks, 2006). Constructive heuristics which can be used to generate initial solutions of good quality include the well-known Savings Algorithm (Clarke and Wright, 1964) and Sweep Algorithm (Gillett and Miller, 1974). In this section, these three constructive heuristics - Savings Algorithm, Sweep Algorithm and random generation - are described. However, each of these constructive heuristics only considers one objective function - in this case, distance - when creating solutions. This thesis therefore proposes a novel initial population generation method based on the multi-criteria decision making method TOPSIS, which can consider both criteria - distance and fuel consumption - in the construction of solutions. The current research will also investigate the extent to which solutions created by TOPSIS may affect the quality of the final Pareto front, and will further consider which ratio comparing the TOPSIS-generated solutions to the randomly-generated solutions leads to the best final Pareto front.

4.3.2 Savings Algorithm

The Savings Algorithm, introduced by Clarke and Wright (1964), is one of the best-known algorithms for generating solutions for VRPs. The main idea behind this algorithm is that a saving of cost can be achieved by merging two routes of two different vehicles. While this algorithm was originally proposed for generating final solutions for VRPs, it has been also used in both its original and modified forms to generate initial populations which can then be further improved using other heuristics. Algorithm 4.6 presents a pseudocode for the Savings Algorithm.

Algorithm 4.6: Savings Algorithm for VRPSPD
$\boldsymbol{Input: Set\ V\ of\ customers, distance\ matrix\ [y_{ij}]_{nxn}}$
$\boldsymbol{Output: Set\ of\ routes}$
$\boldsymbol{Initialise\ routes \leftarrow \{0, 1, 0, 2, 0, 3, 0 \ldots . 0, i, 0, \ldots . 0, n, 0\}}$
$\boldsymbol{Prepare\ saving\ list, S_{ij}}$
$\boldsymbol{for\ every\ pair\ (i, j)\ and\ i \neq j}$
$\quad\quad \boldsymbol{Calculate\ savings\ s_{ij} = y_{0i} + y_{0j} - y_{ij}}$
$\quad\quad \boldsymbol{Add\ s_{ij}\ to\ savings\ list\ \ S}$
$\boldsymbol{endfor}$
$\boldsymbol{sort\ saving\ list\ in\ descending\ order}$
$\boldsymbol{if\ linking\ customer\ i\ and\ j\ is\ feasible}$
$\quad\quad \boldsymbol{add\ link\ to\ the\ route}$
$\boldsymbol{else}$
$\quad\quad \boldsymbol{try\ the\ next\ savings\ in\ the\ list}$
$\boldsymbol{endif}$
$\boldsymbol{Sort\ the\ savings\ in\ descending\ order}$
$\boldsymbol{Starting\ at\ the\ top\ of\ the\ (remaining)\ list\ of\ savings, merge\ the\ two}$ $\boldsymbol{routes\ associated\ with\ the\ largest\ (remaining)\ savings, provided\ that:}$
$\boldsymbol{(a)\ The\ two\ customers\ are\ not\ already\ on\ the\ same\ route}$
$\boldsymbol{(b)\ Neither\ customer\ is\ inferior\ to\ its\ route, meaning\ that\ both}$ $\boldsymbol{customers\ are\ still\ directly\ connected\ to\ the\ depot\ on\ their\ respective\ routes}$ $\boldsymbol{and\ the\ constraints\ on\ vehicle\ capacity\ and\ driving\ time\ are\ not}$ $\boldsymbol{violated\ by\ the\ merged\ route}$
$\boldsymbol{Repeat\ steps\ (a)\ and\ (b)\ until\ no\ additional\ savings\ can\ be\ achieved}$

4.3.3 Sweep Algorithm

Another well-known method for generating an initial population for a VRP using metaheuristics is the Sweep Algorithm proposed by Gillett and Miller (1974). The idea of the algorithm is to group customers that are geographically closer to each other. Customers are then sorted in increasing order by their polar angles with respect to the depot. The generation of an initial population begins with allocation of a randomly chosen customer to a vehicle. The remaining customers are then allocated to the vehicle following the order described above until any constraint is violated. When a constraint is violated, the algorithm introduces a new vehicle for a new route, and continues with the allocation process. This process continues until all customers are assigned to a route. A pseudocode for the Sweep Algorithm is presented below as Algorithm 4.7.

Algorithm 4.7: Sweep Algorithm for VRPSPD
Input: *Coordinates of customer locations*
Output: *Set of Routes*
Arrange customers based on increasing order by their polar angle with respect to the depot
Start a route from the depot
Randomly choose any customer and add it to the route
Add the next customer into the route according to the next polar angle
Keep adding customers until any constraint is violated
When a constraint is violated, end the route and start a new route from the customer
Once all the customers are added to routes, stop the sweep process

4.3.4 Random generation of initial population

In majority of population-based metaheuristics which have been applied to VRPs, initial populations are generated using a sequential insertion heuristic in which customers are inserted in a random order at randomly chosen positions within routes (Berger and Barkaoui, 2003b; García-Villoria and Pastor, 2010; Hicks, 2006). If a customer violates any constraints, that customer is not included in the current route. When all the customers have been considered to be inserted in the route, the current route is closed and a new empty route is initiated to serve the remaining customers. This process continues until all customers are included, which results in an initial population to be added to the population of feasible solutions. This method is fast and simple, with the additional benefit that it also ensures unbiased solutions.

4.4. TOPSIS multi-criteria decision-making method

Multi-criteria decision-making (MCDM) approaches can be divided into two groups: multi-objective decision-making (MODM), and multi-attribute decision-making (MADM). MADM has a set of decision alternatives that are predetermined which can be contrasted with the continuous decision space in MODM. MADM is best suited to ranking alternatives, or selecting the best solution from within a set of alternatives whereas MODM is typically used to find the best solution from infinite possible solutions.

MADM involves finding the best alternatives among a set of feasible alternatives. A standard MADM problem with n alternatives and k criteria can be expressed in matrix format as shown in Figure 4.7 where $A_1, A_2, \ldots\ldots, A_n$ are feasible alternatives, $C_1, C_2, \ldots\ldots, C_k$ are evaluation criteria, z_{ij} is the performance value of alternative A_i under criterion C_j, and w_j is the weight of the criterion.

$$
\begin{array}{cccccc}
 & & w_1 & w_2 & \dots & w_n \\
 & & C_1 & C_2 & \dots & C_k \\
\end{array}
$$

$$
M = \begin{Vmatrix} A_1 \\ A_2 \\ . \\ . \\ . \\ A_n \end{Vmatrix} \begin{Vmatrix} z_{11} & z_{12} & \dots & z_{1k} \\ z_{21} & z_{22} & \dots & z_{2k} \\ . & . & & . \\ . & . & \dots & . \\ . & . & & . \\ z_{n1} & z_{n2} & \dots & z_{nk} \end{Vmatrix}
$$

Figure 4.7: An example of a decision matrix

In the current problem, the customer locations can be considered as the alternatives, while the criteria for the evaluation are distance and GHG emissions and fuel cost. An MADM method - in this case, TOPSIS - is used to rank the considered customers (Hwang and Yoon, 1981). Behzadian et al. (2012) conducted a detailed study on TOPSIS and its applications for use in different research areas.

TOPSIS introduces two points: the ideal, and the nadir. The ideal and nadir points represent the best and worst values of criteria respectively. The ranking of alternatives is based upon the concept that the chosen alternative should have the shortest distance from the ideal point, and the farthest from the nadir.

In each iteration of the proposed constructive heuristic, TOPSIS is used to select a customer to be added to the route based on the values of two criteria - distance, and fuel consumption.

The first criterion considered for TOPSIS is the distance between customers. Measurements for these distances were obtained using

Google Maps API - an application from Google Maps which can calculate accurate travel distances. One of the major benefits of using this application is that it provides an exact driving distance.

The TOPSIS algorithm is presented below with a simple example. In the example, it is assumed that there are five customers (or alternatives) to choose from. The decision matrix is presented in Table 4.1 with the relevant weights.

Table 4.1: Distance and fuel consumption of customers from depot

	Distance (km)	**Fuel consumption(l)**
Customer 1	80	5
Customer 2	75	7
Customer 3	85	10
Customer 4	88	6
Customer 5	79	8

The table here is presented as part of an example to show how a TOPSIS mechanism works. In TOPSIS, two criteria are used to justify the choice of an alternative. Two criteria shown here are distance and fuel consumption and it is assumed that load has been used to calculate the fuel consumption for each leg of the travel. The calculation of fuel consumption is presented in Section 3.2.

The algorithm consists of the following steps, which will be illustrated by continuing to consider the above example.

1. Construct the normalised matrix: This step transforms different attributes given in different measurement units into non-dimensional criteria. This allows comparison across the criteria.

$$\boldsymbol{r_{ij}} = \frac{\boldsymbol{n_{ij}}}{\sqrt{\sum_{i=1}^{m} \boldsymbol{n_{ij}^2}}}, \forall\, \boldsymbol{i} = \mathbf{1}, \dots, \boldsymbol{m}, \boldsymbol{j} = \mathbf{1}, \dots, \boldsymbol{n} \tag{4.3}$$

In our example:

$$r_{ij} = \frac{n_{ij}}{\sqrt{\sum_{i=1}^{m} n_{ij}^2}}, \forall\, i = 1, \dots, 5, j = 1, , 2$$

The values of the normalised matrix are given in Table 4.2.

Table 4.2: Normalised matrix

	Distance (km)	**Fuel consumption (l)**
Customer 1	0.44	0.30
Customer 2	0.41	0.43
Customer 3	0.47	0.60
Customer 4	0.48	0.36
Customer 5	0.43	0.48

2. Build the weighted normalized decision matrix: A weight is assigned to each criterion, set by the decision maker, which expresses the relative importance of that criterion to that decision maker. The weighted normalized decision matrix is produced by multiplying each column of the matrix by its associated weight.

$$\underline{w} = (w_1, w_2, \dots .. w_n), \sum_{i=1}^{n} w_i = 1 \tag{4.4}$$

In our example, both weights are of the same importance $\underline{w} = (0.5, 0.5)$. The weighted normalised matrix is presented as Table 4.3.

Table 4.3: Weighted normalised decision matrix for TOPSIS example

	Distance (km)	**Fuel consumption (l)**
Customer 1	0.1755	0.1812
Customer 2	0.1646	0.2537
Customer 3	0.1865	0.3625
Customer 4	0.1931	0.2175
Customer 5	0.1733	0.2900

3. Determine the ideal and nadir solutions: These two artificial solutions are defined as:

Ideal solution, $A^{*} = \{(max\ v_{ij} | j \in J, i = 1, \dots, m)\ , (min\, v_{ij}\ |\ j \in J', i = 1, \dots., m)\ \}$ (4.5)

Nadir solution, $A^{-} = \{(min\ v_{ij} | j \in J, i = 1, .., m)\ , (max\, v_{ij}\ |\ j \in J', i = 1, \dots, m)\ \}$ (4.6)

where v_{ij} are the values of the weighted normalised decision matrix, J is associated with benefit criteria for which higher values are better, and J' is associated with cost criteria for which lower values are better.

In our example:

$$A^{*} = \{0.1931\ , 0.3625\}$$

$$A^{-} = \{0.1646\ ,0.1812\}$$

4. Calculate the separation measure

$$S_{i*} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{*}\right)^2}\ , \forall i = 1, \dots., m \tag{4.7}$$

$$S_{i-} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{-}\right)^2}\ , \forall i = 1, \dots.., m \tag{4.8}$$

The values are given in Table 4.4.

Table 4.4: Separation measure

	S_{i*}	S_{i-}
Customer 1	0.1821	0.0110
Customer 2	0.1124	0.0725
Customer 3	0.0066	0.1826
Customer 4	0.1450	0.0461
Customer 5	0.0751	0.1091

5. Calculate the relative closeness to the ideal solution

$$C_i = \frac{S_{i-}}{S_{i*} + S_{i-}}, \forall\, i = 1, \dots., m \qquad (4.9)$$

The relative closeness measures in our example are given in Table 4.5.

Table 4.5: Relative closeness measurement

i	**1**	**2**	**3**	**4**	**5**
C_i	0.0568	0.392	0.965	0.241	0.5922

6. Rank the preference order

The solutions are sorted by the values $C_i, i = 1, \dots., m$, where the best solution is the solution with the largest value of C_i. In our example the customer rank is as follows: customer 3, customer 5, customer 2, customer 4 and customer 1.

4.5 A constructive heuristic for VRPSPD based on TOPSIS

In this research, a new constructive heuristic is proposed to build an initial population to be plugged into NSGA-II. The developed constructive heuristic follows the three simple stages identified by Talbi (2009).

1) Initialisation: The choice of initial starting point.

2) Selection: A criterion to choose the next element to be added to the solution.

3) Insertion: The selection of the position in the solution where the new element will be inserted.

The heuristic is iterative. In each iteration, a customer with the best trade-off between the defined criteria - namely the distance to be travelled from the previous customer in the route or depot, and incurred fuel consumption is selected. A route begins at the depot, and the algorithm calculates the values of the two criteria for all the customers. TOPSIS calculates the distance of each customer from both the ideal and nadir points.

All the customers still to be allocated to a route are ranked. They form a list which we will refer to as the restricted candidate list (RCL).

The proposed constructive heuristic is deterministic. In order to generate multiple initial populations for the NSGA-II, a greedy randomisation is proposed to randomly select one customer. From the RCL, a customer from a given percentage denoted by α of top solutions is chosen. A larger α value represents greater randomness - so a α value of 0 denotes pure greediness. The customer ranked first is inserted into the route. The selected customer becomes the new starting point in the next iteration of the constructive heuristic. The process continues until either all customers are allocated to a route, or the time and/or vehicle capacity constraints are violated. If either constraint is violated, a new route starting from the depot is created.

The flowchart presented in Figure 4.8 shows the step-by-step process of the proposed algorithm.

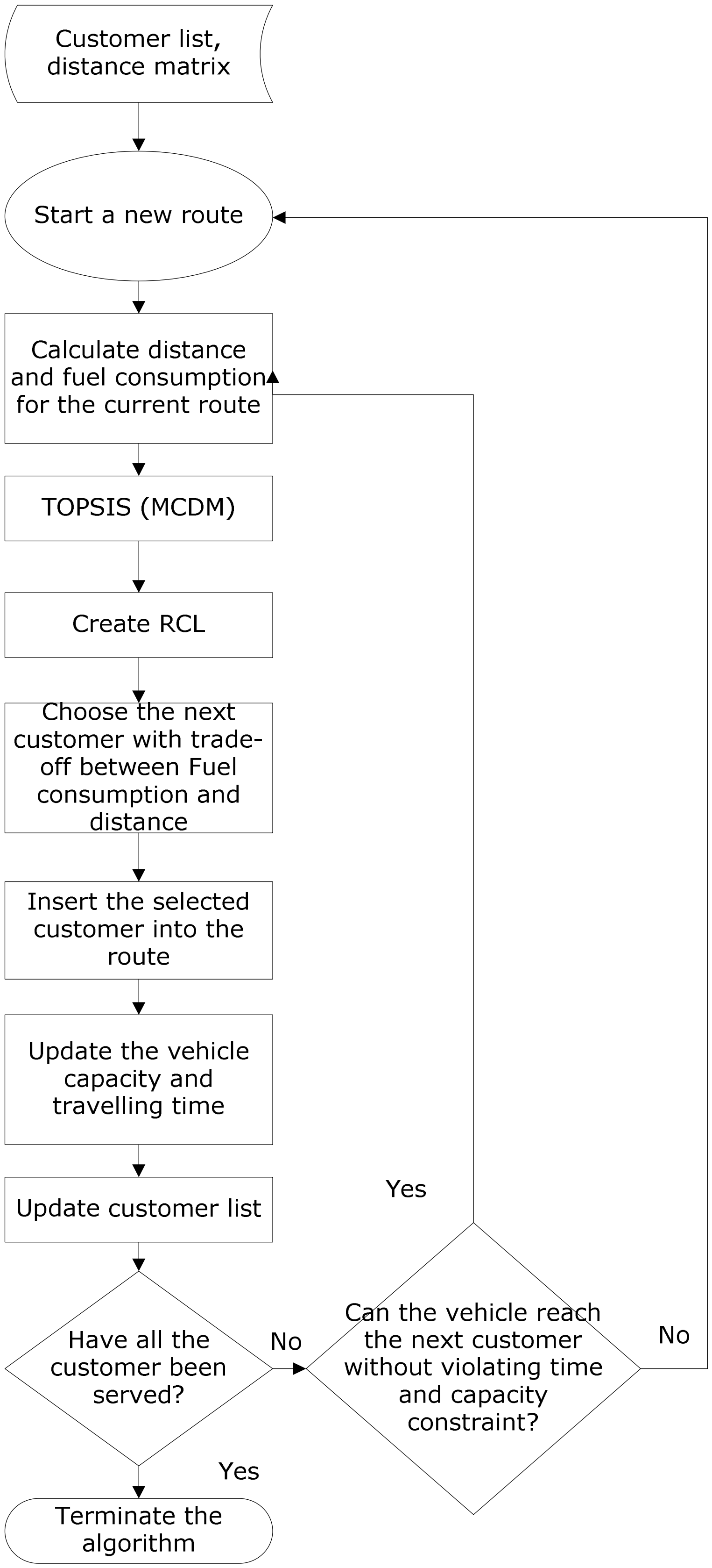


Figure 4.8: A flowchart for the proposed constructive heuristic for the VRP based on TOPSIS

The algorithm starts by calculating the distance between the depot and all customers using Google Maps API. Fuel consimption is calculated as explained in Chapter 3. Travel time is calculated based on vehicle speed. The route of a vehicle always starts from the depot. A customer from the α percent of the TOPSIS-ranked customers (RCL) is chosen randomly and added to the current route.

A check is conducted to see if all the customers have been served. If the answer is yes, the algorithm terminates. If the answer is no, another check is conducted to see if the vehicle can reach the next customer without violating either the driving time constraint or the vehicle capacity constraint. If the answer is yes, the vehicle continues within the same route. If the answer is no, the vehicle returns to the depot, and a new route is initiated.

4.6 Review of the chapter

In this chapter, the components of the multi-objective GA (NSGA-II) specifically designed for the stated VRP including a constructive heuristic for the generation of the initial population, as well as the crossover and mutation operators were described. The selection of the solutions to be passed to the next generation of the algorithm followed the standard NSGA-II, and employed both the sorting of non-dominated solutions into different Pareto front levels and the Crowding distance (Deb et al., 2002).

A novel constructive heuristic to build initial population was proposed. In each iteration, it selected a customer with the best trade-off between the introduced objectives - namely travel distance and fuel consumption.

An MCDM method - in this case, TOPSIS - was used to rank the considered customers (Hwang and Yoon, 1981). TOPSIS calculates the distance of each customer from the ideal point, and from the nadir point. The former is defined as a solution (usually hypothetical) that has the minimum values for both criteria calculated across all customers while the latter consists of maximum values for both criteria.

The solution with the shortest distance from the ideal point and farthest distance from the nadir point was ranked first. All the customers still left to be allocated to a route were ranked. They formed a list, which was referred to as the RCL. The proposed constructive heuristic was deterministic and in order to generate initial population for the NSGA-II, greedy randomisation was proposed to randomly select one customer from the given percentage of top solutions in the RCL. The selected customer became the new starting point in the next iteration of the constructive heuristic. The process continued until all customers were allocated to a route, or until the time or vehicle capacity constraints were violated. If either constraint was not met, a new route starting from the depot was created.

In general, a GA searches the solution space for better solutions by using two genetic operators: crossover, and mutation. In many of the VRPs, crossover operation is negatively affected by its inability to handle feasibility - in other words, customers appearing more than once in a route after the crossover. In order to resolve the feasibility of solutions in the algorithm, the Split Algorithm approach was used. It converts a chromosome into a solution for the corresponding TSP by removing the route delimiters. Crossover and mutation were then performed on the chromosome, which enabled the retention of feasibility - which in this case meant all customers appearing once, without violating either the capacity constraint or the driving time constraint.

Alternating Edge Crossover (AEX) and three Swap Mutations taken from the literature were employed. The main novelty of the developed NSGA-II is the approach to generation of the initial population which uses the TOPSIS method to select a customer to add to the route, allowing for a trade-off between two objectives (distance and fuel consumption, in this case). The impact of using an initial population generated in this way on the final Pareto front will be investigated. The results of the experiments are given in the next chapter.

5. COMPUTATIONAL EXPERIMENTS

This chapter reports the experimental results of the study and the evaluation of its proposed algorithm. It is divided into two main sections. In Section 5.1, solutions from the developed NSGA-II are compared with a real-world problem from a collaborator company with known results - while in Section 5.2, the benchmark Problem instances in Zachariadis and Kiranoudis (2011) and Min (1989) are presented and compared to the NSGA-II results. In Section 5.1.4, the terminating condition for the algorithm is evaluated. Section 5.1.5 presents the effect of combining TOPSIS and randomly generated solutions in the process of initial population to select a combination that would be used in experiments. A comparison between popular initial population generation methods is made in Section 5.1.6. The final result is presented and compared with the solutions of the collaborator company in Section 5.1.7. Section 5.1.8 demonstrates two methods for the decision-making process, and a what-if analysis is conducted in Section 5.1.9. A short discussion is presented in Section 5.3 to conclude the chapter.

5.1. A real-world problem

This study has benefited from access to 180 real-world problem instances from a collaborator company, each describing a daily instance of a VRP. Each Problem instance defined the locations of the central depot and the customers, delivery and pickup demand requirements of each customer, and the capacity limit of the vehicles to be used. All vehicles have the same capacity. One initial assumption made for the experiments was that each customer was serviced by one vehicle or in other words, that no two vehicles would service the same customer for the purpose of splitting the pickup or delivery demand. However, out of the 180 Problem instances, only 20 actually comply with the vehicle capacity constraints and the assumption made here. In these 20 Problem instances, the number of customers ranges between 8 and 20. As an illustration, a distribution of customers around the depot in Problem instance 1 is shown in Figure 5.1. The exact locations are not presented here. Instead, the respective latitudes and longitudes are converted to an equal Cartesian coordinate system and shown to scale. The depot is represented by a square, while the customer locations are represented as circles.

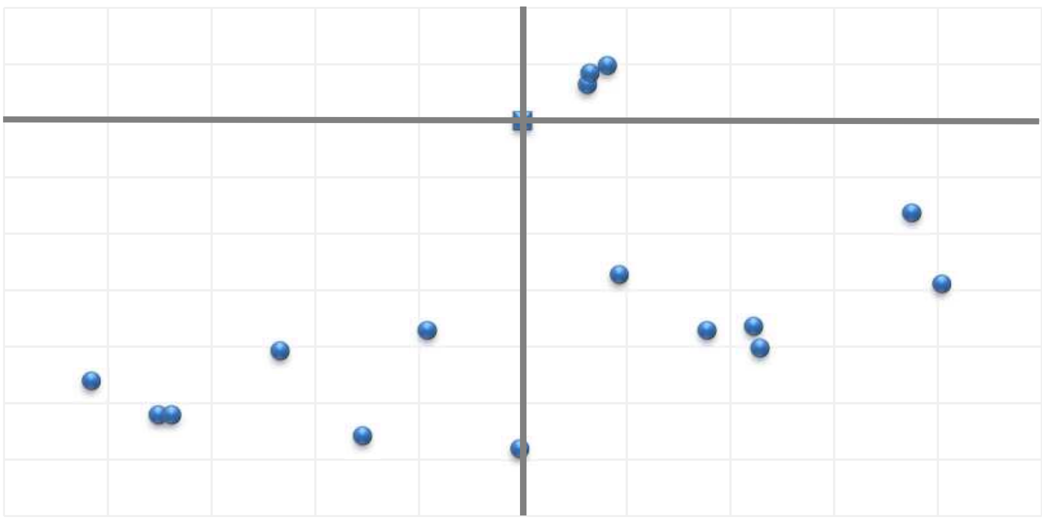


Figure 5.1: Customer locations in a Cartesian coordinate system for Problem instance 1

It can be concluded from the figure that the locations are not distributed uniformly around the depot. In Section 5.2, experiments will be conducted to find out whether this distribution system (uniformity around the depot) affects the final solution. For the experiments presented in this section, the given latitudes and longitudes of customers received from the collaborator company were used to calculate the distances.

Characteristics of the 20 Problem instances are given in Table 5.1. The load of vehicles is evaluated in three different measures: containers, weight and pallets. The relationship between these measures is as follows. Each pallet can hold up to 12 cylinders. The capacity of each vehicle is 24 pallets, or 288 cylinders - which is equivalent to 24,000kg. However, cylinders that are destined for different customers cannot share the same pallet. So, for example, if one customer requires only one cylinder and another customer requires 11 cylinders, the 12 cylinders cannot all be put into one pallet, but must instead be put into two different pallets.

Table 5.1: Characteristics for 20 Problem instances

Problem instance	No. of customer	Maximum distance from depot (km)	Minimum distance from depot	Average distance from depot	Standard deviation distance from the depot	Maximum distance between customer	Minimum distance between customer	Average distance between customer	St Dev distance between customer	Total required collection (in containers)	Total required delivery (in containers)	Total required collection (in kgs)	Total required delivery (in kgs)	Total required collection (in palettes)	Total required delivery (in palettes)
1	16	232.75	35.01	119.54	54.22	332.85	4.93	137.95	73.73	469	310	19651	22108	32	27
2	13	101.12	40.86	70.71	18.23	103.36	3.25	45.32	24.39	324	239	20935	17703	28	24
3	15	96.84	10.00	57.21	26.52	101.47	4.38	44.89	21.52	406	461	25526	30122	31	38
4	11	116.23	11.65	74.02	30.58	120.35	8.58	59.41	28.06	315	471	22902	37406	25	40
5	17	101.13	16.51	53.99	23.06	108.22	1.06	43.24	22.51	189	256	12980	20835	17	28
6	18	127.92	10.00	69.10	29.18	132.79	0.22	51.23	26.31	328	338	24638	29286	27	28
7	8	92.68	10.00	58.93	31.59	98.60	2.36	57.62	26.97	278	256	20931	21515	23	22
8	7	100.26	23.85	68.77	29.23	80.57	1.11	44.82	23.59	130	174	9891	15344	11	16
9	15	116.23	10.39	73.33	29.23	149.05	0.68	61.76	33.96	428	294	30829	25594	38	27
10	16	116.23	26.68	68.57	25.73	129.75	1.24	45.87	25.21	278	370	21520	32725	22	33
11	13	107.81	37.86	70.34	23.66	105.45	0.67	49.62	23.23	282	300	18967	21348	24	25
12	15	114.03	8.81	62.96	31.64	119.34	0.28	52.16	28.04	628	663	47709	53266	52	58
13	16	116.23	26.68	79.00	24.43	119.12	1.38	47.03	26.04	207	254	15165	20927	17	26
14	15	97.61	10.00	58.75	27.54	128.90	1.40	51.86	30.90	561	451	45761	38335	47	40
15	11	127.36	10.00	71.33	33.34	127.12	10.99	58.70	26.81	511	512	29648	32955	37	33
16	18	101.13	23.85	62.82	22.80	123.55	1.11	49.49	26.01	233	310	14777	27450	23	33
17	16	101.13	11.65	70.09	23.59	106.10	0.68	48.05	24.73	326	318	24006	29084	27	29
18	12	127.36	10.00	64.87	30.74	127.12	4.99	45.14	25.14	518	535	32254	41229	40	45
19	12	100.26	24.25	58.56	21.68	102.85	1.35	41.94	23.71	359	301	26048	25165	29	27
20	19	116.23	23.85	61.05	22.62	117.61	1.25	50.85	26.56	282	411	19230	38816	28	38

The following assumptions were made.

1. No customer has a demand larger than the capacity of the vehicle - so no customer should need more than one vehicle to be serviced.

2. Drivers are not allowed to drive more than 10 hours (T = 10 hours).

3. In the Problem instances, the customers are situated in different cities - so the motorway speed limit will be used. After consulting both the motor vehicle guide for truck speed and the collaborator company, the speed level was assumed to be 80km/h or 50miles/h. A what-if analysis is conducted to investigate the effect of different speed levels in Section 5.1.9.1.

All the experiments have been performed on a laptop running Windows 8 with an Intel® Core (TM) i3-4000M CPU @ 2.40GHz processor, while the NSGA-II was implemented using Matlab R2015b.

The values of the parameters for the developed NSGA-II were tuned experimentally or taken from the relevant literature. They are as follows: the population size is 50, the crossover and mutation rates are 0.9 and 0.1 respectively, the terminating condition is yet to be determined (with experiments in this regard being reported in Section 5.1.4), and α in the greedy randomisation is 10% of the restricted customer list (RCL). Hypervolume is used as a metric for evaluating the quality of the generated Pareto fronts. It should be noted here that Hypervolume has been widely used in different multi-objective optimisation problems to calculate the goodness of the solutions.

Hypervolume measures the region defined by an n-dimensional set of points (where n is the number of objectives) which is dominated by the generated Pareto front (Zitzler and Thiele, 1998a). The higher the value of the Hypervolume metric, the better the Pareto front. Many different algorithms have been developed by researchers over the years to calculate the Hypervolume metric - each with its own strengths and weaknesses. Algorithms reported in the literature include Hypervolume via Inclusion-Exclusion (Wu and Azarm, 2000), the LebMeasure Hypervolume Algorithm (Fleischer, 2003), Hypervolume using Overmars, Yap Algorithm and Hypervolume Approximation (Hochstrate and Rudolph, 2006), and the Optimal 3D Hypervolume Algorithm (Beume et al., 2009). In this research, the Exact Exclusive Hypervolume method developed by While et al. (2012) was utilised. In the Hypervolume calculation, the points which are weakly dominated by others are replaced by the ones that dominate those points.

A weakly Pareto-optimal point is defined in the following way. A point x^* in the feasible solutions space S is weakly Pareto-optimal if and only if there does not exist another point x in the set S such that $f(x) < f(x^*)$, where smaller values of f are preferable. This means that there is no point that improves all of the objective functions simultaneously, but there may be points that improve some of the objectives while the other objectives are the same.

Figure 5.2 below presents an example of the Exact Exclusive Hypervolume metric of two Pareto fronts for a minimisation problem.

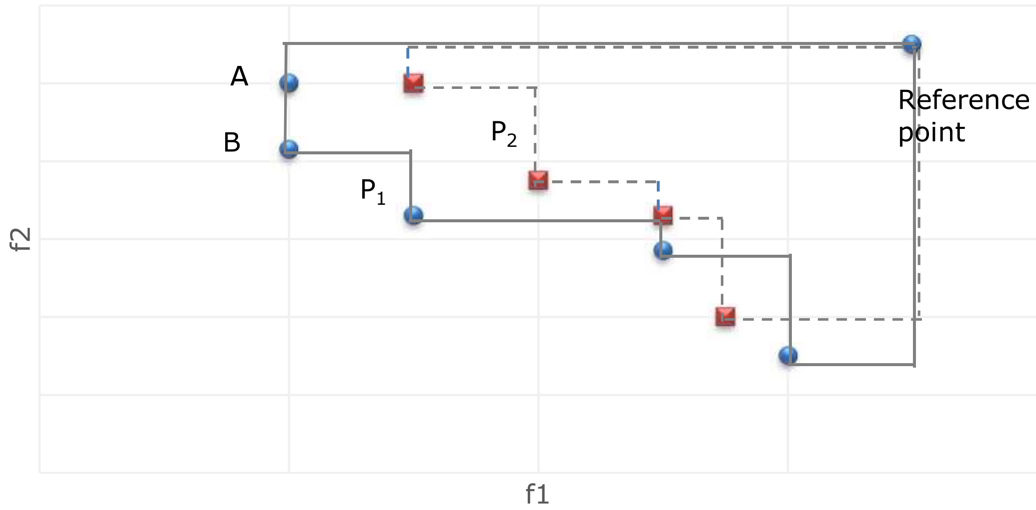


Figure 5.2: A graphical representation of Hypervolume for two different Pareto fronts

Let us assume that the circles in Figure 5.2 represent the first Pareto front (P_1), while the squares represent a second Pareto front (P_2). The second Pareto front is obtained when points from P_1 are excluded. Point B in P_1, weakly dominates point A, which has the same f1 value. As a result, for the purpose of Exact Exclusive Hypervolume calculation, the bounded region for the Hypervolume calculation will now ignore point A. To compare the two Pareto fronts (P_1 and P_2), the regions that comprise the points on the Pareto front and the reference point must be bound. The region bounded by P_1 (indicated by solid lines) is larger than the region bounded by P_2 (indicated by dotted lines) which indicates that Pareto front P_1 has a higher quality of solutions than Pareto front P_2. The choice of reference point is a weak characteristic of Hypervolume calculation, and there is no consensus amongst the literature as to how to properly define it. The approach that is adopted here takes the corresponding coordinates of the two extreme points of the Pareto front to define the reference point.

5.1.1 Demand

For this problem, each customer $i \in V \backslash \{V_0\}$ has a non-negative pickup demand of quantity p_i and delivery demand of quantity d_i. The number of cylinders to be delivered from the depot to customer i and the number of cylinders to be picked up from the customer i are denoted by d_i^c and p_i^c respectively. Different varieties of cylinders are assumed to be compatible with each other, and can be loaded on the same vehicle. The demand expressed as the number of cylinders is mapped to a corresponding number of pallets and weight. For every customer i, its pickup and delivery demand is given also in terms of pallets p_i^p and d_i^p, and the weight $p_i^w$and d_i^w, respectively. Due to different measures of the load, the cylinders, pallets and weight have to be considered separately as capacity constraints. Every vehicle has a fixed capacity.

5.1.2 Vehicles

A fleet of homogenous vehicles, $m \in M$, is available to service the customers. The collaborator company outsources delivery, and has no limit on the number of vehicles at its disposal. The cost is determined based on the travel distance by all the vehicles, and not on the number of vehicles used. Therefore, it is assumed that M identical vehicles exist, each with fixed capacity $C^l, l \in \{c, p, w\}$. A fixed set of parameter values required for calculating the CO_2 emissions were presented in Chapter 3 and also in the Appendix. Some of these parameter values are vehicle independent, while other are vehicle dependent.

A fleet of heavy vehicles has been used in all experiments except in Section 5.1.9.2.

5.1.3 Routes

A route assigned to vehicle m starts at the depot, involves several customers (at least one) and then returns to the depot. A route is a sequence $\{V_0, \ldots . V_i \ldots ., V_0\}$, where all V_i are different. Each vehicle is given a maximum driving time T - to accommodate legal requirements, the health of the driver and safety concerns. In the model, a 10-hour driving time is used as a limit. The speed at which a vehicle is driven, v, is stochastic in nature and is very difficult to predict. For simplicity and after consultation with the collaborator company, the speed of a vehicle is set to 22.22 metres per second which translates to approximately 80 kilometres per hour, or roughly 50 miles per hour.

5.1.4 Terminating conditions for NSGA-II

In the first set of experiments, the terminating conditions for the developed NSGA-II were investigated. In general, there are three terminating conditions that have been employed for GAs (Ishibuchi et al., 1997).

- An upper limit on the number of iterations.
- An upper limit on the number of evaluations of the fitness function.
- The values of the objective functions do not change in a pre-defined number of iterations.

Consultation of the literature did not provide a definite answer as to whether one of these methods holds superiority over the other. In this research, the third terminating condition from the above list has been chosen. To justify the final choice for the upper limit, experiments were conducted with various numbers of iterations (100, 200, 300, 400, 500, 600 and 700 iterations) at the point where there was no change in the objective functions.

In the experiments, the NSGA-II was run 10 times. As an illustration, solutions presented in Figure 5.3 show the best Pareto front with respect to Hypervolume from the 10 runs for instance 1.

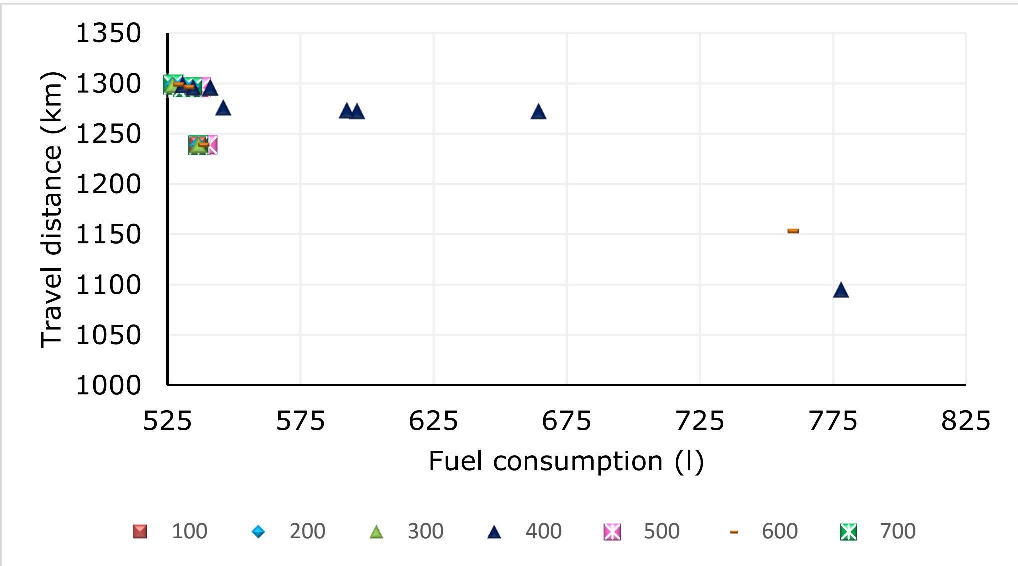


Figure 5.3: Pareto fronts for different numbers of iterations with no changes to the values of the objective functions as terminating conditions in Problem instance 1

Figure 5.3 presents the Pareto fronts obtained by using seven different numbers of iterations as terminating conditions. The corresponding Exact Exclusive Hypervolume values are given in Table 5.2.

Table 5.2: Hypervolume values of Pareto fronts for different numbers of iterations with no changes to the values of the objective functions as terminating conditions in Problem instance 1

No. of iterations where no changes occurred	Hypervolume value
100 iterations	5.64E+04
200 iterations	5.76E+04
300 iterations	5.76E+04
400 iterations	**8.30E+04**
500 iterations	5.74E+04
600 iterations	6.41E+04
700 iterations	5.76E+04

Similar results were found on four other instances. The figures were similar and are not shown here (Please refer to the Appendix, page 270 for the other four figures). Based on the five instances, it was decided that 400 iterations provided optimum solutions based on the trade-off between quality of solutions and time required to achieve these solutions.

The terminating condition of 400 iterations when no changes occur provides the highest value for Hypervolume (shown in bold) - and this is therefore chosen as the terminating condition for our algorithm.

5.1.5 Combination of TOPSIS and randomly generated solutions in the initial population

The initial population generation involves both TOPSIS and random construction of solutions. One of the research problems in the design of a GA is the quality of the initial population. The presence of a higher quality initial population in a GA is likely to lead to better solutions in a reasonable amount of time. However, randomly generated solutions - which may be of lower quality - can still contribute to the evolution of solutions and a search of the wider solution space. An investigation was conducted to establish what would be an adequate combination of both (a) solutions generated by TOPSIS and greedy randomisation (and such solutions will be referred to as TOPSIS in the remaining part of the section) and (b) randomly generated solutions - which would together lead to a Pareto front with best solutions.

The hypothesis for this research is that an adequately defined combination of TOPSIS and greedy randomisation provides a good initial population set that leads to a better final Pareto front than would a randomly generated initial population.

In the experiments, the initial population was generated by varying the percentage of solutions generated by TOPSIS and greedy randomisation while the remaining solutions were randomly generated. For example, T70 (70% TOPSIS) means that out of 50 solutions, 35 will be generated using TOPSIS, while the other 15 will be randomly generated.

Consequently, a total of 11 combinations were considered - starting with T0, which denoted that all solutions were generated randomly, up to T100, which denoted that the initial population consisted solely of TOPSIS solutions. The Pareto fronts generated by the NSGA-II were ranked by their Hypervolume values, where rank 1 denoted the largest Hypervolume. The average ranks of all Pareto fronts (with 11 combinations run 10 times leading to 110 in total) across all NSGA-II runs obtained on one Problem instance, given as a box and whisker plot, are shown in Figure 5.4. The box and whisker plot is shown in increasing order of the percentage of TOPSIS solutions from left to right.

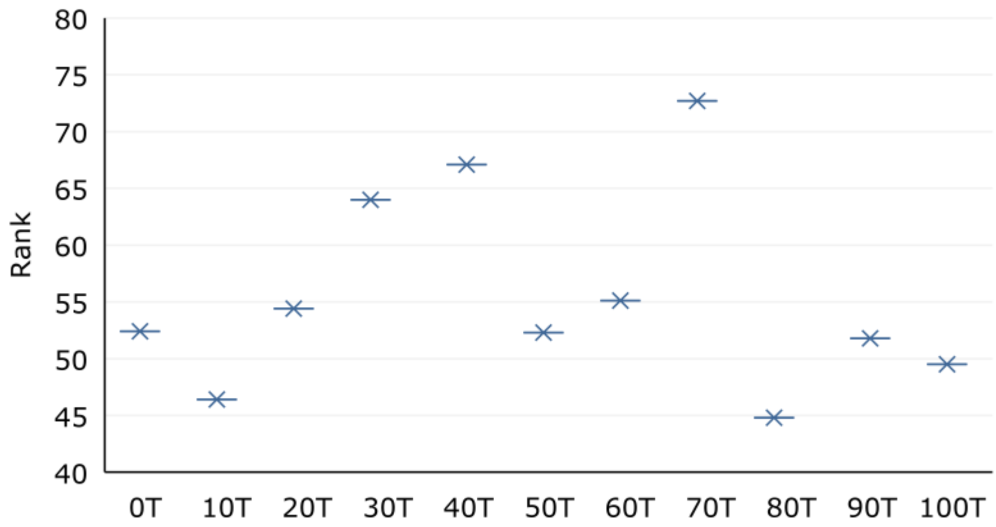


Figure 5.4: Average ranks of Pareto fronts obtained using different percentages of TOPSIS solutions in the initial population generation method for Problem instance 1

It can be seen that the combination of 80% TOPSIS and 20% randomly generated solutions in the initial population has the lowest average rank. Similar results were obtained when the algorithm was run on the remaining 19 problem instances. The results for all 20 problem instances are presented in Table 5.3. The smallest values for the sum of rank are shown in bold in the table.

Table 5.3: Ranks of Pareto fronts obtained using different percentages of TOPSIS solutions in initial population generation method for 20 Problem instances

Problem instance	T0	T10	T20	T30	T40	T50	T60	T70	T80	T90	T100
1	524	464	544	640	671	523	551	727	**448**	518	495
2	609	632	663	623	564	700	544	506	417	**386**	461
3	667	509	668	459	469	559	446	700	**437**	507	684
4	509	664	464	513	580	775	447	617	**427**	573	536
5	753	562	562	500	460	536	514	609	**413**	745	451
6	607	594	477	487	499	620	603	600	**476**	541	601
7	656	565	495	390	653	646	647	519	**382**	592	560
8	607	614	716	404	554	612	652	489	**328**	570	559
9	617	687	588	447	469	427	742	606	**439**	472	611
10	673	409	593	468	587	494	636	708	**447**	636	454
11	682	552	517	574	650	681	397	668	**400**	492	492
12	556	576	579	518	492	604	523	579	**485**	574	619
13	431	602	506	589	728	674	572	**428**	530	563	482
14	525	469	519	536	813	554	530	489	**418**	707	545
15	566	555	519	573	669	607	536	625	**345**	451	659
16	551	504	567	406	586	613	725	694	**399**	528	532
17	698	447	692	388	503	630	523	523	**438**	638	625
18	478	606	522	556	733	590	587	477	**410**	605	541
19	709	599	506	588	657	368	715	533	**425**	497	508
20	484	498	502	521	529	**472**	659	694	516	693	537

The results from Table 5.3 show that the combination of 80% TOPSIS and 20% randomly generated solutions provided the best values for Hypervolume (shown in bold) in 17 out of 20 problem instances.

5.1.6 Comparison of methods for initial population generation

In this section, initial population generation methods are investigated to evaluate whether the combination of TOPSIS and greedy randomisation can indeed provide a good Pareto front. This approach is compared to both the Sweep Algorithm and randomly generated initial populations, which are two common population generation methods. In the investigation of methods to be used to generate initial population, another very common algorithm - the Savings Algorithm - is also included. One of the major drawbacks of using the Savings

Algorithm with a GA is that it produces a single solution, while the GA is a population-based metaheuristic. Nevertheless, it is still worth investigating whether the single solution generated by the Savings Algorithm has any role in the final solution produced by the NSGA-II. The solution generated by the Savings Algorithm would be located on the Pareto front if it had any role in the process. However, experimental results show that solution generated by the Savings Algorithm did not qualify for the Pareto front in the initial population. Therefore, the Savings Algorithm was not considered for use in the initial population generation method.

The Pareto fronts generated by the developed NSGA-II with different initialisation methods are evaluated by Hypervolume. Figure 5.5 shows the Pareto fronts that were achieved by three different initial population generation methods, while the Hypervolume values of the produced Pareto fronts are given in Table 5.4.

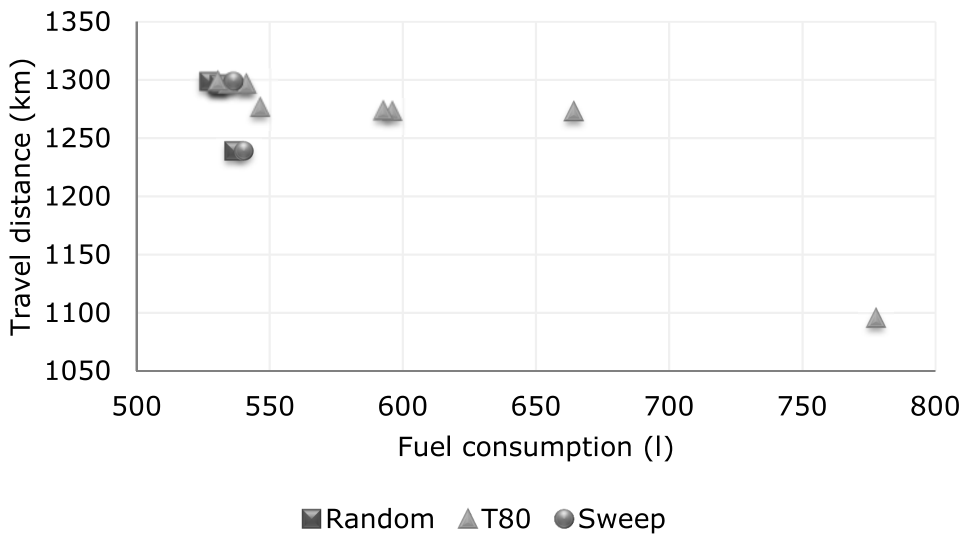


Figure 5.5: Pareto fronts obtained for three initial population generation methods for Problem instance 1

Figure 5.5 illustrates that the Pareto front obtained by the combination of 80% TOPSIS and 20% random generation (T80) offers the best possible solutions. The proposed method produces the Pareto front that has the largest Hypervolume (as shown in Table 5.4) compared to the other two methods. The largest Hypervolume value for each Problem instance is given in bold in the table.

Table 5.4: Hypervolume values of Pareto fronts for three initial population generation methods for 20 Problem instances

Problem instance	**Random generation**	**T80**	**Sweep Algorithm**
1	3.61E+05	**6.10E+05**	3.94E+05
2	4.98E+03	**6.54E+03**	2.66E+03
3	1.19E+04	**1.35E+04**	1.20E+04
4	7.60E+03	**7.85E+03**	6.57E+03
5	7.53E+03	**7.54E+03**	6.41E+03
6	1.07E+04	**1.20E+04**	9.64E+03
7	4.92E+04	**4.94E+04**	4.87E+04
8	2.67E+04	**2.76E+04**	2.68E+04
9	1.33E+04	**1.57E+04**	8.81E+03
10	1.03E+04	**1.14E+04**	5.86E+03
11	4.70E+03	7.07E+03	**7.09E+03**
12	2.14E+04	2.12E+04	**2.87E+04**
13	1.01E+04	**1.05E+04**	7.50E+03
14	1.33E+04	**1.40E+04**	1.33E+04
15	8.37E+03	**9.41E+03**	8.16E+03
16	9.38E+03	**1.03E+04**	9.54E+03
17	2.94E+03	**3.56E+03**	2.98E+03
18	5.18E+03	**5.19E+03**	5.18E+03
19	3.13E+03	**3.15E+03**	3.15E+03
20	1.99E+04	**2.28E+04**	1.98E+04

Based on the results in Table 5.4, conclusion can be drawn that the proposed combination of TOPSIS and randomly generated solutions serves better than random generation and the Sweep Algorithm.

5.1.7 Comparison of results produced by NSGA-II and the collaborator company

First experiment aims to evaluate the quality of results produced by NSGA-II compared to the results which are optimal with respect to a single objective, travel distance and fuel consumption, separately. For that purpose, CPLEX was used on the instances from the collaborator which are of the smaller size, namely CPLEX was able to solve to optimality the problems in which the number of customers were smaller or equal to than 11. The values of the minimum distance and fuel consumption produced by CPLEX and NSGA-II are presented in Table 5.7. Note: solutions with minimum distance and minimum fuel consumption obtained by NSGA-II are often different solutions. The column Difference shows the difference between the value of the objective functions produced by CPLEX and NSGA-II given as %. It is difficult to set a strict threshold for the difference values which will support the claim that NSGA-II is of good quality. Nevertheless, the % values between 4.33 and 8.47 indicate that the results obtained by NSGA-II are comparable to single objective optimisation solutions.

Table 5.5 Comparison of results from CPLEX and NSGA-II

Problem instance	No. of customers	Travel distance (km)				Fuel consumption (l)			
		Time (s)	CPLEX	NSGA-II	Difference	Time (s)	CPLEX	NSGA-II	Difference
4	11	20	450.43	486.25	-7.37%	55	230.08	251.36	-8.47%
7	8	37	293.43	306.71	-4.33%	70	151.03	162.12	-6.84%
8	7	24	210.23	227.87	-7.74%	69	110.5	117.45	-5.92%
15	11	33	401.32	428.98	-6.45%	75	215.23	232.17	-7.30%

In the following experiments, the solutions provided by the collaborator company and the NSGA-II solutions are compared. The collaborator company considered travel distance as the only objective that they minimised. Also, they calculated the Euclidian distance between customers - whereas the actual driving distance generated using Google Maps API is employed in our model. To be able to compare these results, the real travelled distances in the routes produced by the company are also presented. Table 5.6 shows solutions for 20 Problem instances. There are three sets of results to be compared in Table 5.6: one given by the collaborator company, and two sets of solutions produced by NSGA-II (which are taken from the best Pareto front in terms of Hypervolume). The two NSGA-II sets represent the solutions with the lowest fuel consumption and those with the smallest travel distance. The differences between the solutions from the NSGA-II and the company are also shown as percentages, where a negative value (given in bold) means that the solution generated by the NSGA-II has a better corresponding value than the company's solution.

Table 5.6: Comparison of solutions for 20 Problem instances between the collaborator company and NSGA-II

Problem instance		**Collaborator company**	**NSGA-II (Lowest fuel consumption)**	**% difference**	**NSGA-II (Smallest travel distance)**	**% difference**	**Time (s)**
1	Fuel consumption (l)	531.23	530.69	**-0.10%**	777.65	46.39%	22
	Travel distance (km)	1295.00	1298.53	0.27%	1095.15	**-15.43%**	
	No. of vehicles	4	4	0.00%	2	**-50.00%**	
2	Fuel consumption (l)	289.69	233.88	**-19.27%**	249.68	**-13.81%**	30
	Travel distance (km)	517.97	475.00	**-8.30%**	412.18	**-20.42%**	
	No. of vehicles	2	2	0.00%	2	0.00%	
3	Fuel consumption (l)	326.25	208.28	**-36.16%**	232.85	**-28.63%**	28
	Travel distance (km)	600.18	495.78	**-17.40%**	421.67	**-29.74%**	
	No. of vehicles	4	4	0.00%	3	**-25.00%**	
4	Fuel consumption (l)	346.28	251.36	**-27.41%**	284.01	**-17.98%**	29
	Travel distance (km)	538.36	515.97	**-4.16%**	486.25	**-9.68%**	
	No. of vehicles	2	3	50.00%	2	0.00%	
5	Fuel consumption (l)	272.61	226.37	**-16.96%**	306.95	12.60%	28
	Travel distance (km)	502.44	469.07	**-6.64%**	445.30	**-11.37%**	
	No. of vehicles	3	2	**-33.33%**	2	**-33.33%**	

Problem instance		Collaborator company	NSGA-II (Lowest fuel consumption)	% difference	NSGA-II (Smallest travel distance)	% difference	Time (s)
6	Fuel consumption (l)	364.41	289.18	**-20.64%**	336.22	**-7.74%**	28
	Travel distance (km)	591.99	580.88	**-1.88%**	515.53	**-12.91%**	
	No. of vehicles	3	2	**-33.33%**	2	**-33.33%**	
7	Fuel consumption (l)	211.52	162.12	**-23.35%**	162.12	**-23.35%**	37
	Travel distance (km)	385.56	306.71	**-20.45%**	306.71	**-20.45%**	
	No. of vehicles	2	2	0.00%	2	0.00%	
8	Fuel consumption (l)	197.30	117.45	**-40.47%**	164.99	**-16.38%**	31
	Travel distance (km)	433.75	231.25	**-46.69%**	227.87	**-47.46%**	
	No. of vehicles	3	2	**-33.33%**	2	**-33.33%**	
9	Fuel consumption (l)	345.90	304.71	**-11.91%**	339.16	**-1.95%**	27
	Travel distance (km)	690.92	652.66	**-5.54%**	534.50	**-22.64%**	
	No. of vehicles	3	3	0.00%	2	**-33.33%**	
10	Fuel consumption (l)	302.22	293.47	**-2.90%**	317.88	5.18%	31
	Travel distance (km)	654.96	524.74	**-19.88%**	504.78	**-22.93%**	
	No. of vehicles	4	2	**-50.00%**	2	**-50.00%**	
11	Fuel consumption (l)	282.77	243.43	**-13.91%**	263.30	**-6.89%**	31
	Travel distance (km)	482.91	510.52	5.72%	468.50	**-2.98%**	
	No. of vehicles	2	2	0.00%	2	0.00%	
12	Fuel consumption (l)	391.79	265.89	**-32.13%**	323.34	**-17.47%**	26
	Travel distance (km)	601.83	604.09	0.38%	550.08	**-8.60%**	
	No. of vehicles	3	4	33.33%	3	0.00%	
13	Fuel consumption (l)	300.77	276.41	**-8.10%**	276.41	**-8.10%**	32
	Travel distance (km)	569.57	500.98	**-12.04%**	500.98	**-12.04%**	
	No. of vehicles	3	2	0.00%	2	0.00%	
14	Fuel consumption (l)	366.80	275.49	**-24.89%**	341.13	**-7%**	30
	Travel distance (km)	782.82	620.78	**-20.69%**	551.05	**-29.60%**	
	No. of vehicles	5	4	**-20%**	3	**-40%**	
15	Fuel consumption (l)	452.75	232.17	**-48.72%**	254.11	**-43.87%**	34
	Travel distance (km)	628.68	466.99	**-25.72%**	428.98	**-31.77%**	
	No. of vehicles	2	3	50.00%	3	50.00%	
16	Fuel consumption (l)	319.62	309.21	**-3.26%**	323.60	1.24%	35
	Travel distance (km)	621.97	595.53	**-4.25%**	541.05	**-13.01%**	
	No. of vehicles	4	2	**-50.00%**	2	**-50.00%**	
17	Fuel consumption (l)	279.03	292.02	4.66%	307.46	10.19%	34
	Travel distance (km)	493.73	488.29	**-1.10%**	461.30	**-6.57%**	
	No. of vehicles	2	2	0.00%	2	0.00%	
18	Fuel consumption (l)	289.81	206.03	**-28.91%**	242.87	**-16.20%**	27
	Travel distance (km)	519.42	439.89	**-15.31%**	399.37	**-23.11%**	
	No. of vehicles	3	3	0.00%	3	0.00%	
19	Fuel consumption (l)	243.87	197.98	**-18.81%**	247.34	**1.42%**	28
	Travel distance (km)	433.47	408.09	**-5.85%**	406.08	**-6.32%**	
	No. of vehicles	2	2	0.00%	2	0.00%	
20	Fuel consumption (l)	338.02	304.62	**-9.88%**	350.82	3.79%	30
	Travel distance (km)	716.11	720.89	**0.67%**	642.48	**-10.28%**	
	No. of vehicles	4	4	0.00%	3	**-25.00%**	

The interpretation of the results is as follows. In Problem instance 1, the NSGA-II was able to obtain a solution with a smaller distance than the one that the company achieved (15.43% better) at the expense of increased fuel consumption (46.39%). For the same Problem instance, a solution with the lowest fuel consumption produced by NSGA-II reduced fuel consumption by 0.10% compared to the company's solution, at the small price of a 0.27% increase in travel distance. In 11 of the Problem instances, the NSGA-II produced better solutions with respect to both objectives (given in bold). In the other nine Problem instances there were mixed results - in other words, the NSGA-II improved one objective compared to the company's solution at the expense of another objective. Interestingly, in Problem instance 15, both NSGA-II solutions improved both objectives despite requiring a larger number of vehicles.

The generated solutions in the Pareto front provide the logistics manager with insight into the trade-off between the travel distance and the fuel consumption that can be achieved. This approach enables the manager to express preferences a posteriori, contrary to the approaches in which multiple objectives are combined into a single-objective function.

5.1.8 Managerial insights into the decision making

In this problem statement, there are two objectives: travel distance and fuel consumption. The company would always like to simultaneously have the shortest possible distance to travel and the lowest possible fuel consumption. Achieving a single solution that minimises both objectives is not always possible. An example can be seen in Figure 5.6, which shows trade-off values for the two objective functions.

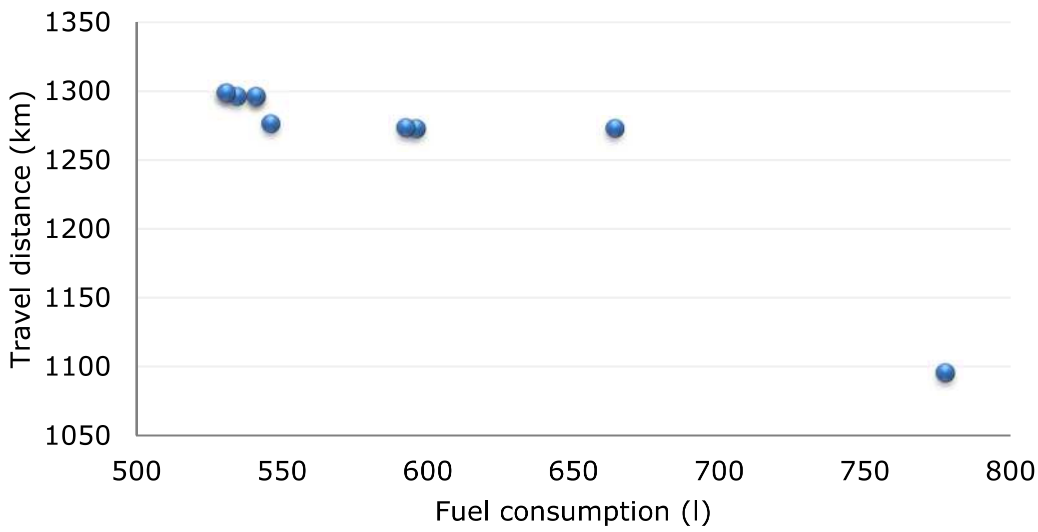


Figure 5.6: Generated Pareto front for Problem instance 1

Usually, the decision maker would like to find a trade-off solution between the two objectives where both of them have sufficiently good values. Two of the methods for selecting the preferred solutions from the Pareto front are presented below.

5.1.8.1 Use of marginal rate of substitution in the selection of a solution

The marginal rate of substitution (MRS) is a term generally used in economics. The MRS is the rate at which a consumer can give up some amount of one good in exchange for another good while maintaining the same level of utility.

As an illustration, let us look at the solutions of the best Pareto front obtained for Problem instance 1. Both Table 5.7 and Table 5.8 show eight solutions on the Pareto front. Solutions 1 and 8 represent the corner solutions from the Pareto front. Table 5.7 shows the price in terms of fuel consumption that has to be paid in order to improve the travelled distance, while Table 5.8 shows the opposite - in other words, by how much fuel consumption improve if travel distance worsens. The fourth column in Table 5.7 shows the difference between the best fuel consumption achieved (in solution 1) and the fuel consumption in the corresponding solution - while in Table 5.8 it shows the difference between the fuel consumption in the corresponding solution and the worst value achieved (in solution 8). A negative value indicates improvement, while a positive value indicates worsening of the objective value. Similarly, the sixth column in Table 5.7 shows how much the travel distance is improved (or worsened, as in Table 5.8) by comparing each solution with the corner solution (in this case, solution 8). The fifth and the seventh columns present the changes in percentage terms. The solutions in bold correspond to the lowest fuel consumption in Table 5.7, and the smallest travel distance in Table 5.8.

Table 5.7: MRS with respect to fuel consumption

Solution	**Fuel consumption** $(\boldsymbol{l})$	**Travel distance** $(\boldsymbol{km})$	**Difference between fuel consumption**	**%**	**Difference between travel distance**	**%**
1	**530.68**	1298.53				
2	534.47	1296.02	3.78	0.71%	-2.50	-0.19%
3	541.16	1296.02	10.47	1.97%	-2.50	-0.19%
4	546.17	1275.94	15.48	2.92%	-22.59	-1.74%
5	592.59	1273.10	61.90	11.67%	-25.42	-1.96%
6	596.03	1272.48	65.35	12.31%	-26.04	-2.01%
7	664.23	1272.48	133.54	25.16%	-26.05	-2.01%
8	777.64	1095.15	246.96	46.54%	-203.37	-15.66%

Table 5.7 demonstrates that where the major concern is to minimise fuel consumption, solution 1 should be chosen but if the aim is to reduce travel distance as well, other solutions from the Pareto front could be considered. This table gives the MRS, which in this case means the amount by which improving the travel distance worsens fuel

consumption. For example, in Solution 3, an improvement in the distance by 0.19% from the best value achieved would see the corresponding value for fuel consumption deteriorate by 1.97%. Solution 2 has a 0.19% smaller travel distance than solution 1, but this is accompanied by a 0.71% increase in fuel consumption. Solution 4, on the other hand, reduces the distance by 1.74%, with the fuel consumption increasing by 2.92%.

Table 5.8: MRS with respect to distance

Solution	**Fuel consumption** $(\boldsymbol{l})$	**Travel distance** $(\boldsymbol{km})$	**Difference between fuel consumption**	**%**	**Difference between travel distance**	**%**
1	530.68	1298.53	-246.96	-31.76%	203.37	18.57%
2	534.47	1296.02	-243.17	-31.27%	200.87	18.34%
3	541.16	1296.02	-236.48	-30.41%	200.87	18.34%
4	546.17	1275.94	-231.47	-29.77%	180.78	16.51%
5	592.59	1273.10	-185.05	-23.80%	177.95	16.25%
6	596.03	1272.48	-181.60	-23.35%	177.32	16.19%
7	664.23	1272.48	-113.41	-14.58%	177.32	16.19%
8	777.64	**1095.15**				

Table 5.8 demonstrates that where the major concern is to minimise travel distance, solution 8 should be chosen but if the aim is to reduce fuel consumption as well, other solutions from the Pareto front could be considered. This table gives the MRS, which in this case means the amount by which improving fuel consumption worsens the travel distance. For example, in Solution 3, by increasing the distance by 18.34% from the best value achieved, one can improve fuel consumption by 30.41%. Solution 2 has the same distance as solution 3, but the fuel consumption decrease by 31.27%.

5.1.8.2 Use of TOPSIS in the selection of a solution

The TOPSIS method that is used in the initial population generation for the NSGA-II can be also used to select one solution from the generated Pareto front. A specific Problem instance in which there are eight solutions in the Pareto front will now be considered - these solutions are given in Table 5.9. These solutions are evaluated against two attributes; fuel consumption and travel distance. Different weights for these attributes will be considered, and the results are given in Table 5.10.

Table 5.9: Pareto solutions for Problem instance 1

Solution	**Fuel consumption (l)**	**Travel distance (km)**
1	530.68	1298.53
2	534.47	1296.02
3	541.16	1296.02
4	546.17	1275.94
5	592.59	1273.10
6	596.03	1272.48
7	664.23	1272.48
8	777.64	1095.15

Table 5.10: A posteriori decision making with varying weights of TOPSIS

Weights		**Solutions ranking**							
Fuel consumption (l)	Travel distance (km)	Best → Worst							
0	1	8	7	6	5	4	2	3	1
.1	.9	8	4	1	2	5	6	3	7
.2	.8	8	4	1	2	3	5	6	7
.3	.7	4	1	2	3	8	5	6	7
.4	.6	4	1	2	3	5	6	7	8
.5	.5	4	1	2	3	5	6	7	8
.6	.4	4	1	2	3	5	6	7	8
.7	.3	1	2	4	3	5	6	7	8
.8	.2	1	2	3	4	5	6	7	8
.9	.1	1	2	3	4	5	6	7	8
1	0	1	2	3	4	5	6	7	8

Table 5.10 shows the solution ranking produced by TOPSIS under different weights of fuel consumption and travel distance. The decision

maker can now choose the best solution based on their requirements and their understanding of the relative importance they attach to the objectives.

The decision-making process will be affected by the chosen approach to selecting the final solution. Single-objective optimisation methods produce only one solution to be presented to the decision makers. They only have the option to change the importance of the objectives - usually specified in terms of numerical values, which often creates an added burden for decision makers and investigate the effect this produces. A weighted sum of objective values can generate a Pareto front by changing the weights only if the Pareto front is convex (see for example, Jakob and Blume (2014)). If the Pareto front is non-convex, it is possible that parts of the front cannot be obtained by the weighted sum. Therefore, its use is problematic in cases where no a-priori knowledge of the shape of the Pareto front is given. In the presented model, the decision maker has multiple solutions on the Pareto front which enables the selection of one solution depending on the decision maker's preferences regarding the relative importance of the objectives. The Pareto front enables the decision maker to assess the trade-off between objectives and make a final decision tailored to their preferences.

5.1.9 What-if analysis

In the fifth group of experiments, a number of scenarios were designed by varying the speed and capacity of the vehicles. In our previous experiments, all vehicles were driven with the speed of 80km/h, and only heavy vehicles were considered. Section 5.1.9.1 and 5.1.9.2 discuss the effect of variations in speed and capacity of vehicles on the final result.

5.1.9.1 Effect of vehicle speed on Pareto front

In this experiment, four different speed levels are introduced: 50, 60, 70 and 80km/h. Figure 5.7 presents the generated final Pareto fronts for each speed level obtained for Problem instance 1. The same conclusion holds in all other instances.

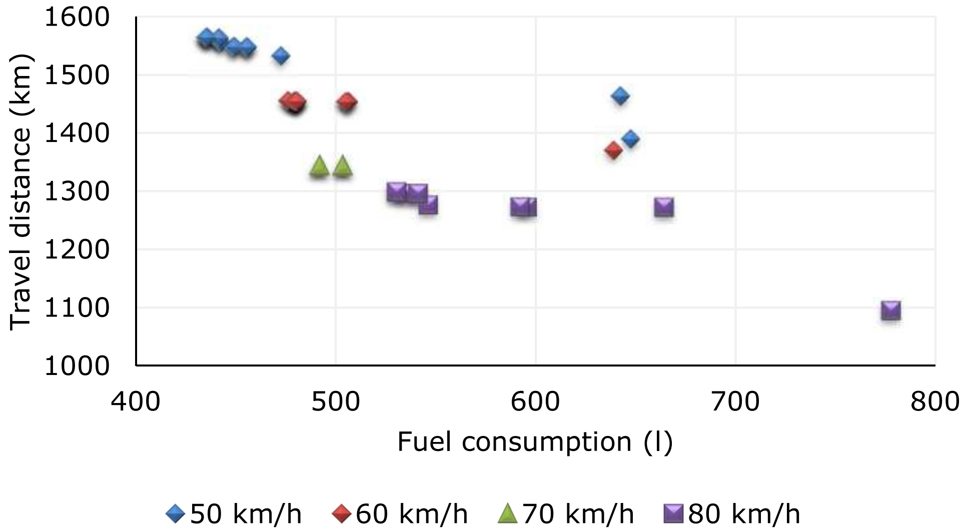


Figure 5.7: Pareto fronts for four different speed levels for Problem instance 1

The obtained results confirm that lower vehicle speeds incur lower fuel consumption. However, at the same time, lower speed means less distance that can be travelled within the allocated driving time - so the total travel distance is larger, as more routes (more vehicles) are needed. Higher speed implies that the vehicle can cover a larger distance within the given time limit - so the total travel distance is shorter, but this comes at the higher price of larger fuel consumption.

In the next experiment, the speed is considered to be different in different parts of the route. The speed is assumed to be 48km/h or 30miles/h where the distance between two customers on a route is shorter than 48 kilometres or 30 miles (since 30miles/h is the usual speed limit within cities). If the distance is longer, it is assumed that the vehicle would be driven at a regular speed of 80km/h. The results are shown in Figure 5.8.

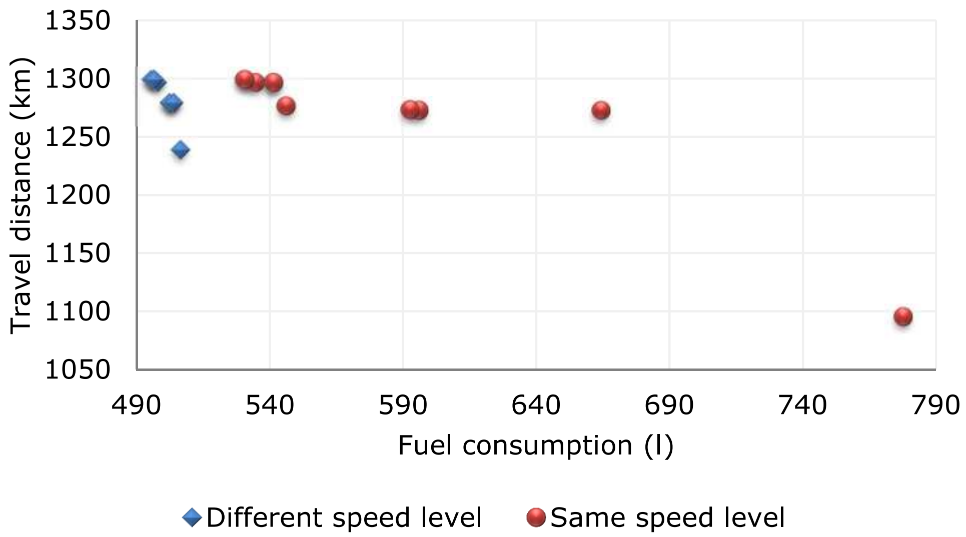


Figure 5.8: Pareto fronts with same and different speed levels for Problem instance 1

The results show that the travel distance remains almost the same with both the same and different speed levels but fuel consumption is reduced when different speed levels are used for different parts of the route. With proper guidance and driver training, fuel consumption can be reduced by simply driving at the right speed for each part of the route.

5.1.9.2 *Effect of vehicle size on Pareto front*

Research into costs, emissions and the effect of vehicle size was conducted in Koç et al. (2016), where three types of vehicles available in the market were considered. Table 5.11 presents the parameter values required for the calculation of fuel consumption for three different types of vehicles: light, medium and heavy vehicles, as taken from Koç et al. (2016). Experiments were conducted to gain insights into the best usage of vehicle types while optimising the objective functions.

Table 5.11: Parameter values to calculate fuel consumption for a fleet of light, medium and heavy vehicles

Notation	Description	Light vehicle	Medium vehicle	Heavy vehicle
w^h	Curb weight (kg)	3500	5500	14000
f^h	Vehicle fixed cost (£/day)	42	60	95
k^h	Engine fraction factor (kj/rev/litre)	0.25	0.20	0.15
N^h	Engine speed (rev/s)	38.34	36.67	30.0
V^h	Engine displacement (litre)	4.5	6.9	10.5
C_d^h	Coefficient of aerodynamics drag	0.6	0.7	0.9
A^h	Frontal surface area (m^2)	7	8	10
n_{tf}^h	Vehicle drive train efficiency	0.40	0.45	0.50
C^p	Pallet capacity (pcs)	4	12	24
C^c	Cylinder capacity (pcs)	48	150	288
C^w	Weight capacity (kg)	4000	12500	24000

Source: (Koç et al., 2016)

In the first group of experiments, fleets of three different types of homogeneous vehicles were considered in relation to Problem instance 1 to find the effect of each of the vehicle types on the Pareto front. Figure 5.9 presents Pareto fronts for three different vehicle types (light, medium and heavy vehicles) for Problem instance 1. For light and medium types of vehicles - due to their smaller capacity - the constraint that a vehicle cannot visit a customer more than once was relaxed.

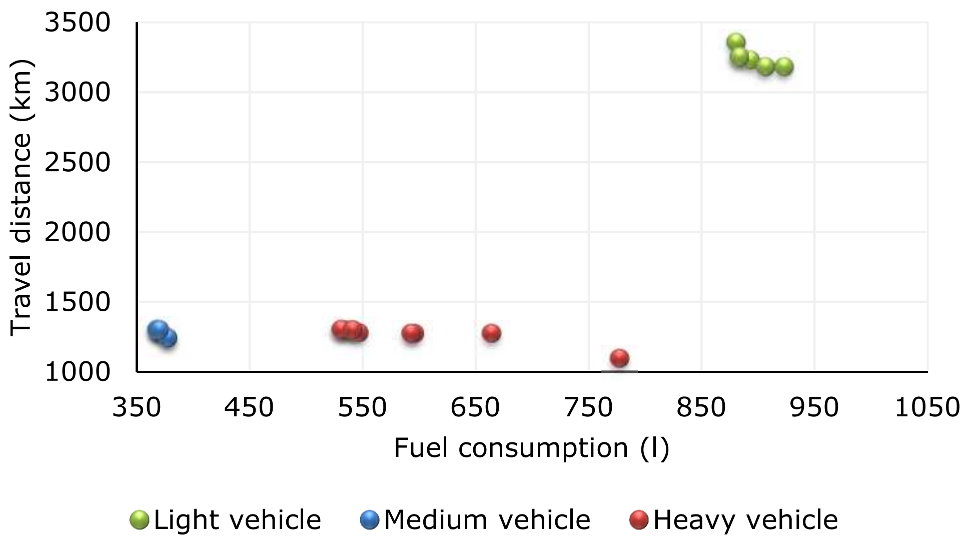


Figure 5.9: Pareto fronts for homogeneous fleets of light, medium and heavy vehicles for Problem instance 1

The figure suggests that for this particular Problem instance, a fleet of medium vehicles offers the best solutions. The Pareto front for heavy vehicles has one solution with a smaller travel distance than the equivalent for the fleet of medium vehicles. When using a fleet of medium vehicles, fuel consumption improved while travel distance remained comparable to the fleet of heavy vehicles. All of the solutions had better fuel consumption, but some of the travel distances were longer than was the case for the equivalent solutions using heavy vehicles - while some of them were shorter. These results suggest that for this particular Problem instance - the distance and demand for pickup and delivery were more suitable for the medium type vehicles than the heavy type. The least attractive result of the three was generated by using the fleet of light vehicles. Depending on the requirements of the company, they can either use heavier vehicles if the sole purpose is to minimise travel distance or medium vehicles, if they want to minimise fuel consumption. While light vehicles should have offered the best result in terms of fuel consumption, their limited capacity means that it would be unwise to use them where pickup and delivery demands are high.

One other interesting takeaway from this experiment is the number of vehicles required for each vehicle type. The total number of vehicles required was 17 for the fleet of light vehicles, seven for the fleet of medium vehicles, and four for the fleet of heavy vehicles. These results suggest that the use of heavy vehicles significantly reduces the number of drivers required compared to medium and light vehicles. However, this cannot conclusively suggest that the use of heavy vehicles for different Problem instances would provide similar results. The choice of vehicle type depends on both the distance between customers and pickup and delivery demand. Light vehicles, for example, can be considered when demand is low, and the travelling distance is very short - with short being subjective here, but for ease of understanding it is assumed that this would refer to any distance that can be covered by light vehicles within a short period of time, so up to 30 miles. On the other hand, heavy vehicles may be used when distance is long, and demand is high. The use of medium vehicles can be thought to be placed in the middle of the other two extreme cases.

In the second group of experiments, a heterogeneous mixture of vehicles were considered. Two sets of vehicles were considered: a set of light vehicles, and a mixture of both light and heavy vehicles. The goal was to see whether the heterogeneous fleet would provide better results - in the form of a better Pareto front - than the homogeneous fleet of light vehicles. To run the experiment for the heterogeneous fleet of light and heavy vehicles, some changes were made regarding how the customers were selected. Some of the customers had delivery or pickup demand that exceeded the capacity of the light vehicles - so light vehicles had to visit these customers more than once to complete the job. For experiments with the heterogeneous fleet, these customers were considered solely for the heavy vehicles while the rest of the customers were shared between light and heavy vehicles, while minimising fuel consumption and travel distance. Figure 5.10 presents solutions for a homogeneous fleet of light vehicles and a heterogeneous fleet of light and heavy vehicles.

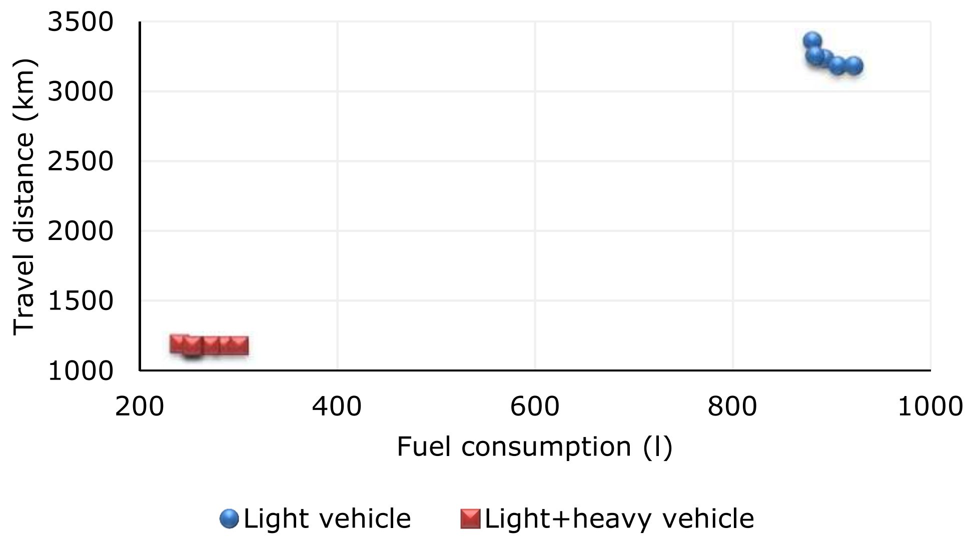


Figure 5.10: Pareto fronts for homogeneous fleet of light vehicles and heterogeneous fleet of light and heavy vehicles for Problem instance 1

Using the heterogeneous fleet of light and heavy vehicles reduced both the travel distance and fuel consumption considerably, as observed in Figure 5.10.

The number of vehicles required was also reduced. Whereas 17 vehicles were required for the fleet of light vehicles, the heterogeneous fleet of light and heavy vehicles reduced this number to eight (of which six were light vehicles and two were heavy vehicles).

Similar experiments were conducted for the other 19 Problem instances. In each case, the heterogeneous fleet of light and heavy vehicles was able to reduce both fuel consumption and travel distance compared to the homogeneous fleet of light vehicles.

The heterogeneous fleet of light and heavy vehicles is most likely to produce better results than the fleet of homogeneous vehicles. However, 20 Problem instances is a small sample size from which to reach a definitive conclusion. In-depth analysis should be conducted in the future to better understand this relationship, and reach a conclusive answer.

5.2. Evaluation of the developed NSGA-II on benchmark Problem instances from the literature

The majority of the benchmark VRP instances presented in the literature require optimisation of a single objective (Golden et al., 1984; Karaoglan et al., 2011; Montané and Galvão, 2006; Tasan and Gen, 2012), or multiple objectives combined into a single objective (Ai and Kachitvichyanukul, 2009; Koç et al., 2014; Ombuki et al., 2006; Wang and Chen, 2012). A limited number of benchmark problems are available in the literature that are aimed towards multiple objectives (Gong et al., 2018; Psychas et al., 2017; Xu et al., 2008) and no instances have been found that require optimisation of both distance and fuel consumption simultaneously. Researchers such as Gong et al. (2018) and Psychas et al. (2017), who researched similar problems, encountered the same lack of benchmark Problem instances and generated their own bespoke problem sets to compare their results. Unfortunately, the benchmark instances used in Gong et al. (2018) and Psychas et al. (2017) were not readily available and could therefore not be used in our experiments to test against our algorithm.

Some common benchmark instances and their data generation procedures are presented below. Many of the benchmark instances included time windows and service time, which are irrelevant to this study and will not be considered further. Most of the benchmark instances for simultaneous pickup and delivery Problems were taken from the CVRP instances that included only delivery data and not pickup data. Different researchers used different procedures to generate the pickup data. The following table lists some of the benchmark instances found in the literature.

Table 5.12: Benchmark instances from the literature and their objective functions

Benchmark instances	**Objective function**	**References**
(Min, 1989)	Travel distance	(Çatay, 2010; Gajpal and Abad, 2009)
(Augerat et al., 1998)	Travel distance	(Tasan and Gen, 2012)
(Salhi and Nagy, 1999)	Travel distance	(Avci and Topaloglu, 2015; Çatay, 2010; Gajpal and Abad, 2009; Montané and Galvão, 2006; Subramanian et al., 2011)
	Transportation fixed cost + variable cost	(Goksal et al., 2013)
(Dethloff, 2001)	Travel distance	(Avci and Topaloglu, 2015; Çatay, 2010; Gajpal and Abad, 2009; Montané and Galvão, 2006; Sayyah et al., 2016; Subramanian et al., 2008, 2011; Wassan et al., 2008)
	Transportation fixed cost + variable cost	(Ai and Kachitvichyanukul, 2009; Goksal et al., 2013)
	Minimum waiting time, fuel consumption, delivery distance	(Gong et al., 2018)
(Nagy and Salhi, 2005)	Travel distance	(Wassan et al., 2008)
	Transportation fixed cost + variable cost	(Ai and Kachitvichyanukul, 2009)
(Dell'Amico et al., 2006)	Transportation fixed cost + variable cost	(Ai and Kachitvichyanukul, 2009)
Zachariadis and Kiranoudis (2011)	Travel distance	(Goksal et al., 2013; Wang et al., 2015)

The benchmark instances are explained further below.

The Solomon benchmark Problem instances (Solomon, 1987) were among the first instances created, and have since been used by many other researchers to generate their own benchmark instances. The original problem instances included delivery demand with time windows. Many researchers who did not include time windows in their problem excluded time window data.

Min (1989) presented a benchmark instance where a library was required to pick up and deliver library materials such as books, films, video tapes, boxes and envelopes to 22 branch libraries scattered around the Columbus metropolitan area. These were real world data collected from the public library of Columbus and Franklin County, USA.

The data used by Augerat et al. (1998) introduced pickup demands that were generated randomly between [0,26].

Instances in Dethloff (2001) were generated randomly for 50 customers. Coordinates of the customers were uniformly distributed. Delivery demand was generated following a uniform distribution in the interval [0,100]. Pickup demand was computed as $P_i = (0.5 + r)d_i$, where r was taken from a uniform distribution in the interval $[0,1]$.

Nagy and Salhi (2005) proposed benchmark instances for a simultaneous pickup and delivery VRP. The original Problem instances given by Christofides (1979) were used, and the original demand data was split into delivery and pickup demand. Delivery demand fluctuated between 7 and 30. For each customer i, a ratio r_i was calculated as $min\,({}^{x_i}/_{y_i}, {}^{y_i}/_{x_i})$ - where x_i and y_i were the coordinates of customer i. The delivery demand was then set as $q(i) = r_i.t(i)$, and pickup demand was set as $p(i) = (1 - r_i).t(i)$.

Dell'Amico et al. (2006) derived their first set of data from Solomon's benchmark instances, neglecting the time windows. Each figure for demand (d_i) for customer i given in the instances was treated as their delivery demand, ranging between 0 and 50 and their pickup demands were generated using the following equations: $P_i = \lfloor (1-\gamma)d_i \rfloor$ if i was even, and $P_i = \lfloor (1+\gamma)d_i \rfloor$ if i was odd, where $\in [0.2, 0.8]$. A second set of data was generated as described in Toth and Vigo (2002), where demand was generated from a normal distribution with mean value equal to 50 and standard deviation equal to 20. For the third set of instances, pickup demand was computed as $P_i = (0.5 + r)d_i$ - where r was taken from a uniform distribution in the interval $[0,1]$.

Zachariadis and Kiranoudis (2011) modified the problems given in Montané and Galvão (2006) by randomly generating the delivery and pickup demands. The pickup demand was generated within the intervals used for generating the delivery demand in the original CVRP instances given in Solomon (1987). The arc costs were obtained by calculating the Euclidean distances between customer locations, so that the generated cost matrix was both symmetric and satisfied the triangular inequality.

It is observed that no specific data set was previously available that dealt with multi-objective optimisation problems and the VRPSPD.

One of the major difficulties in comparing solutions obtained for the benchmark Problem instances is caused by the use of different objective functions. The majority of the benchmark problem instances are single-objective optimisation problems. To compare the solutions obtained by single-objective optimisation methods with the NSGA-II is difficult. Nevertheless, it was decided to evaluate the quality of solutions of the developed NSGA-II with respect to distance and fuel consumption against the solutions given in the literature. In benchmark instances where fuel consumption were not readily available for comparison, the value was calculated from the respective benchmark solutions. The developed algorithm was evaluated on the benchmark instance of Min (1989) and the 12 large-scale VRPSPD instances solved by Zachariadis and Kiranoudis (2011). The former is one of the earliest benchmark instances, and the latter is one of the most recent sets of benchmark instances which are readily available in the literature. Table 5.13 presents the results for the Min (1989) instance, and Table 5.15 presents the results for the instances in Zachariadis and Kiranoudis (2011). Min (1989) formulated the problem as a library delivery and pickup system for the public library of Columbus and Franklin County, Ohio. The stated problem had 22 branch libraries scattered around the Columbus which needed to be served by two vehicles. The distance was given in miles and the delivery and pickup demand were given in pounds. To be consistent with our model, these were changed to equivalent kilometres and kgs.

Table 5.13: Comparison of results produced by NSGA-II with results in Min (1989)

	Min (1989)	**NSGA-II (Lowest fuel consumption)**	**% difference**	**NSGA-II (Smallest travel distance)**	**% difference**	**Time (s)**
Fuel consumption $(\boldsymbol{l})$	91.37	87.18	-4.59%	92.71	1.47%	35
Travel distance $(\boldsymbol{km})$	151.28	154.50	2.13%	143.23	-5.32%	

It can be seen from Table 5.13 that the NSGA-II was able to find good trade-off solutions for the benchmark problem instance. In the solution from the obtained Pareto front with the best value for fuel consumption, the NSGA-II improved fuel consumption by 4.59% at the cost of increasing the travel distance by 2.13%. On the other hand, in the solution from the obtained Pareto front with the best value for distance, fuel consumption were increased by 1.47% but travel distance was reduced by 5.32%. Other solutions on the Pareto front contain solutions representing a trade-off between fuel consumption and distance.

In the following sections, we discuss the Zachariadis and Kiranoudis (2011) benchmark problem instances in detail.

Table 5.14: Characteristics of benchmark Problem instances in Zachariadis and Kiranoudis (2011)

Problem instance	**Number of customers**	**Vehicle capacity**	**Delivery demand**	**Pickup demand**
r101	100	200	1458	2339
r201	100	1000	1458	2262
c101	100	200	1810	3070
c201	100	700	1810	2910
R1_2_1	200	200	3513	4406
R2_2_1	200	1000	3513	4358
C1_2_1	200	200	3530	5370
C2_2_1	200	700	3770	6010
R1_4_1	400	200	7109	10433
R2_4_1	400	1000	7109	9571
C1_4_1	400	200	7190	12470
C2_4_1	400	700	7560	10050

Table 5.15 presents a comparison between the results produced by the NSGA-II which uses different methods of initial population generation, including T80 (where 80% of the solutions are generated with TOPSIS while the remaining 20% are generated randomly), random generation and the Sweep Algorithm and in Zachariadis and Kiranoudis (2011),

who used the Arc Promise Algorithm. All the experiments were conducted with $\alpha = 10\%$ and population size = 50.

Table 5.15: Comparison of objective function for three initial population generation methods with benchmark Problem instances in Zachariadis and Kiranoudis (2011)

Problem instances	Benchmark	T80	Difference to benchmark	Random generation	Difference to benchmark	Sweep Algorithm	Difference to benchmark
r101	1009.95	1120.33	9.85%	2028.09	50.20%	1390.67	27.38%
r201	666.20	754.32	11.68%	1574.55	57.69%	983.75	32.28%
c101	1220.18	1344.59	9.25%	2482.53	50.85%	1350.56	9.65%
c201	662.06	715.68	7.49%	2149.65	69.20%	1155.99	42.73%
R1_2_1	3375.19	4539.00	25.64%	10785.11	68.71%	5229.69	35.46%
R2_2_1	1665.58	2719.52	38.75%	9202.04	81.90%	3729.02	55.33%
C1_2_1	3641.88	4129.91	11.82%	10878.61	66.52%	4610.60	21.01%
C2_2_1	1726.73	2568.44	32.77%	8649.34	80.04%	3705.22	53.40%
R1_4_1	9668.18	13403.5	27.87%	32850.84	70.57%	16684.68	42.05%
R2_4_1	3560.72	7668.14	53.56%	10639.44	66.53%	8149.92	56.31%
C1_4_1	11125.14	14617.2	23.89%	35499.62	68.66%	14574.00	23.66%
C2_4_1	3549.20	6415.35	44.68%	26130.10	86.42%	9747.63	63.59%

Each of the solutions obtained using T80 produces better results than those from the NSGA-II with initial population generated either randomly and or with the Sweep Algorithm. This is also confirmed by the values of Hypervolume presented in Table 5.16 (which consider both objectives - travel distance and fuel consumption).

Table 5.16: Hypervolume values obtained on benchmark Problem instances

Problem instance	T80	Random generation	Sweep Algorithm
r101	**12.52**	2.37	10.59
r201	**144.56**	57.59	138.57
c101	**14.66**	1.36	11.26
c201	**13.89**	1.94	11.85
R1_2_1	**255.61**	10.56	183.96
R2_2_1	**275.99**	17.53	220.34
C1_2_1	**578.34**	11.81	236.49
C2_2_1	**345.81**	10.91	158.24
R1_4_1	**1581.37**	72.88	1501.32
R2_4_1	**2261.35**	85.58	1702.64
C1_4_1	**4828.03**	82.71	2305.79
C2_4_1	**2560.73**	83.40	1603.38

Although T80 performs better than randomly generated initial population or initial population generated by Sweep Algorithm, the differences between the NSGA-II solutions and benchmark solutions are still quite large with the current set of parameters ($\alpha = 10\%$ and population size = 50). The following table shows time for three different methods of initial population generation method with benchmark instances in Zachariadis and Kiranoudis (2011).

Table 5.17: Comparison of time for three initial population generation methods with benchmark Problem instances in Zachariadis and Kiranoudis (2011)

Problem instance	**T80 (time, s)**	**Random generation (time, s)**	**Sweep Algorithm (time, s)**	**Problem instances**	**T80 (time, s)**	**Random generation (time, s)**	**Sweep Algorithm (time, s)**
r101	92	94	95	C1_2_1	152	160	170
r201	102	102	104	C2_2_1	193	194	194
c101	63	67	68	R1_4_1	612	618	618
c201	80	81	86	R2_4_1	575	575	575
R1_2_1	201	203	209	C1_4_1	1121	1135	1140
R2_2_1	183	183	184	C2_4_1	988	989	991

The next experiments investigate whether using either a different value of α in TOPSIS or a different population size can lead to better results. In the construction of a route, parameter α determines the number of top ranked solutions which will be identified by TOPSIS. $\alpha = 2\%$ is selected for the next experiment. This means that if, for example, there are 400 customers in the first step in the route construction, the algorithm will consider the first eight top ranked solutions. Figure 5.11 presents two sets of Pareto fronts with $\alpha = 2\%$ and $\alpha = 10\%$ from benchmark instance c201.

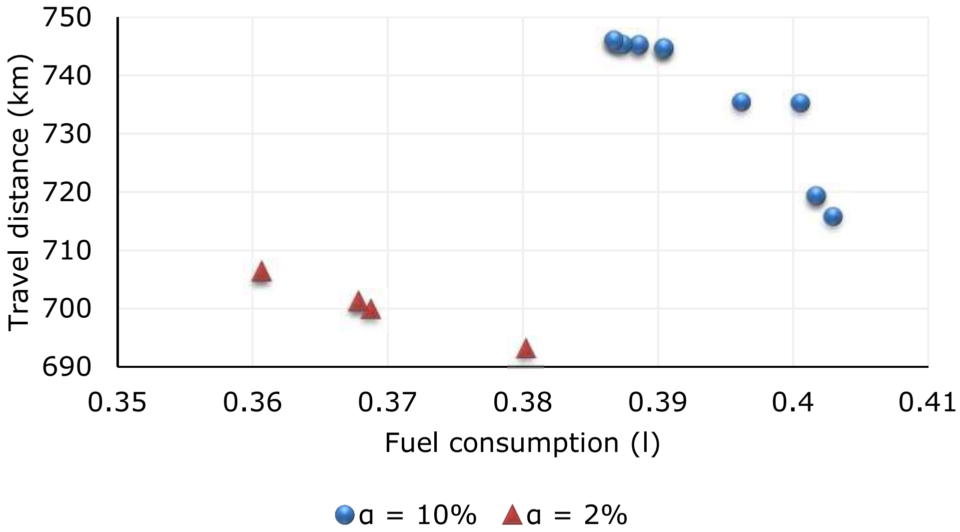


Figure 5.11: Pareto front for benchmark instance c201 with $\boldsymbol{\alpha} = \mathbf{10}\%$ and $\boldsymbol{\alpha} = \mathbf{2}\%$

The Pareto front obtained by $\alpha = 2\%$ and population size $= 200$, outperforms the Pareto front obtained by $\alpha = 10\%$ and population size $= 50$. Similar results were also found on other benchmark instances, where using $\alpha = 2\%$ and population size $= 200$ reduced both travel distance and fuel consumption. Table 5.18 shows the minimum values of both objectives for the other benchmark instances. Negative values (given in bold) represent solutions from NSGA-II that have better values than their corresponding benchmark solutions.

Table 5.18: Comparison of objective function values of NSGA-II with different values of $\boldsymbol{\alpha}$ and population size and benchmark problem instances in Zachariadis and Kiranoudis (2011)

Problem instances		**Benchmark results**	$\boldsymbol{\alpha} = \mathbf{10}\%$ **Population = 50**			$\boldsymbol{\alpha} = \mathbf{2}\%$ **Population = 200**		
			NSGA-II	**% difference**	**Time (s)**	**NSGA-II**	**% difference**	Time (s)
r101	Fuel consumption (l)	0.53	0.52	**-1.92%**	92	0.51	**-3.92%**	124
	Travel distance (km)	1009.95	1120.30	9.85%		1009.95	**0.00%**	
r201	Fuel consumption (l)	0.48	0.46	**-4.35%**	102	0.41	**-17.07%**	119
	Travel distance (km)	666.20	754.32	11.68%		671.70	0.82%	
c101	Fuel consumption (l)	0.57	0.54	**-5.56%**	63	0.50	**-14.00%**	93
	Travel distance (km)	1220.18	1344.59	9.25%		1261.44	3.27%	
c201	Fuel consumption (l)	0.54	0.39	**-38.46%**	80	0.36	**-50.00%**	113
	Travel distance (km)	662.06	715.68	7.49%		693.05	4.47%	
R1_2_1	Fuel consumption (l)	1.95	2.14	8.88%	201	1.57	**-24.20%**	233

Problem instances		Benchmark results	$\alpha = 10\%$ Population = 50			$\alpha = 2\%$ Population = 200		
			NSGA-II	**% difference**	**Time (s)**	**NSGA-II**	**% difference**	Time (s)
	Travel distance (km)	3375.19	4539.00	25.64%		3378.76	0.11%	
R2_2_1	Fuel consumption (l)	1.04	1.68	38.10%	183	1.00	**-4.00%**	211
	Travel distance (km)	1665.58	2719.52	38.75%		1668.81	0.19%	
C1_2_1	Fuel consumption (l)	1.8	1.62	**-11.11%**	152	1.56	**-15.38%**	190
	Travel distance (km)	3641.88	4129.91	11.82%		3837.75	5.10%	
C2_2_1	Fuel consumption (l)	0.99	1.43	30.77%	193	0.99	**0.00%**	228
	Travel distance (km)	1726.73	2568.45	32.77%		1790.26	3.55%	
R1_4_1	Fuel consumption (l)	5.81	5.97	2.68%	612	4.25	**-36.71%**	727
	Travel distance (km)	9668.18	13403.54	27.87%		10074.55	4.03%	
R2_4_1	Fuel consumption (l)	2.18	4.64	53.02%	575	2.23	2.24%	713
	Travel distance (km)	3560.72	7668.13	53.56%		3882.17	8.28%	
C1_4_1	Fuel consumption (l)	5.12	5.69	10.02%	1121	4.85	**-5.57%**	1328
	Travel distance (km)	11125.14	14671.23	24.17%		12354.73	9.95%	
C2_4_1	Fuel consumption (l)	2.06	3.85	46.49%	988	2.09	1.44%	1201
	Travel distance (km)	3549.20	6415.35	44.68%		3845.45	7.70%	

Time required by the algorithm is shown in the table but it is worth mentioning here that the purpose of the table is to compare the quality of the solutions, rather than to compare the time.

To draw comparisons between the benchmark problem instances and the solutions obtained by NSGA-II, fuel consumption were calculated for each of the problem instances. By comparing the benchmark solutions with NSGA-II solutions for $\alpha = 10\%$, we were able to find five benchmark problem instances where the NSGA-II solutions had performed better than the benchmark instances for one of the objectives (fuel consumption). When the experiment was completed with $\alpha = 2\%$, five more benchmark instances were found (making a total of 10 out of 12) where the NSGA-II solutions had performed better than the solutions of the benchmark instances for the fuel consumption objective. In the two instances where the solutions from NSGA-II were outperformed by Zachariadis and Kiranoudis (2011), the difference was only 2.24 and 1.44% respectively.

The solutions produced by NSGA-II were outperformed in every instances by Zachariadis and Kiranoudis (2011) with regard to travel distance. However, the differences between the two sets of solutions were relatively small - ranging from 0.11% to 9.95%. For the four benchmark instances where the number of customers was 400, the differences were 4.03, 8.28, 9.95 and 7.70%. For the other eight instances, the minimum difference was 0% and the maximum difference was 5.10%.

This could be identified as one of the major limitations of the algorithm. The algorithm works well with a smaller number of customers but when a larger number of customers is introduced, it struggles to produce optimal solutions as would be anticipated.

The next step was to perform an in-depth analysis of the characteristics of the benchmark instances that may possibly cause solutions from NSGA-II to be outperformed. The location of customers relative to the depot was calculated for the benchmark instances. It was found that in the benchmark instances, the customer locations were almost equally distributed around the depot. The percentages of customer locations around the depot are presented in Table 5.19.

Table 5.19: Percentage of customers in different quadrants in the benchmark instances in Zachariadis and Kiranoudis (2011)

Problem instance	1st quadrant	2nd quadrant	3rd quadrant	4th quadrant
r101	28%	22%	30%	20%
r201	28%	22%	30%	20%
c101	27%	23%	25%	25%
c201	23%	23%	26%	28%
R1_2_1	27%	29%	20%	24%
R2_2_1	27%	29%	20%	24%
C1_2_1	32%	27%	21%	20%
C2_2_1	14%	32%	24%	30%
R1_4_1	25%	28%	21%	26%
R2_4_1	25%	28%	21%	26%
C1_4_1	31%	20%	17%	32%
C2_4_1	16%	30%	32%	22%

By contrast, it was identified that, in the real-world data received from the collaborator company - customer locations are not equally distributed. In other words, customers were clustered together to a larger extent than in the artificially generated instances. The relevant data is presented in Table 5.20. It was established that the developed algorithm performed better on the instances which contain clustered customers as opposed to randomly generated locations of customers.

Table 5.20: Percentage of customers in different quadrants in the real-world Problem instances

Problem instance	**1st quadrant**	**2nd quadrant**	**3rd quadrant**	**4th quadrant**
1	19%	38%	44%	0%
2	0%	62%	38%	0%
3	0%	7%	67%	27%
4	9%	64%	27%	0%
5	0%	76%	18%	6%
6	0%	72%	22%	6%
7	13%	50%	25%	12%
8	0%	43%	57%	0%
9	6%	47%	47%	0%
10	0%	69%	31%	0%
11	0%	54%	46%	0%
12	7%	0%	86%	7%
13	0%	88%	12%	0%
14	7%	7%	73%	13%
15	0%	18%	73%	9%
16	0%	72%	28%	0%
17	6%	56%	38%	0%
18	0%	0%	92%	8%
19	0%	83%	17%	0%
20	0%	42%	58%	0%

Another possible reason for achieving comparatively poorer solutions than anticipated relates to the calculation of fuel consumption. The NSGA-II uses fuel consumption as one of the criteria for selecting customers in the construction of a route, and also as one of the objectives to optimise. However, the coordinates of the customers in the benchmark instances were artificially generated and consequently the distances were not given in real measurement units (for example, kilometres or miles). Therefore, the choice of speed becomes irrelevant which would affect the calculation of fuel consumption. Also, the demand data presented in the benchmark instances has little or no impact on the final solution. If the demand data is scaled up or down, the solution will remain the same with respect to the distance - but the calculation for fuel consumption will be affected. This can be illustrated using a small example. In the example, it is assumed that there are three customers. The location of the depot and customers, as well as their pickup and delivery demands, are given in Table 5.21.

Table 5.21: The effect of demand change on the solution

	Coordinate		**Delivery (1^{st})**	**Pickup (1^{st})**	**Delivery (2^{nd})**	**Pickup (2^{nd})**
Depot	100	100	0	0	0	0
Customer 1	200	300	4300	0	430	0
Customer 2	400	200	6100	500	610	50
Customer 3	500	500	2780	2500	278	250

The possible solutions with corresponding distance and fuel consumption values are presented in Table 5.22. The best values are shown in bold.

Table 5.22: Different routes and their corresponding distance and fuel consumption

Route	**Travel distance 1^{st} (km)**	**Fuel consumption 1^{st} (l)**	**Travel distance 2^{nd} (km)**	**Fuel consumption 2^{nd} (l)**
0-1-3-2-0	**1216.62**	437.29	**1216.62**	**319.78**
0-1-2-3-0	1329.13	**437.06**	1329.13	345.28
0-2-1-3-0	1466.08	485.89	1466.08	381.24
0-2-3-1-0	**1216.62**	437.96	**1216.62**	319.85
0-3-1-2-0	1466.08	568.83	1466.08	389.53
0-3-2-1-0	1329.13	519.13	1329.13	353.49

As can be seen from the table - when the load changes, even in scale, the solution for fuel consumption also changes. The first instance had two different solutions with best values for the two objectives while in the second instance, a single optimal solution optimised both objectives simultaneously.

The calculation of fuel consumption emphasises factors including the heating value of a diesel fuel engine, the speed of the vehicle, the engine speed and the engine fraction factor - together with the real distance. By way of reminder, the equation for fuel consumption given in Section 3.3 was:

$$\sum_{i,j\in V}\sum_{m\in M} 0.00145 * \frac{y_{ij}}{v} x_{ij}^{m} + \sum_{i,j\in V}\sum_{m\in M} 7.35^{-7} * v^2 x_{ij}^{m} + \sum_{i,j\in V}\sum_{m\in M} 1.33^{-8} * \left(w + Z_j^{m,w}\right) * y_{ij} x_{ij}^{m}$$

where:

$y_{ij} = travelled\ distance\ between\ point\ i\ and\ j$

$Z_j^{m,w} = load\ of\ vehicle\ m\ after\ delivery\ and\ pickup$

The third term in the objective function calculates the load part. The weight of the vehicle is assumed to be 14,000 kg based on Koç et al. (2016). If the load is too small in comparison to the vehicle weight, its impact on the calculation becomes insignificant and this can produce a different result, as seen in Table 5.22.

It can therefore be argued that benchmark instances designed for the single-objective VRP cannot be assumed to be automatically compatible with multi-objective optimisation problems.

5.3. Review of the chapter

Various combinations of TOPSIS and randomly generated solutions were considered for the initial population generation. To identify the best combination, a series of experiments was run on the 20 Problem instances provided by the collaborator company. The experiments were run 10 times - producing a total of 110 Pareto fronts (10 times multiplied by 11 combinations) for each instance. The Hypervolume values of these 110 Pareto fronts were ranked, and a combination of 80% TOPSIS and 20% randomly generated solutions was shown to have the lowest sum of rank - indicating the superiority of this combination over the 10 others.

The selected combination of 80% TOPSIS and 20% random generation was then evaluated against two common initial population generation methods: random generation, and the Sweep Algorithm. For all 20 Problem instances, the proposed algorithm performed better than these two alternatives - as confirmed by the corresponding Hypervolume values. A single factor ANOVA test was conducted to justify that the solutions from the three algorithms were different. This test confirmed that the three algorithms did not produce same result. This in turn proved that the initial population generation method does affect the final solution, and that the proposed method was better than the two considered alternatives for the given Problem instances.

The NSGA-II results were evaluated against the results provided by the collaborator company. Comparison of 20 Problem instances showed that the NSGA-II produced better solutions than the collaborator company.

The output of the NSGA-II is a Pareto front that corresponds to solutions that represent a trade-off between the travel distance and incurred fuel consumption. The Pareto front with corresponding multiple solutions gives an opportunity to the logistics manager to express a posteriori preferences towards the importance of objectives, and choose a preferred solution. The Pareto front provides a visual representation of the trade-off.

Two what-if analyses were undertaken to investigate the effect of speed and size of vehicle on the final solution. An experiment to find the effect of speed on the final solution showed that fuel consumption could be reduced with lower speed - although this also increased travel distance. One of the reasons why distance increased when lower speed was used was that with lower speed, the vehicles had to make more short trips - as they could not travel longer distances, and had to return to the depot. Conversely, higher speed reduced the travelled distance, but increased the corresponding fuel consumption.

Experiments with a fleet of heterogeneous vehicles revealed that a combination of light and heavy vehicles reduced the number of vehicles used, fuel consumption and distance considerably. However, this conclusion may not hold true in all cases. This combination of results could change based on the pattern of customer locations and the variability of customer demand - so further investigation is required.

Benchmark Problem instances were selected from amongst the literature to investigate the performance of the algorithm on the artificially generated data with different numbers of customers. Results showed that the NSGA-II T80 outperformed NSGA-II with initial population either randomly generated or generated by the Sweep Algorithm. However, it did not outperform solutions obtained by Zachariadis and Kiranoudis (2011). There are two possible reasons for this. First, their locations of customers were uniformly generated around the depot which is not the case in the real-world problem of our collaborator. Second, the coordinates for the distances of their customers were not given in real measurement units - which jeopardises the calculation of fuel consumption. In the experiment, it was also found that in eight of the problem instances out of twelve - solutions by NSGA-II outperformed on one objective (fuel consumption) but did not perform as well with regard to the other objective (travel distance). In the eight Problem instances where solutions produced by NSGA-II outperformed the benchmark solutions, the number of customers was relatively small (100 and 200) - compared to the other four, where there were 400 customers. It could therefore be suggested that the developed algorithm works well for smaller numbers of customers, but may struggle to produce such good results when the number of customers is large.

6. SHARED TRANSPORTATION OUTSOURCING DECISION

In the previous chapters, we have established that distance and CO_{2e} emissions in the form of fuel consumption can be considered for a multi-objective VRPSPD and that combining the NSGA-II with a new initial population generation method provides better solutions in a VRPSPD setting. We have also seen that multi-objective optimisation provides good results for both homogeneous and heterogeneous vehicle fleets within the collaborator company.

This chapter investigates the cost of outsourcing the collaborator company's transport logistics operations through either asset-specific RL (where vehicles would only be used by the collaborator company), or asset-shared RL (where vehicles are shared by two or more companies). This chapter is not aiming to prove that multi-client outsourcing reduces the cost. The purpose of this chapter is rather to calculate the fuel consumption impact of the outsourcing decision. It contributes an environmental costs perspective to the overall outsourcing decision.

The concept of the shared transportation outsourcing decision is discussed in Section 6.1 which is followed by an explanation of the TCT in outsourcing decisions in Section 6.2. Risks and benefits of shared transportation outsourcing decisions are presented in Section 6.3 and 6.4 respectively. In Section 6.5, the various factors in the shared transportation outsourcing decision are debated - including cost, strategy, environment, and functional characteristics.

Recommendations for reducing fuel consumption in transportation logistics are presented in Section 6.6. A hypothetical numerical example is presented in Section 6.7, comparing both fuel consumption and fuel cost and the travelled distance. The chapter concludes with a short discussion of the outcome.

6.1. Outsourcing

The link between outsourcing, VRPs and RL was studied and described earlier in Section 2.5. This link can be expanded to incorporate the idea of sharing of transportation logistics by two or more companies that might have similar or different demand patterns. This study is based on TCT, which deals with economies of scale and various other transactions in a decision-making process for any organisation. There are other theories (such as RBT, or Supply Chain Management Theory) available in this research area through which an outsourcing decision could be explained. The rationale for choosing to apply TCT here is discussed in more detail in Section 6.2.

McIvor (2009) and Williamson (2008) examined the outsourcing decision from the TCT perspective. They suggest that TCT specifies conditions that determine the conditions for economic exchange externally. They also recommend that the level of investments specific to transactions should be considered by any organisation in the event of an economic exchange and this should act as the principal determinant in deciding if the exchange is to be managed internally or outsourced to a third-party logistics provider. Based on their reasoning, the decision to outsource transportation logistics can be seen as an event of economic exchange between a third-party logistics provider and an OEM, which can be explained by TCT. We have chosen TCT to explain the complexity regarding sharing transportation logistics of outsourced vehicles. The decision of outsourcing transportation logistics and incorporating two or more companies in the same fleet of vehicles will be explained later through an experiment in Section 6.7. First, the concept of outsourcing is presented.

Outsourcing means subcontracting a part of the OEM's functions and/or processes to a third-party logistics provider which was previously performed by the OEM itself (Grabara and Kot, 2010; Reeves Jr. et al., 2010). Hsiao et al. (2010, p.396) considered the definition from Lieb et al. (1993) and enhanced it (as quoted below) to incorporate cost and time horizons to provide a more precise definition of logistics outsourcing - which had previously considered the function without looking at these factors in any detail.

> *"Logistics outsourcing is a process that involves the use of external logistics companies for performing activities that have traditionally been performed within a firm and where the shipper and logistics company enter into an agreement for delivering services at specific costs over some identifiable time horizon".*

OEMs generally expect to achieve a benefit from the successful implementation of an outsourcing strategy. The most common and quantifiable benefits of outsourcing relate to the comparative cost advantage and can include cost savings, reduced capital expenditure, capital infusion, greater flexibility, increased access to skill and talent, and increased focus on core functions (Kremic et al., 2006). Other potential benefits of outsourcing are explained in Section 6.4 and while some of these cannot be measured directly in monetary terms, they may still be no less important. While it is possible that these benefits can be achieved by taking a decision to outsource, there are also many risks which could mean that outsourcing turns out to be less advantageous than was hoped (Section 6.3). Figure 6.1 portrays the typical factors in an outsourcing decision for any particular function of a firm.

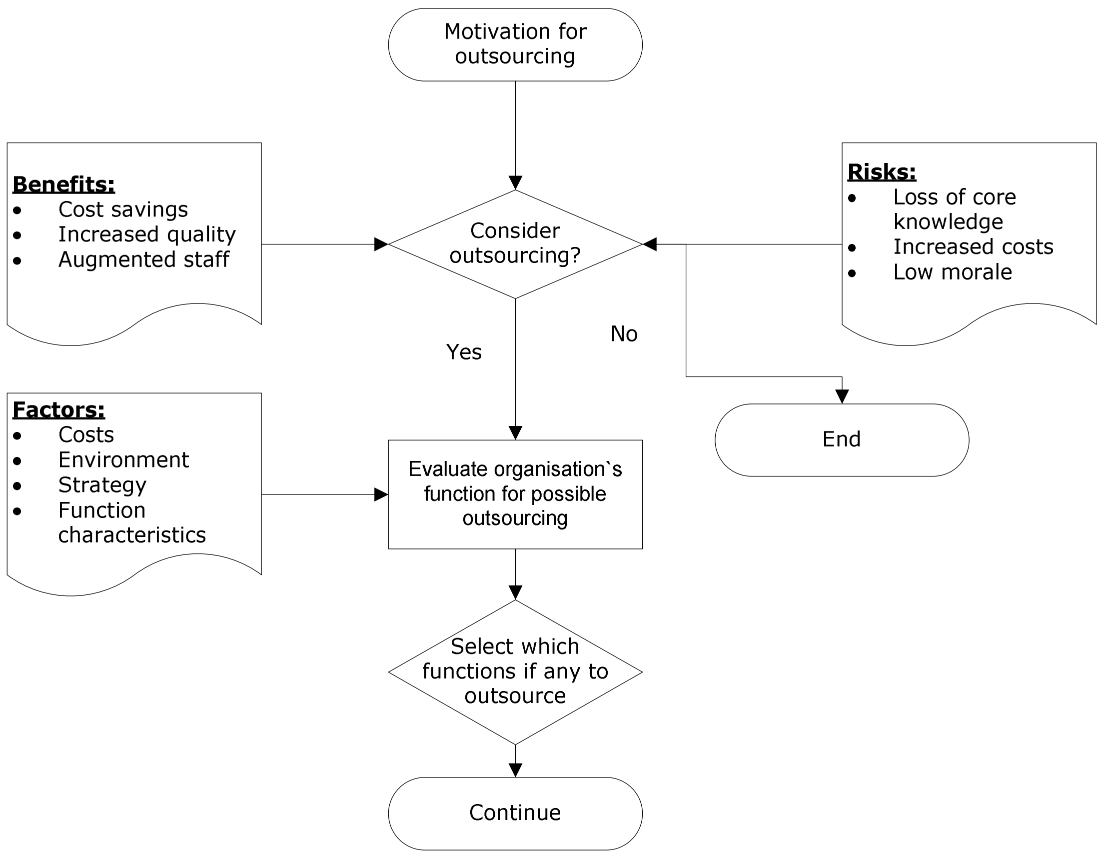


Figure 6.1: Flowchart for outsourcing decision making
Source: (Kremic et al., 2006)

The figure demonstrates where the motivators, benefits, risks and factors are typically encountered in an outsourcing decision-making process. Motivators are the reasons underlying the initial decision while factors are the elements that determine the functions of the organisation that can be considered for outsourcing. Kremic et al. (2006) suggested that there are three major motivators for any outsourcing decision: cost, strategy and politics. The first two motivators commonly drive outsourcing decision-making for private industries, while political agendas often drive outsourcing decision-making for public enterprises (Kakabadse and Kakabadse, 2000). One more motivator may be added to their list: environmental sustainability, which often guides the outsourcing decision-making process for both public and private enterprises. Environmental sustainability refers to the impact of CO_2 and other GHG emissions, and also to other ways in which the environment may be affected. Any outsourcing decision - particularly the decision of whether to outsource transportation logistics - may be linked with the goal of optimising the transportation system to reduce the impact of CO_2 and other GHG emissions.

However, it is debatable whether environmental sustainability should properly be considered to fall within the classification of motivators already established by Kremic et al. (2006), or whether it can be defined separately. It could be argued that environmental sustainability does not have any direct link to the other motivators of cost, strategy and politics. On the other hand, it could also be argued that environmental sustainability can be politically and strategically desirable and can further be linked to lowering or increasing costs.

In an outsourcing decision, it is not necessary that all motivators are present. Even a single motivator may be strong enough to trigger an outsourcing decision - though a combination of motivators could equally be involved in the decision-making process.

This chapter of the thesis investigates the strength of the effect of environmental sustainability in deciding when to outsource transportation or not.

It is not within the scope of this research to find the motivators for outsourcing decision-making. Rather, it is assumed that the initial outsourcing decision has been already taken based on strategic, cost or political motivators - without environmental sustainability being considered. The research would investigate how environmental considerations affect decisions as to precisely when a company should outsource.

The benefits and risks associated with outsourcing are presented later in the chapter. In Section 6.2, TCT is explained in more detail as a suitable basis for examining the outsourcing decision.

6.2. Transaction Cost Theory on outsourcing decision-making

TCT was originally developed as an economic theory that looks into a firm as a governance entity rather than a productive entity. TCT explains a firm through its legal, organisational and entrepreneurial characteristics. TCT has a wide range of applications in sociology, politics, business strategy, corporate finance and marketing. TCT can also be applied to explain why a firm chooses to perform all or some of its activities in-house, to procure provision from the market, or to outsource to a third party under a long-term arrangement.

Williamson (1985) suggests that the determination of whether outsourcing should happen lies in comparing the transaction costs of in-house and outsourcing options. In case of in-house activity, the transaction costs include internal bureaucratic management costs, the costs of gathering the right skills (which is separate from the additional cost of wages and salaries), the cost of managing uncertainty and so on. On the other hand, the transaction costs of outsourcing (in its simplest form) typically include the costs of searching for and subsequently selecting a service provider, bargaining with them, and enforcing compliance by them. These costs are, in principle, identifiable and quantifiable when transactions are simple and straightforward. However, simplicity is not always found in outsourcing scenarios. The principal factors which determine whether an outsourcing transaction will remain simple or become complex are environmental uncertainty (bearing in mind that any situation not within the administrative and technological umbrella of a firm is defined as an environment), opportunism, risk and uncertainty, bounded rationality and core company assets (or asset specificity). The degree of complexity of a transaction in turn determines the levels of costs involved. Huo et al. (2018) identified the following relationships.

- Demand uncertainty increases opportunism.

- Supply uncertainty decreases opportunism.
- Technology uncertainty has no significant effect on user or provider specific assets.
- User specific assets increase opportunism.
- Provider specific asset decrease opportunism.
- Demand and supply uncertainty have a positive impact on user specific assets, but an insignificant effect on producer specific assets.

A complex situation of relationships can therefore emerge - making a purely rational decision based on a rigorous optimisation exercise virtually impossible.

As a result, instead of resorting solely to the rigorous mathematical optimisation of variables, TCT also applies processes of decision making based on "bounded rationality". Bounded rationality is the idea that informational limitations, cognitive limitations and finite time limits can all restrict the ability of an individual to take a purely rational decision (Holbrook, 2002). For this purpose, analysis using TCT employs three important concepts: asset specificity, uncertainty, and frequency of the transaction. These can be used to decide between the two extremes of the sourcing decision: vertical integration, or outsourcing (McIvor, 2000). In their research, Reeves Jr. et al. (2010) explained these three concepts more closely. According to them, the frequency of transactions affects the outsourcing decision in ways that include economies of scale and sensitivity to reputation, and uncertainty refers to both behavioural and environmental shock. The third concept - asset specificity - is affected by both bounded rationality and behavioural and environmental uncertainty. In summary, TCT suggests that outsourcing decisions have a cost containment objective that can be compared.

The availability of a dedicated fleet for outsourced transportation logistics should rationally lead to specific utilisation of assets. The OEM can train the drivers according to their own standards, it is easier to control the brand name, and vehicles can be updated by the third-party logistics provider according to the guidelines stated by the OEM. There is less uncertainty, and the frequency of transactions is easy to predict over a certain period.

The central idea of outsourcing, as viewed through the TCT, rests upon the assumption that the benefit accrued from outsourcing will outweigh the losses or costs that may be incurred from any apprehended or unapprehended sources. Analysis of risk and benefit therefore constitutes an integral part of TCT.

The various risks associated with the outsourcing decision-making process are discussed in more detail in Section 6.3. The potential benefits of outsourcing are discussed in Section 6.4.

6.3. Risks of sharing transportation in outsourcing

Risk can be summarised as "the variance of a probability distribution of possible gains and losses associated with a given alternative" *(*Bahli and Rivard, 2003)*.* Lockamy and McCormack (2010) stated that risk has several components - with lack of knowledge about an event being a major component of risk that can affect the ability of an entity to manage that event properly.

The possibility of collaborating with another organisation to share outsourced transportation logistics can have associated risks. General risks of outsourcing include changes in the boundary of the supplier, uncertainty regarding supplier performance, the supplier having opportunistic bargaining power, the supplier having the upper hand in competencies and loss of immediate control, the collaborating company having more power in negotiation, and loss of control to the collaborating company (Ngwenyama and Bryson, 1999).

Kremic et al. (2006) updated the list of risks provided by Ngwenyama and Bryson (1999) with an expanded list that includes outsourcing transport logistics. Their expanded list also includes:

- the possibility of unrealised hidden costs;
- the loss of flexibility;
- an unfavourable contract or poor selection of contract partner;
- the loss of knowledge/skills and/or corporate memory, and the difficulty in requiring a function;
- the loss of control/core competence;
- the potential for a power shift to the supplier;
- problems with the supplier - potentially taking the form of poor performance or bad relations, opportunistic behaviour, or not giving access to their best talent or technology;
- the loss of customers, opportunities or reputation;

- the introduction of uncertainty, or a changing environment;
- creating poor morale, or employee issues;
- the loss of existing synergy;
- the inadvertent creation of a competitor;
- conflict of interest;
- security issues;
- the creation of a false sense of lack of responsibility; and
- legal obstacles and skill erosion.

All the risks from this list can also be applied to the sharing of vehicles with another company.

This list is in no way exhaustive and it should be remembered that it is important to be able to identify the potential risks beforehand, so that one can prepare to address and mitigate risks as much as possible.

6.4. Benefits of sharing transportation in outsourcing

Averting risks and reaping benefits are the major challenges of any outsourcing decision. In many cases, it has been found that making short-term cost savings is one of the major objectives of the OEM. However, it should be noted that the OEM can also reduce their long-term capital investments if they plan and implement their outsourcing decision strategically. According to Kremic et al. (2006), outsourcing transportation logistics and sharing the third-party logistics provider with another company may confer the following benefits: reduced capital expenditure, capital infusion, transfer of fixed cost to variable cost, better utilisation of assets, increased speed, greater flexibility, increased access to the latest technology, access to more highly skilled drivers, access to a larger pool of drivers, a better pay structure for drivers, the elimination of problem functions, the chance to copy competitors, reduced political pressures or scrutiny, legal compliance, and better accountability or management.

Some of the key benefits will now be explained in more detail.

- Reduced capital expenditure: Investment in new transportation vehicles is by no means a small expense. It includes costs such as the buying or renting new vehicles, hiring drivers, maintaining drivers and the vehicles, and various overhead costs. By outsourcing these activities and possibly sharing its transportation with another company - the OEM may get rid of the requirement for these extra investments.

- Capital infusion: It follows from the previous point that the extra expenditure avoided by outsourcing can now be used to boost capital available for other investments.

- Transfer of fixed cost to variable cost: The business can transform what could previously have been a significant fixed cost into a variable cost. A variable cost is dependent upon the number of times the activity is actually used as compared to a fixed cost, which will be incurred regardless of use. Since demand for transportation is likely to fluctuate, it might be easier to manage the finances of the business if the transportation cost became a variable cost rather than fixed - as any idle time can be eliminated in the process. If transportation is outsourced and shared with another company, it may be possible to reduce this cost even further.

- Access to the latest technology, and more highly skilled drivers: Logistics providers specialising in transportation are expected to have access to the latest technology, and tend to regularly update their vehicles and skills to keep up with their competitors. By outsourcing, an OEM can take advantage of these facilities which might not otherwise be possible for OEMs where transportation is not their core activity. In this way, an OEM can gain access to more highly skilled and talented drivers.

Both risk aversion, and the possibility of attaining benefits, can provide the basis for a decision to outsource.

6.5. Factors for sharing transportation in outsourcing

Based on a survey of more than 1,200 companies, Deavers (1997) identified five main objectives of outsourcing: improving company focus, accessing world-class capabilities, acceleration of benefits from re-engineering, sharing of risk, and freeing of resources for other purposes. Ordoobadi (2009), on the other hand, produced three broad categories of objectives - strategic, operational and financial - which he subsequently divided into several subcategories. These subcategories along with their corresponding main objectives are shown in Table 6.1.

Table 6.1: Objectives of outsourcing

Main objectives	Subcategory
Strategic objectives	• Expansion to a new market • Ability to focus on core activities • Gaining access to world-class technology, improving customer service • Differentiation from competitors
Operational objectives	• Lack of internal expertise • Labour issues • Operational flexibility • Handling of non-value added activities
Financial objectives	• Reduction in operating and transaction costs (internal bureaucratic cost) • Avoiding large investments • Reduction in employee base

Source: (Ordoobadi, 2009)

These three categories of objectives also correspond to the three managerial levels of decision making. Strategic objectives generally define the job of top-level management while operational and financial objectives are more of a concern for the middle and bottom-level managers. The gap between these levels and objectives remains a concern, as top-level management can often reach a decision without properly understanding the relevant operational and functional objectives. This section of the research tries to bridge the gap between strategic and operational decision making by incorporating the cost component into the decision-making process for sharing transportation logistics.

The general types of objectives which have been presented can be specifically related to transportation outsourcing.

- Strategic objectives: Outsourcing the transportation process enables the OEM to expand into new markets by accessing the greater capacity of the logistics provider who specialises in transportation, and will therefore have a far greater reach than the

OEM. Outsourcing also frees up resources, allowing the OEM to concentrate on its core activities. The logistics providers are also continuously updating their transportation mode and methods - allowing them to employ excellent technologies that were not within the scope of the OEM's operation. By sharing transportation with another company, fuel consumption and cost of travel can be reduced further.

- Operational objectives: Assuming that transportation is not the core activity of the OEM, there would be a lack of internal expertise in this area. Freeing the OEM of this operation allows the OEM to ease some of the organisational pressure on the individuals working on this sector. The logistics provider can bring some flexibility to the process with their pool of vehicles and their availability.

- Financial objectives: Financial benefit can be achieved by outsourcing the transportation process, as there will be a reduction in the operating cost for the vehicles, and no further need for the OEM to invest a large sum in vehicle acquisition and maintenance. The number of drivers employed directly by the OEM can be downsized to zero, which will also lead to a considerable saving in this category of expenditure.

Much of the existing literature identifies the TCT's focus on cost savings as the determining factor in outsourcing decisions. Companies are able to consider outsourcing to reduce their costs when suppliers' costs are sufficiently low, taking into account added overheads, profit and transaction costs and when suppliers can deliver a service for a lower price (Kremic et al., 2006). Previous researchers have also discussed the full range of factors which might impact outsourcing decisions, and according to Kremic et al. (2006), these can be grouped into four categories: cost, environment, strategy, and functional characteristics.

6.5.1 Cost

Cost is one of the major factors in a decision-making process, as a properly executed outsourcing decision can result in significant savings. A survey of 7,500 public firms in Australia revealed that the outsourcing of cleaning services saved an average of 46 percent over in-house performance of the same services (Domberger and Fernandez, 1999). In addition to the obvious costs that would be likely to have initially prompted the outsourcing initiative, there are also some additional indirect and social costs that might be associated with in-house performance of the job (Maltz and Ellram, 1997).

Less infrastructure and support systems are required when one has fewer employees (Kremic et al., 2006) - so outsourcing may result in a more agile and efficient OEM, while some OEMs also outsource to achieve better cost control. Indirect costs of outsourcing may also include contract monitoring and oversight, contract generation and procurement, intangibles and other transition costs. Capital expenses incurred by the relationship should also be calculated as cited by Kremic et al. (2006) for the outsourcing decision-making process. The social costs of outsourcing which could include lower morale, higher absenteeism and lower productivity are sometimes very difficult to quantify, but they may nevertheless be significant. These qualitative categories of data may introduce a vagueness in the process of calculating the cost of outsourcing.

Despite this ambiguity, many firms outsource to reduce costs and therefore the higher the internal cost to perform the function relative to the expected cost of purchasing the service, the more likely the function is to be outsourced. One of the key economic benefits of outsourcing - first suggested by Razzaque and Sheng (1998), and later confirmed by Liu and Tyagi (2016) - is a popular practice which allows the outsourcing firm to reduce its fixed costs (such as expenditures on equipment, information technology, and fixed salaries of employees) and convert them into a variable cost in the form of the purchase price that the outsourcing firm pays. Razzaque and Sheng (1998) found that more than 50% companies cited cutting the fixed costs of transportation and distribution, freeing up or reducing staff, focusing on the core business and cutting internal administrative costs as major reasons for outsourcing. The concept proposed by Razzaque and Sheng (1998) can therefore be supported, and it can further be stated that when an OEM converts its fixed costs to variable costs, in terms of transportation outsourcing - the OEM is reducing its investments by employing only what is needed at that particular point in time, thus reducing any unwanted downtime or idle time.

According to Vining and Globerman (1999), there are three types of costs that are relevant in the choice between any in-house function and outsourcing: production costs, bargaining costs and opportunism costs, with the latter two being costs of governance. An opportunism cost is incurred when at least one party is acting on self-interest, but does so in bad faith. It is considered likely that this may arise more frequently in the case of outsourcing, as distribution of profit becomes more relevant when there are dealings between separate organisations.

Production costs are either the costs of internal production or the direct purchase price. Bargaining costs comprise the costs from negotiating contract detail, the costs of negotiating subsequent changes to the contract when risks arise in the post-contract stage, the costs of monitoring the performance of the third party, and the costs of disputes that arise if neither party wishes to use pre-agreed resolution mechanisms (particularly where those mechanisms relate to "contract breaking"). While only the first component of bargaining costs is encountered at the time of contracting, all other components of bargaining costs mentioned above can be anticipated and dealt with in the outsourcing decision.

Although analytically it is possible to provide a clear distinction between bargaining and opportunism costs, in practice, they are difficult to differentiate as it is usually in the interest of an opportunistic supplier to claim that their behaviour resulted from an unexpected change in circumstances or associated risk. In most cases, it becomes difficult for the firm to determine whether or not such a claim is true. This inability to distinguish between legitimate bargaining and opportunism therefore itself raises outsourcing costs (Akerlof, 1997).

Vining and Globerman (1999) also argued that there are three major issues that are likely to determine the sum of bargaining and opportunism costs: activity complexity, contestability and asset specificity. Activity complexity defines the degree of difficulty in specifying and monitoring the terms and conditions of a transaction. Empirical evidence suggests that product complexity raises the probability of internalisation. A contestable market is one where only a few logistics providers are immediately available to provide any given service, but many other providers would quickly become available if the price paid by the outsourcing provider exceeded the average cost incurred by contracts. An asset is "specific" if it makes a necessary contribution to the production of a particular product, and it has a much lower value in any alternative uses.

Considering these three factors, it can be suggested that the problem of sharing transportation logistics with another company falls into the categories of low activity complexity and low asset specificity. The activity of transporting goods to and from the customer can be labelled as a less complex activity as the task is to simply collect the products from the producer and deliver it to the customer. The transportation itself is not difficult to perform - rather, the difficult part arises in scheduling and vehicle space optimisation. This combination provides an argument for outsourcing, and more specifically for the sharing of transportation logistics. Outsourcing offers the potential to reduce the cost of the activity, as well as minimal bargaining and opportunism costs. Low activity complexity implies that the outsourcing firm can easily acquire sufficient knowledge and information to specify contract terms precisely. With low asset specificity, inefficient or opportunistic contracts can be quickly replaced.

Sink et al. (1996) argued that there are 12 different events that might trigger a company to become interested in outsourcing: (i) corporate restructuring, (ii) changes in logistics management, (iii) changes in executive management, (iv) corporate cost, (v) market and product line extension, (vi) increasing customer demand, (vii) mergers and acquisitions, (viii) new markets, (ix) customer use of just-in-time, (x) labour costs, (xi) instituting a quality improvement program and (xii) CEO directives to investigate the feasibility of outsourcing. In this research, (vi), (ix), (x) and (xi) are considered relevant as potential causes in outsourcing decision making and these events are therefore discussed in more detail below.

- Increasing customer demand: With increasing customer demand, it is necessary to understand whether current demand is stable enough for the company to invest in transportation. If it is not stable enough, and it cannot be predicted within a short period, investing in transportation is not feasible. Increased or diversified customer demand will make it easier to outsource transportation logistics, and to share this function with another company. Taking this decision will allow the company to reach customers further away.
- Customer use of just-in-time: In a scenario where customers are now expecting just-in-time delivery of their products, use of an

external logistics provider who specialises in quick delivery seems logical.

- Labour costs: Labour costs are significant in transportation logistics, and hiring a new workforce can increase fixed costs. Outsourcing the activity can therefore save a large sum of money.
- Instituting a quality improvement program: Companies require people with expertise who can deal with vehicle routing optimisation. They need to keep themselves up to date with the latest breakthroughs and technologies. Keeping such experts on hand requires the institution of a quality improvement program, so that the experts will be able to renew their skills and knowledge. By outsourcing the transportation management process, one can reduce this investment.

Although OEMs expect an outsourcing decision to generate significant cost savings, there are no guarantees that the expected savings will be realised. Several studies - for example, Bryce and Useem (1998), Pepper (1996), Vining and Globerman (1999), and Welch and Nayak (1992) have found that, in many problem instances, the expected cost savings had been overestimated, and costs were in fact much higher after outsourcing. Intuitively, when OEMs produce in-house, their fixed costs rationally become sunk costs when they decide on their prices and as a result, price competition is intense. On the other hand, when they outsource and then compete on prices, the conversion of fixed costs into variable costs implies that they compete with reduced fixed costs and higher variable costs, allowing them to sustain higher prices

(Liu and Tyagi, 2017). In other words, competing firms can engage in outsourcing even when it does not lead to any cost savings and of course, any cost savings provided by outsourcing will only add to this beneficial effect.

6.5.2 Strategy

Many researchers have studied outsourcing decisions, but few have extended the study beyond a simple cost-benefit analysis (Ngwenyama and Bryson, 1999). However, a mix of both cost-benefit analysis and strategic analysis is expected to provide an efficient structure for the decision-making process. McIvor (2000) drew attention to this vital aspect indicating that the outsourcing decision was previously taken without strategic considerations, and with very little consideration for the long run competitiveness of the OEM. Recently, the main drivers for outsourcing appear to be shifting away from a sole focus on cost towards also including strategic issues such as critical knowledge and flexibility and perhaps the most commonly cited strategic reason for outsourcing is to allow the firm to better focus on its core competencies.

When determining a firm's core competencies, it must be remembered that this refers to the skill or knowledge set and not to the products or functions themselves. Quinn and Hilmer (1994) suggested that, in order to qualify as a core competency, the work should be flexible and have a long-term platform that is capable of adaptation or evolution. It should be limited in number, meaning that one company should not have more than five core competencies; it should have a unique source of leverage in the value chain, and it should be an area where the company dominates. Notwithstanding the fact that retaining core competence within the domain of an OEM's in-house activities is considered advisable, this should not be rigidly adhered to as a dogmatic point of principle. The chance to make use of superior technology, if available on favourable terms, should not be turned down without at least giving it a second thought.

The second strategic factor is critical knowledge, which refers to unique data or technology fed into other processes that may be deemed critical but not core in the generic sense. Lack of internal human resources is another factor identified within the strategy category that can play a vital role in steering a company towards outsourcing transportation logistics. Transport service providers maintain and update specialist expertise and technological support for routing and transport planning that would be much harder to achieve and maintain for an OEM - whose main business focus is in a different area, and whose transport department's size would struggle to achieve a level of expertise similar to that of the specialist transport services provider. The other strategic factors are quality and flexibility. Quality can be maintained or even improved if a relationship is built with the logistics provider. The logistics provider can be flexible with their service and provide a better quality as they specialise in this field.

In a more recent study, Kang et al. (2014) classified outsourcing strategies into the two primary categories of efficiency-seeking and innovation-seeking outsourcing strategies. Efficiency-seeking outsourcing strategies are defined as the outcome of management's intent to achieve productivity and cost reduction goals by transferring normal processes and routine activities to external suppliers. On the other hand, innovation-seeking outsourcing strategies are defined as the outcome of management's intent to build innovative capabilities by transferring novel and customised activities to external suppliers. The two strategies, while being designed to achieve two different visions for the OEM, also contrast in their relationships with vital parameters in the business.

The following table summarises these relationships, as depicted by Kang et al. (2014).

Table 6.2: Outsourcing strategies

	Efficiency-seeking outsourcing	**Innovation-seeking outsourcing**
Demand	Predictable	Unpredictable
Task characteristic	Routine, standardised	Novel, customised
Driving factors	Low cost, consistent quality	Flexibility, variety
Uncertainty	Low	High
Process measurability	High	Relatively low
Knowledge intensity	Low	High
Strategic position	Low cost based	Differentiation based

Source: (Kang et al., 2014)

The sharing of outsourced transportation logistics can be regarded as an efficiency-seeking outsourcing strategy as the task is routine and standardised, uncertainty is relatively low, and the strategic position is based on low cost.

In two separate studies, Holcomb and Hitt (2007) and Quinn and Hilmer (1994) also proposed that by following the two strategic approaches outlined below, managers might best utilise their companies' skills and resources.

- While the company concentrates on its core competencies, it can achieve definable pre-eminence and provide unique value for customers.
- At the same time, the company should strategically outsource any other activities that are not part of its core competencies to logistics providers.

They expected that combining these two strategies could prove beneficial for companies for four reasons. First, they would maximise returns on internal resources. Second, well-developed core competencies provide some insurance against future competitors. Third, companies can take advantage of the innovativeness and specialisation of external suppliers. Finally, combining these strategies can decrease risk and reduce the need for investment.

Transporting goods between the OEM and the customer is a routine task, and is often not the core activity of the OEM. Aside from the specific aspect of developing software for optimising the routing problem, there is very little or no knowledge required for this process. Quality and flexibility are also important factors in the outsourcing decision. Based on the discussion here and the efficiency-seeking strategy mentioned by Kang et al. (2014) – it resembles the current problem of sharing simultaneous collection and delivery of products with another company. It can also be assumed that demand for products will stay within a predictable range over a certain period, and the uncertainty attached to this is relatively low.

6.5.3 Environment

The term "environment" in this context describes both the internal and external environments faced by the OEM. External environmental factors such as political pressures have undeniable influence on public sector firms, although this is less applicable in the private sector. The internal political environment may also influence the outsourcing decision. Company culture, employee relationships, the manager's ability to handle internal politics, and financial health of the company are some of the factors that greatly influence the internal political environment. Another environmental factor which has been identified is the legal environment. Legal factors relate to the degree to which the OEM's functions are "tied up" in current legal arrangements. Union agreements, contracts with other suppliers, and other rules and regulations that govern the performance of a function, such as veteran preferences and minority initiatives are some of the legal factors faced by OEMs. In general, the more legal hurdles the firm has to overcome, the less likely the function is to be outsourced. The last environmental factor identified is the actions of competitors and the potential for conflict of interest.

6.5.4 Functional characteristics

This category relates to the characteristics of the functions themselves. The structure of a function also affects the decision to outsource. Several factors have been identified that fall into this category. The complexity of a function, asset specificity, and the number of employees impacted are likely to influence the decision on whether to outsource a function.

6.6. Recommendations to reduce fuel consumption

Considering that one of the motivating factors for outsourcing has been identified as improving environmental sustainability, reducing fuel consumption seems to represent a logical progression of that thought process. Some of the recommendations with a view to reducing fuel consumption are discussed below.

<u>Driver performance</u>: Having better drivers can affect how the vehicles are driven. Improvements to driver mentality, pay structure, resting periods and training programs are some of the elements that can enhance driver performance. Ensuring proper resting periods, for example, can improve mental stability for drivers, as they would not be subjected to unduly rigorous work. By increasing the drivers' weekly resting period from two days to three, for example (by giving them a 10 hour per day schedule instead of 8 hours per day), the drivers would be much more relaxed when they return to their jobs after their longer breaks. This is easier to arrange in an outsourcing context, as the logistics provider has the luxury of a large pool of drivers and can easily manipulate their work to provide the drivers with a better schedule. The introduction of a better pay structure ensures more intensive competition among skilled drivers that may also be reflected in their on-job performance. Lee et al. (2002) found that drivers could pay more attention to the road under conditions of higher velocity and

shorter headways. Suijs et al. (2015) also mentioned that drivers were able to reduce so-called “phantom jam” occurrences by following in-car advice. These types of arrangement can lead to better driving performance.

Driving performance: Driving a vehicle in certain ways can lead to lower emissions. Less braking and moderate acceleration are two of the common factors that, if maintained, can reduce fuel consumption by almost 20%. Better drivers are more likely to drive in this way and therefore secure these benefits. In addition, the driver could be advised to turn off the engine when sitting idly in traffic. By this simple method, the driver can actively lower his vehicle’s fuel consumption.

Vehicle performance: Performance of the vehicle can be improved and its emissions reduced significantly if there is a proper maintenance schedule. Proper maintenance includes - but is not limited to - the use of a proper cleaning agent, changing of air filters, changing of engine oil, and use of optimum tyre pressure.

Use of economic vehicles can also reduce fuel consumption. In a recent study by Sullivan et al. (2004), it was found out that direct injection diesel vehicles had 25% lower emissions than baseline gasoline vehicles while electric vehicles caused practically zero fuel consumption. Any company that acquires access to these types of economic vehicles would therefore be able to actively lower its emissions.

Routing and capacity optimisation: By optimising routing, one may be able to reduce emissions. Providing a dedicated parking zone for the vehicles reduces emissions, as the vehicles do not need to keep driving to find a suitable parking spot. Combining the load for multiple customers can also reduce the driving time for the logistics provider, and thereby reduce the overall fuel consumption.

6.7. Numerical examples with hypothetical scenario

The experiments conducted in this section begin with the assumption that the decision to outsource the transportation logistics system has already been taken. The main point to consider at this stage is whether the third-party logistics provider should either be fully dedicated to one company, or should retain the freedom to also satisfy the logistics needs of other companies. Only one set of data for one company is available for this experiment, so another set of hypothetical data is furnished to conduct this experiment. To differentiate between the two companies, let us name one of them the 'collaborator company' (whose real data is available) and the other hypothetical one 'company Z'.

Assumptions for the experiments are set out below.

- The products from both companies are compatible with each other. They could both be gas cylinders, or different compatible items.
- No one customer has a demand larger than the capacity of the vehicle- so no customer should need more than one journey to be serviced.
- Drivers are not allowed to drive more than 10 hours per day.

There are the following four different possible scenarios with different combinations of demand patterns and customer locations for the two companies.

1. Similar demand patterns and close customer locations for both companies.
2. Different demand patterns and close customer locations for both companies.
3. Similar demand patterns and far customer locations for both companies.
4. Different demand patterns and far customer locations for both companies.

All other parameter values, objective functions and constraints are same as the previous experiments in Chapter 4. The four scenarios can be shown as in Table 6.3.

Table 6.3: Four scenarios considering demand patterns and customer locations

	Similar demand	**Different demand**
Close location	1	2
Far location	3	4

Customers from both companies, as stated earlier, have both close and far locations. New customer locations are chosen randomly within a radius of 8 kilometres (5 miles) from their original counterparts for close locations. For far locations, they are placed randomly between 9 and 80 kilometres' (5.6 and 50 miles') radius from their original counterparts and are chosen in such a way that none of the locations is within 9 kilometres' (5.6 miles') radius of another.

The demand pattern for the 'collaborator company' is known. To generate a similar demand pattern for 'company Z', 10% is added to each demand for delivery and pickup. To generate a different demand pattern, 90% is added to the ones that have low demand whereas 90% is subtracted from the ones that have higher demand. The choices of low and high demand are made subjectively. There is no prior experiment or research to suggest these values, so they are chosen arbitrarily.

The following five experiments were completed for both close and far locations.

- Known demand for the 'collaborator company'.
- Similar demand patterns for both 'company Z' and the 'collaborator company'.
- A similar demand pattern for 'company Z'.
- Different demand patterns for both 'company Z' and the 'collaborator company' .
- A different demand pattern for 'company Z'.

Each experiment was run 10 times, similar to the previous experiments in Chapter 4, with 80% TOPSIS and the best run was selected according to the highest value of the hypervolume.

The first experiment covered scenarios 1 and 2. The best Pareto fronts obtained for each of the scenarios are set out below.

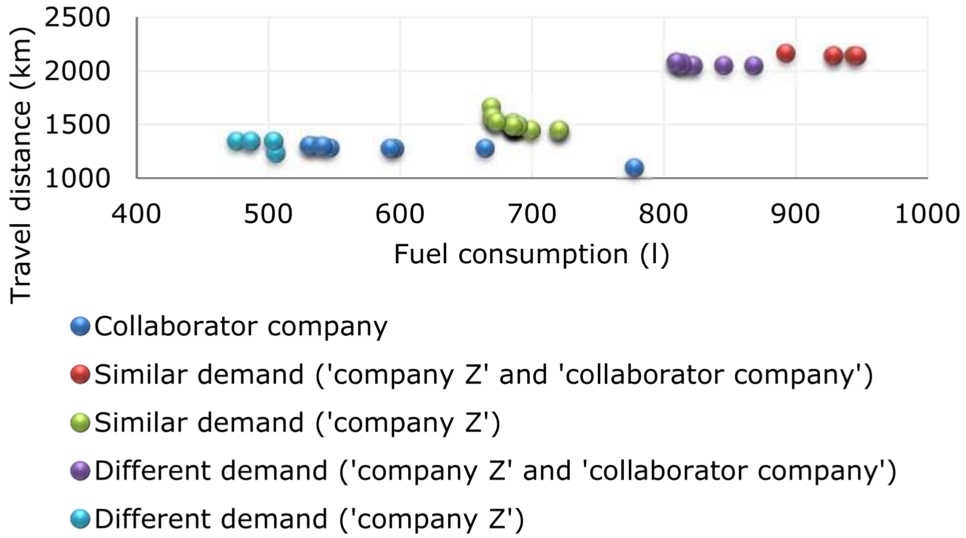


Figure 6.2: Pareto fronts for scenario 1 and scenario 2 with close customer locations for 'company Z' and the 'collaborator company' with similar and different demand patterns

Choosing a solution from the Pareto front is an altogether different research proposition, as explained in the earlier chapters. To compare the results, let us consider the two corner points from each Pareto front.

Table 6.4: Comparison for scenario 1 and scenario 2 with close customer locations for 'company Z' and the 'collaborator company' with similar demand patterns

Similar demand pattern	**NSGA-II (Smallest travel distance)**		**NSGA-II (Lowest fuel consumption)**	
	Fuel consumption (l)	**Travel distance** (km)	**Fuel consumption** (l)	**Travel distance** (km)
'Collaborator company'	777.65	1095.15	530.69	1298.53
Similar demand ('company Z')	720.88	1444.30	669.46	1658.90
Total ('company Z' and 'collaborator company')	1498.53	2539.45	1200.15	2957.43
Similar demand ('company Z' and 'collaborator company')	946.28	2137.33	928.70	2139.76
Difference	-36.85%	-15.83%	-22.62%	-27.65%

Table 6.5: Comparison for scenario 1 and scenario 2 with close customer locations for 'company Z' and the 'collaborator company' with different demand patterns

Different demand pattern	**NSGA-II (Smallest travel distance)**		**NSGA-II (Lowest Fuel consumption)**	
	Fuel consumption (l)	**Travel distance** (km)	**Fuel consumption** (l)	**Travel distance** (km)
'Collaborator company'	777.65	1095.15	530.69	1298.53
Different demand ('company Z')	505.48	1225.15	475.75	1340.77
Total ('company Z' and 'collaborator company')	1283.13	2320.30	1006.44	2639.30
Different demand ('company Z' and 'collaborator company')	868.53	2047.21	809.67	2080.23
Difference	-32.31%	-11.77%	-19.85%	-21.18

The results of these two experiments suggest that combining the performance of logistics for these two companies could reduce both the travelled distance and cost. This scenario is definitely helpful, as it benefits both the companies. It is worth considering that any terms and conditions negotiated with the logistics company will impact that benefit, but this factor is not within the scope of this study.

In both experiments, the number of vehicles required remained the same for individual and combined routing.

The next set of experiments was conducted for scenarios 3 and 4 with far customer locations for 'company Z' and the 'collaborator company'. The results are shown below.

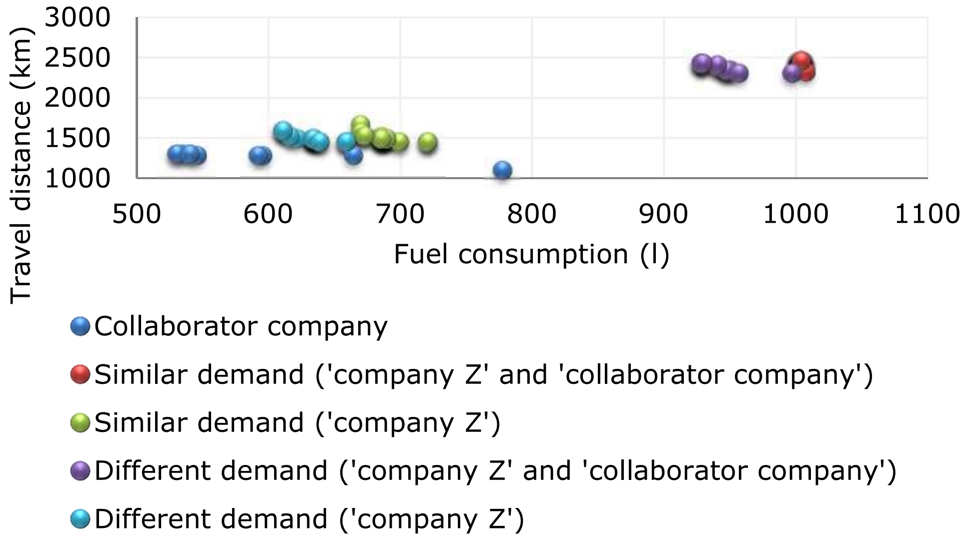


Figure 6.3: Pareto fronts for scenario 3 and scenario 4 with far customer locations for 'company Z' and the 'collaborator company' with similar and different demand patterns

The combined results for scenarios 3 and 4 are presented in tabular form and shown in Table 6.6 and Table 6.7.

Table 6.6: Comparison for scenario 3 and scenario 4 with far customer locations for "company Z" and the "collaborator company" with similar demand patterns

Similar demand pattern	**NSGA-II (Smallest travel distance)**		**NSGA-II (Lowest Fuel consumption)**	
	Fuel consumption (l)	**Travel distance** (km)	**Fuel consumption** (l)	**Travel distance** (km)
'Collaborator company'	777.65	1095.15	530.69	1298.53
Similar demand ('company Z')	720.88	1444.30	670.33	1565.60
Total ('company Z' and 'collaborator company')	1498.53	2539.45	1201.02	2864.13
Similar demand ('company Z' and 'collaborator company')	1007.63	2317.06	1004.31	2449.98
Difference	-32.76%	-8.76%	-16.38%	-14.46%

Table 6.7: Comparison for scenario 3 and scenario 4 with far customer locations for 'company Z' and the 'collaborator company' with different demand patterns

Different demand pattern	NSGA-II (Smallest travel distance)		NSGA-II (Lowest Fuel consumption)	
	Fuel consumption (l)	Travel distance (km)	Fuel consumption (l)	Travel distance (km)
'Collaborator company'	777.65	1095.15	530.69	1298.53
Similar demand ('company Z')	658.85	1444.3	611.56	1583.90
Total ('company Z' and 'collaborator company')	1436.68	2539.45	1142.25	2882.43
Similar demand ('company Z' and 'collaborator company')	996.93	2301.76	929.37	2425.23
Difference	-30.61%	-9.36%	-18.64%	-15.86%

The results presented here were from the two experiments with varying demand patterns for customers at far locations. The result here shows that, for the chosen scenario sharing transportation logistics between these two companies improves both cost and travelled distance for both similar and different demand patterns.

The results of Table 6.4, Table 6.5, Table 6.6 and Table 6.7 can be rationalised into the original format of Table 6.3 to combine the results of the four experiments with varying customer locations (similar/different) and demand patterns (similar/different). This summary is presented in Table 6.8.

Table 6.8: A quick glance at the combined result from different scenarios

		Similar demand		Different demand	
		Fuel consumption	Travel distance	Fuel consumption	Travel distance
Close location	NSGA-II (Smallest travel distance)	-36.85%	-15.83%	-32.31%	-11.77%
	NSGA-II (Lowest fuel consumption)	-22.62%	-27.65%	-19.85%	-21.18
Far location	NSGA-II (Smallest travel distance)	-32.76%	-8.76%	-30.61%	-9.36%
	NSGA-II (Lowest fuel consumption)	-16.38%	-14.46%	-18.64%	-15.86%

The results presented here refer back to the four scenarios that were originally presented in Table 6.3: similar demand patterns and close customer locations, different demand patterns and close customer locations, similar demand patterns and far customer locations, and different demand patterns and far customer locations. In all the scenarios, combining transportation logistics for the two companies might lower both the cost and travelled distance.

The importance of this experiment lies in deciding whether transportation logistics should be shared and if they are to be shared, whether this should be done with a company that has either a similar or different type of demand pattern. Companies making different products that are compatible with each other can reap the benefit from transportation sharing.

6.8 Review of the chapter

This chapter considered transportation outsourcing to investigate the effect on cost from the use of an external transport provider under asset-sharing with other companies, and looked at whether this could result in cost reductions in comparison to the asset-specific type of outsourcing approach that the collaborator company is currently pursuing. The chapter based its analysis on TCT as the underpinning theory for outsourcing decisions. Experiments were conducted based on the multi-objective algorithm developed in Chapter 4 to highlight the strength of the effect on environmental performance of the outsourcing decision under different scenarios.

One of the reasons that outsourcing was not considered by our collaborator was that the exact cost savings or impact that would flow from such an approach was unknown. This exercise puts a price on this ambiguity. The experiments suggest that by sharing vehicles with other companies, it is possible to reduce both travel distance and fuel consumption.

Four experiments were conducted with regard to both different and similar demand patterns, and close and far customers of the other company.

The Pareto fronts identified for each of the experiments show that when the transportation is shared, the travelled distance and cost are both less than if this function was performed individually under all experiment scenarios. However, it is possible that alternative datasets will show less clear support for asset-sharing transportation logistics, depending on locations' proximity and demand similarity. The further away locations are, and the more similar demand patterns are, the less significant collaboration benefits will be.

However, in practice, these scenarios might not be easy to replicate. It could be difficult to find companies that fit this experiment profile, as the customer locations might be completely different from the ones experimented with, and the products might not be as compatible. This requires further investigation, as the savings could be just as significant as was found in the current examples.

Assuming that multiple companies could be found that fit the experiment profile, some risks still need to be addressed. Although asset-sharing is a way to reduce travel distance and fuel consumption, it must be acknowledged that additional risks may be introduced when two companies are sharing transportation. Some of the more significant risks are that conditions may become less flexible, security issues become more prominent as each company has to rely on their partners to be as conscious about security as they are, and that the provider may undesirably take control of operational aspects. The companies may also share some other concerns when they agree to outsource transportation - such as losing scope for planning, loss of customer interface, loss of service level, and loss of prioritisation.

Companies that have products which are compatible with each other can enjoy the benefits from transportation sharing when the relevant risk factors are also factored into the decision-making process.

The collaborator company did have discussions regarding asset-sharing of transportation, but decided against pursuing it at that point of time. Their argument was that fuel consumption was not one of their major concerns at that time, and they believed they were getting optimal solutions from their algorithm. Their other argument was that the decision not to outsource and specifically not to employ asset-sharing came as a strategic decision rather than an operational one. The prospect of cost savings was still not visible to the top-level decision maker who was part of the strategic decision-making process. The current experiment has provided the collaborator company with a new structure for multi-objective optimisation under asset-sharing and therefore an ability to compute and demonstrate its potential benefits.

7. CONCLUSIONS AND FUTURE WORK

The VRP is already a well-known and thoroughly researched branch in the field of combinatorial optimisation problems and yet there are branches of the VRP itself that can still be investigated further. This thesis has presented work examining a conjunction between RL, VRPs and environmental protection.

Research was conducted to link RL and its various activities to narrow down the research scope. Product collection or pickup was established as one of the major sectors of RL. Product collection is an important part of the extended type of VRP known as VRP with simultaneous pickup and delivery problems, or VRPSPD.

To investigate the impact of product type on VRPSPD, products were categorised by their PLCs, MVTs, return types and types of supply chain. The collaborator on the project was a company whose operations involve the delivery and pickup of gas cylinders. Looking back to those categories, a gas cylinder is a product which has a long life cycle, low MVT, and is returned when it is in the end-of-use stage.

In the context of RL, the topic of environmental degradation has recently been promoted. This additional attention has led to the development of GVRP (linking RL and VRP) that deals with various GHG and CO_2 emissions. A function to calculate fuel consumption was taken and modified from the existing literature. In order to address the second research question posed by this thesis, this fuel consumption function took into account parameters including efficiency parameters for diesel engines, aerodynamic drag, drive train efficiency, and engine fraction factors.

To address research question 1 posed in Section 1.3, the VRP was formulated as a multi-objective optimisation problem, requiring minimisation of fuel consumption and travel distance. A multi-objective evolutionary algorithm - NSGA-II - was developed, incorporating Alternating Edge Crossover and Swap Mutation operators tailored for the VRP. A Split Algorithm was used to preserve the feasibility of the evolved solutions. A particular novelty in the design of the NSGA-II was the process of initial population generation, which employed TOPSIS and greedy randomisation in the construction heuristics.

Experiments were undertaken to investigate the terminating conditions for NSGA-II, and the effect of TOPSIS and randomly generated solutions on the quality of the generated Pareto fronts. The number of iterations with no changes in the solution in terms of objective function values was chosen as the terminating condition. The test results suggested that having 400 consecutive iterations when the solution did not improve produced the best solutions. The best combination of TOPSIS and randomly generated solutions was identified as being 80% TOPSIS and 20% randomly generated solutions.

To answer research question 2 posed in Section 1.3, the developed algorithm was evaluated against real-world problem instances obtained from an industrial collaboration. A statistical analysis of the obtained results proved that solutions generated by TOPSIS combined with randomly generated solutions did actually contribute to the quality of the generated Pareto fronts as measured by hypervolume. The comparison of the NSGA-II results with the results from the collaborator company showed that the NSGA-II performed better in most of the problem instances.

The developed algorithm provided the logistics manager with a trade-off between the travel distance and fuel consumption. The problem instances of the collaborator company contained relatively small numbers of customers. In this research, it was assumed that the vehicle fleet was homogeneous (in most of the experiments) and consisted of vehicles that had the same characteristics. One experiment was conducted with a fleet of heterogeneous vehicles and the result showed that using this fleet of heterogeneous vehicles reduced both distance and fuel consumption. However, further research is required to provide more insight.

The experiment on outsourcing investigated the effect of sharing transportation logistics with other companies, and evaluated whether choosing to share transportation would result in the reduction of fuel consumption. This bridged a gap between the strategic and operational decision-making processes that had previously lacked integration - addressing the aspect of research question 2 that considered how these two decision-making processes might be integrated. To answer research question 3, a multi-objective algorithm was used to evaluate the economic benefit of the decision to outsource.

The Pareto fronts identified by the algorithm support the conclusion that travel distance and fuel consumption could have been reduced if transportation logistics had been shared.

The output of the NSGA-II is a Pareto front that corresponds to solutions that are a trade-off between travel distance and fuel consumption. The Pareto front with corresponding multiple solutions gives an opportunity to the logistics manager to express a posteriori preferences towards the importance of objectives and choose a solution which best reflects these by using the visualisation of the occurring trade-offs on the Pareto front.

Contribution of the research to existing knowledge and practices

The proposed study has both theoretical and practical significance in the field of RL and VRPs. There are three main types of contribution to any theory, according to Crane et al. (2016). They are:

- theory generation;
- theory application; and
- theory testing and refinement.

The two-by-two matrix at Figure 7.1 is therefore proposed as a general guideline to decide upon the changes in utility and scope. It will be used to demonstrate where this research work stands.

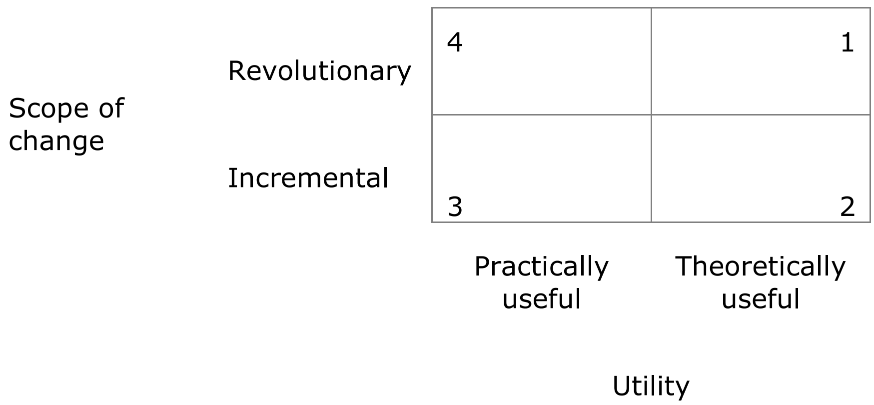


Figure 7.1: 2X2 matrix to analyse the utility and scope of change generated in a study

The contribution of the research that was presented in this thesis will be explained using this matrix. The first piece of research conducted within the thesis - dealing with multi-objective optimisation considering environmental degradation factors and CO_{2e} emissions in the form of fuel consumption - falls into category 3, as the problem it defines involves some practical aspects of RL and the VRP. Some rudimentary changes were made in the algorithm that extended the generally accepted method of producing the final solution. Practical usefulness of the revised algorithm can be said to have been achieved when the proposed NSGA-II was able to produce solutions that were better than the results of the collaborator company.

The second part of the research focused on the decision-making process for outsourcing. A study was carried out to determine whether the OEM should outsource their transportation logistics, and whether they should share transportation logistics with another company. This idea in itself is not new but the objectives defined for the decision-making do provide a novel understanding of the problem. This research may therefore be thought to fall between quadrants 3 and 4 and is pushed closer to the boundary of quadrant 4 by its new objective functions, which are fuel consumption and travel distance.

This research can therefore be identified as having made the following major contributions.

- A novel multi-objective optimisation algorithm for VRP.
- Consideration of the environmental degradation factor for a problem in the context of VRPs and RL.
- Evaluating and comparing solutions from the proposed algorithm against solutions used in the real world where this algorithm provided a more feasible and practical solution than those which were previously available to the collaborator company.
- The advancement of the theory of outsourcing decisions using numerical modelling.

Effect on vehicle routing decision making

The current RL solution practised by the collaborator company only considered distance as its sole objective for minimisation in their simultaneous pickup and delivery problems. In this research, it was observed that only looking at one criterion would not be sufficient to portray the complexity of the overall problem. An NSGA-II algorithm - well-known in the field of multi-optimisation research - was designed to enable the optimisation of both fuel consumption and travel distance. One of the benefits of considering multiple objectives is that the final solution is not solely dependent upon one criterion which means that the solution set will provide a wide range of options for the decision maker to choose from based on their preferences.

An example can be drawn from one of the problem instances from the collaborator company. Optimising only one objective resulted in fuel consumption of 437.29 litres. With the same set of customers, it is expected that route will remain the same when we are only optimising driving distance. However, when the load was changed but the routes remained the same, the final solution resulted in fuel consumption of 319.78 litres - so there was a decrease in fuel consumption while the distance and number of vehicles used remained the same.

With only distance as the objective, the final solution will always be the same even if the demand for pickup and delivery varies. However, with multiple objectives and especially when fuel consumption are under consideration, the solution will vary even if the number and locations of the customers remain the same. The load or demand on pickup and delivery has a direct impact on the calculation of fuel consumption and consequently also on how the customers are selected for routing.

It was demonstrated by an example that solely optimising distance does not necessarily lead to solutions with good values for other objectives. To get a complete picture, multiple objectives should be considered, and these objectives need to be optimised simultaneously to offer better trade-off solutions to decision makers.

Future research

The following areas of inquiry are proposed for future research.

- Effect of different collection strategies: Only one collection strategy was considered in this research. Two other strategies - namely periodic schedule and call service - would each imply a different RL structure. Future research could investigate how these strategies affect the objective functions.

- Incorporating three or more objectives in the multi-objective optimisation problem: This research problem was formulated as a bi-objective optimisation problem with fuel consumption and travel distance as its two objectives. It would be interesting to see the effect of other objectives - such as the number of vehicles required, routing costs, and time penalties if collection and delivery have to be performed within defined time windows on the final solutions.

- Larger number of customers: The developed algorithm could be evaluated on problem instances with a larger number of customers than 400 already tested in this thesis. Further experiments could be carried out to provide more insight into how the parameters of the algorithm - such as the value of α (which represents the level of randomisation in using TOPSIS in the construction heuristic), number of initial population, and the terminating condition affect the generated solutions. With a larger number of customers, the terminating condition chosen for this research might not be adequate.

- Spatial distribution of location of customers: In addition, the algorithm could also be evaluated on problem instances with special spatial distribution of locations - such as easily identifiable clusters of customers. Clustering of customers was not considered in the development of the proposed NSGA-II but it turned out to be important when comparing solutions with benchmark problem instances. The algorithm requires further refinement to accommodate these special type of problems.

- Heterogeneity of vehicles: The effect of introducing heterogeneity of vehicles on final solutions could be assessed. What-if analysis showed that a combined fleet of light and heavy vehicles outperformed a fleet of homogeneous vehicles. In-depth analysis is required to understand this phenomenon, and to investigate whether this would also hold true in instances with varying customer locations and demand patterns.

- VRP with time windows: Inclusion of the time window constraint is important in the study of VRPs. The development of the current model that was motivated by a real-world problem where time windows were not important for delivery. Inclusion of time windows would portray many real-world scenarios where it is important to service the customers within defined time windows but this change would also add complexity to the model.

- Experimenting with different terminating conditions: Three terminating conditions were mentioned in this thesis. Many studies on VRPs and other optimisation problems have adopted various terminating conditions. With the number of customers increasing for different problems, a wider range of terminating conditions could be experimented to arrive at the optimal condition.

- Inclusion of risk and benefit in the outsourcing decision-making process: The outsourcing decision was evaluated through a mathematical model. However, by also incorporating risk and benefit into the model, it would be possible to analyse their effects on the final solutions and hence move the practice forward.

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APPENDIX

In this appendix, the parameters to be used in the calculation of CO_2 emissions or equivalent fuel consumption are presented.

ξ = Fuel to air mass ratio

This ratio represents the mass of fuel to air present in a combustion process, such as in an internal combustion engine or industrial furnace. The fuel to air ratio is commonly used in the gas turbine industry, as well as in government studies of internal combustion engines.

κ = Heating value of a typical diesel fuel $\left({}^{kj}/_{g}\right)$

The heating value of a substance is the amount of heat released during the combustion of a specified amount of it. The energy value is a characteristic for each substance. It is measured in units of energy per unit of the substance - usually mass, such as kj/g

ψ = Conversion factor ($g\ /\ s$ to $l\ /\ s$)

This is the conversion factor used to convert one gram of water mass to a litre of CO_2.

$\boldsymbol{\lambda = \xi/\kappa\psi}$

v =Speed of vehicle (m/s)

The speed at which a vehicle travels on arc is usually imposed by traffic regulations. It is assumed for practical reasons that in a vehicle journey all parameters will remain constant on a given arc (though load may change from one arc to another). The data taken from Qian and Eglese

(2016) suggests that the best fuel efficiency can be achieved at around 60km/h.

θ_k = Road angle on route k

For the purpose of simplicity, it has been assumed for the current problem that the road angle will be zero for the entire duration of travel. When hilly areas are present in the problem, this value can be changed - which will have an effect on the calculation.

τ = Acceleration

Acceleration is part of the calculation - but for simplicity it is assumed that there would be no acceleration, hence the value is considered to be 0.

Cr = The coefficient of rolling resistance

Normal force between wheel and surface is defined as the coefficient of rolling resistance.

$$\boldsymbol{\alpha_{ij}^k = \tau + gsin\theta_k + gc_r sin\theta_k}$$

Some of the values used in the expressions depend on what types of vehicles are being used. For this purpose, the current study has considered three types of vehicles: light duty, medium duty and heavy duty. All information in this regard is taken from Koç et al. (2014). The relevant vehicle-specific parameters are set out below.

Fuel consumption in litres over distance y for vehicle m can be calculated using the following expression.

$$\boldsymbol{F^m = \lambda\left(k^m N^m V^m \,{}^{y}\!/_{v} + M^m \gamma^m \alpha y + \beta^m \gamma^m y v^2\right)}$$

Fuel consumption generally refers to the specific travel distance by a vehicle on specific amount of fuel at a particular speed. In this particular example, the total fuel utilised by the vehicle for the travel distance is considered as fuel consumption. From the travel distance and with the amount of fuel consumed, the efficiency of the vehicle driven can be found.

$w^h =$ Curb weight (kg)

The load of a vehicle is made up of empty load and carried load. Vehicles (trucks) are usually classified based on their gross vehicle weight rating (GVWR), which is defined as the maximum allowable total weight of the vehicle including its empty mass, fuel and any load carried. The empty mass of the vehicle (including fuel and fluids such as engine oil) is termed its curb weight. The United States Federal Highway Administration has classified vehicles based on their GVWR into the three categories mentioned above - light duty, medium duty and heavy duty (Koç et al., 2014). In practical terms, it is concluded that vehicles carry approximately as much cargo as their curb weight.

Vehicle type affects the engine fraction factor, engine speed, engine displacement, aerodynamic drag, frontal surface area and vehicle driver train efficiency. Vehicle curb weight and payload (or capacity) also play an important role in routing decisions (Koç et al., 2014). However, according to Campbell (1995), if large vehicles are replaced by a larger number of small vehicles, emissions are likely to increase - even though a heavy duty vehicle which has a larger engine consumes more fuel per kilometre than a light duty vehicle. It is mentioned in

DEFRA (2012) that a 17-ton heavy duty vehicle emits 18% more CO_2 per kilometre when fully loaded and 18% less CO_2 when empty, relative to emissions at half-load.

k^h = Engine fraction factor $(kJ/rev/l)$

In mechanical systems such as internal combustion engines, this term refers to the power lost in overcoming the friction between two moving surfaces.

N^h = Engine speed $({}^{rev}/_{s})$

Revolutions per second is a measure of the frequency of rotation - more specifically, the number of rotations around a fixed axis in one second. This aspect would often be measured as revolutions per minute. It is used as a measure of rotational speed of a mechanical component.

V^h = Engine displacement (l)

Engine displacement is the volume swept by all the pistons inside the cylinders of a reciprocating engine in a single movement from top dead centre (TDC) to bottom dead centre (BDC). It is commonly specified in cubic centimetres $(cc\ or\ cm^3)$, litres (l), or (mainly in North America) in cubic inches (CID).

C_d^h = Coefficient of aerodynamic drag

The drag coefficient is a common measure in automotive design as it pertains to aerodynamics. Drag is a force that acts parallel to, and in the same direction as, the airflow. The drag coefficient of an automobile impacts the way that automobile passes through the surrounding air.

A^h = Frontal surface area (m^2) for vehicle h

The frontal surface area of the vehicle, measured in metres squared, is considered here. Different surface areas are presented in Figure A.1: Relationship between temperature and air density1.

$\boldsymbol{\beta^h = 0.5C_d^h\rho A^h}$

ρ = air density

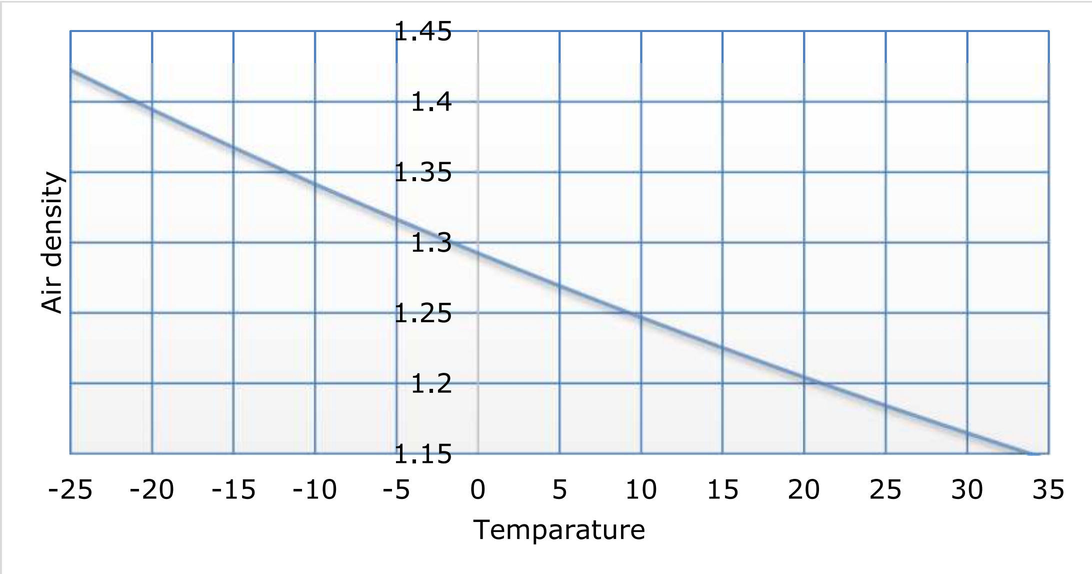

Figure A.1: Relationship between temperature and air density

n_{tf}^h = Vehicle drive train efficiency

The drive train of a motor vehicle is the group of components that delivers power to the driving wheels.

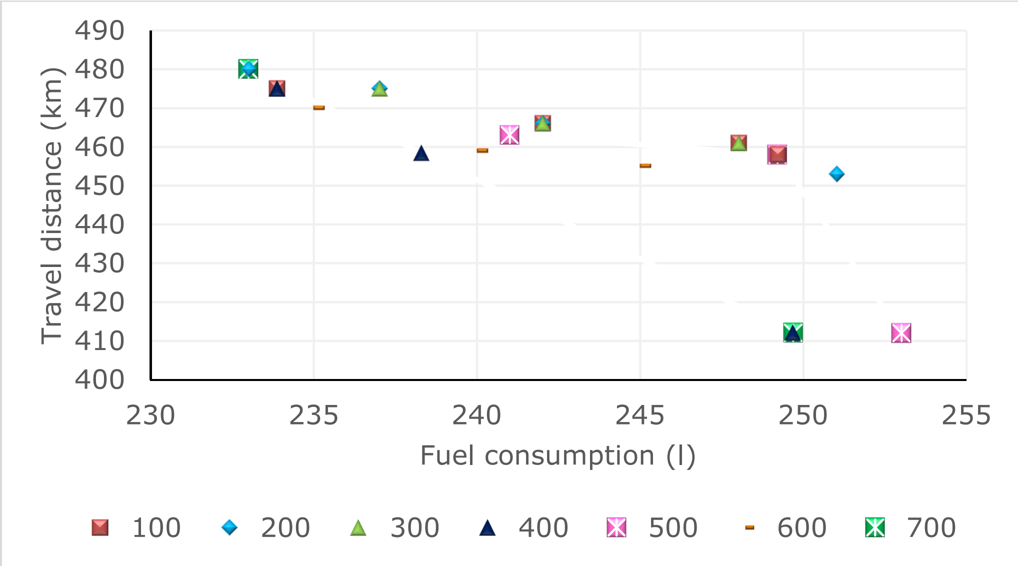

Figure A.2: Pareto fronts for different numbers of iterations with no changes to the values of the objective functions as terminating conditions in Problem instance 2

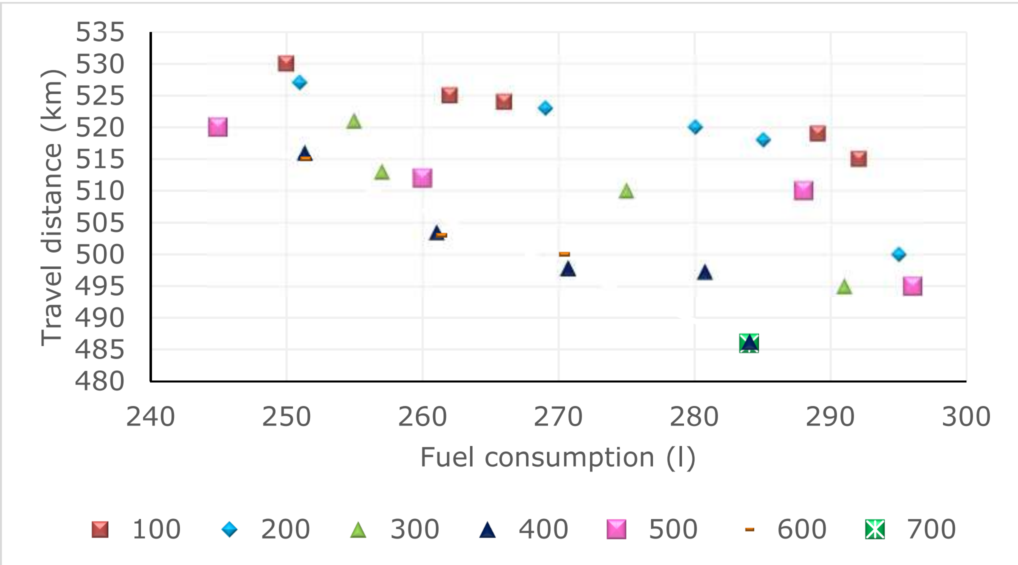

Figure A.3: Pareto fronts for different numbers of iterations with no changes to the values of the objective functions as terminating conditions in Problem instance 4

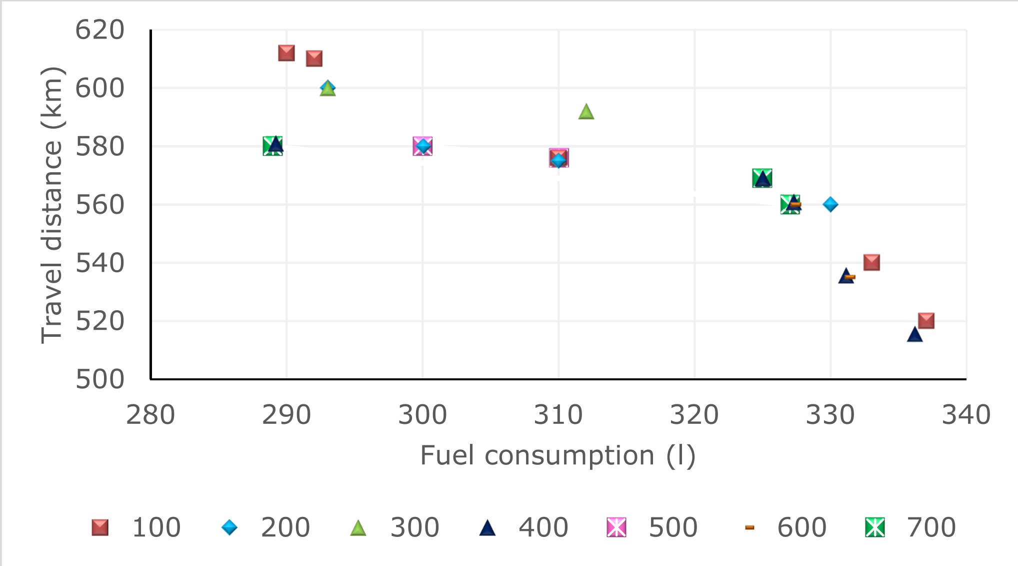

Figure A.4: Pareto fronts for different numbers of iterations with no changes to the values of the objective functions as terminating conditions in Problem instance 6

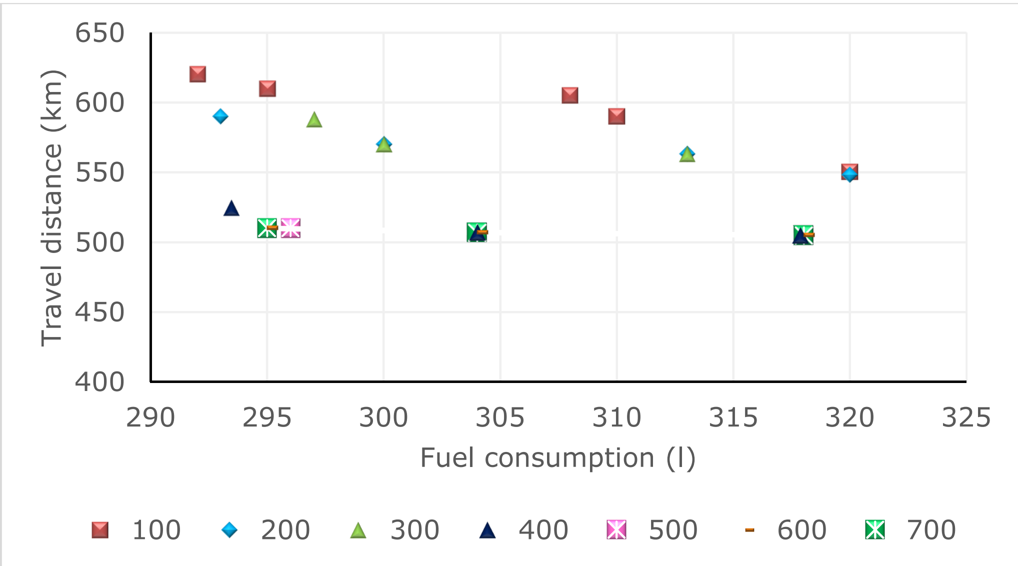

Figure A.5: Pareto fronts for different numbers of iterations with no changes to the values of the objective functions as terminating conditions in Problem instance 10