

GREEN LOCATION AND ROUTING PROBLEMS WITH CONVENTIONAL VEHICLES AND DRONES

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CONVENTIONAL VEHICLES AND DRONES

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May 2019

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ABSTRACT

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Green Location and Routing Problems extend the network design problems that consider location and routing decisions by explicitly accounting environmental impacts such as CO₂ emissions caused by fuel or energy consumption of delivery vehicles. These environmental impacts estimated by fuel or energy consumption models are affected by several factors including payload and speed of delivery vehicles. We present four new green location and routing problems where we consider these factors while calculating the environmental impacts. We first introduce the Green Location-Routing Problem, in which vehicle payload and speed decisions are incorporated to a location-routing problem and the fuel consumption of trucks is estimated and minimized. Second, we study the Green Hub Location Problem, where we minimize the fuel consumption by optimizing truck payload and speed decisions on a hub network. Third, we present a freight transportation problem called the Drone Delivery Problem, where the integration of trucks and drones is used to make deliveries. Drone speed is considered as a decision of the problem in order to minimize energy consumption of drones while not exceeding the drone range. Fourth, we study an extension of the Drone Delivery Problem, called the Stochastic Drone Delivery Problem, where uncertainty of wind speed and its impact on the drone speed are considered.

Keywords: Location, Routing, Freight transportation, Environmental impacts, Energy (fuel) consumption.

ÖZET

GELENEKSEL VE İNSANSIZ HAVA ARAÇLARININ KULLANILDIĞI YEŞİL YER SEÇİMİ VE ROTALAMA PROBLEMLERİ

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Yeşil Yer seçimi ve Rotalama Problemleri, dağıtım araçlarının yakıt veya enerji tüketiminden kaynaklanan karbondioksit emisyonu gibi çevresel etkilerin açık bir şekilde hesaba katıldığı, yer seçimi ve rotalama kararlarını dikkate alan ağ tasarımı problemlerinin bir uzantısıdır. Yakıt veya enerji tüketim modelleri tarafından hesaplanan bu çevresel etkiler, içerisinde aracın taşıdığı yük ve hızı olmak üzere birçok faktörden etkilenmektedir. Çevresel etkileri hesaplarken, bu faktörleri de göz önünde bulundurduğumuz dört yeni yeşil yer seçimi ve rotalama problemi sunmaktayız. İlk olarak, aracın taşıdığı yük ve hız kararlarını, bir yer seçimi-rotalama problemine dahil eden ve kamyonların yakıt tüketimini hesaplayıp, en azlayan, Yeşil Yer Seçimi-Rotalama Problemi tanımlanmıştır. İkinci çalışmada, bir ana dağıtım üssü ağı üzerinde kamyonun taşıdığı yük ve hız kararlarını en iyileyerek, yakıt tüketimini en azlayan, Yeşil Ana Dağıtım Üssü Yer Seçimi Problemi sunulmuştur. Üçüncü olarak, teslimatların yapılabilmesi için, kamyon ve insansız hava araçlarının birlikte kullanıldığı, İnsansız Hava Araçları Teslimat Problemi adı verilen bir yük taşımacılığı problemi çalışılmıştır. İnsansız hava araçlarının menziline kalıp enerji tüketimini en azlayabilmek için, insansız hava araçlarının hızları, problemin bir karar değişkeni olarak düşünülmüştür. Son çalışmada ise, İnsansız Hava Araçları Teslimat Probleminin bir uzantısı olarak, rüzgar hızının belirsizliğinin ve bunun insansız hava araçlarının hızına etkisinin hesaba katıldığı, Rassal İnsansız Hava Araçları Teslimat Problemi sunulmuştur.

Anahtar sözcükler: Yer seçimi, Rotalama, Yük Taşımacılığı, Çevresel etkiler, Enerji (Yakıt) tüketimi.

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Chapter 1

Introduction

Supply chain management entails designing, planning and coordination activities for movements of a product or delivery of services from the supplier to the customer. However, it is known that some of these activities are harmful to the environment. Taking the right steps for the design activities is critical in order to improve the environmental performance of a supply chain, and these decisions often manifest themselves in the form of network design problems.

Sustainability for systems is a term which is often used in lieu of ‘improved environmental performance’ or to denote the ways in which ‘reduction of externalities’ of the particular system can be achieved, and not necessarily in its literal meaning which has been characterized as the ability of the system to exist permanently provided that the environment around the system allows it to do so. Here, we do not delve into such discussions and refer the reader to a fuller discussion on the issue by [1], and take ‘sustainable’ systems on the face value as it appears in various references. What we will do, however, is to differentiate the terms ‘sustainable’ and ‘green’, with emphasis being on the latter, through classification of the extant literature. We start by offering a proposed classification for sustainable logistics design problems as shown in Figure 1.1.

Sustainable logistics network design can be separated into two categories,

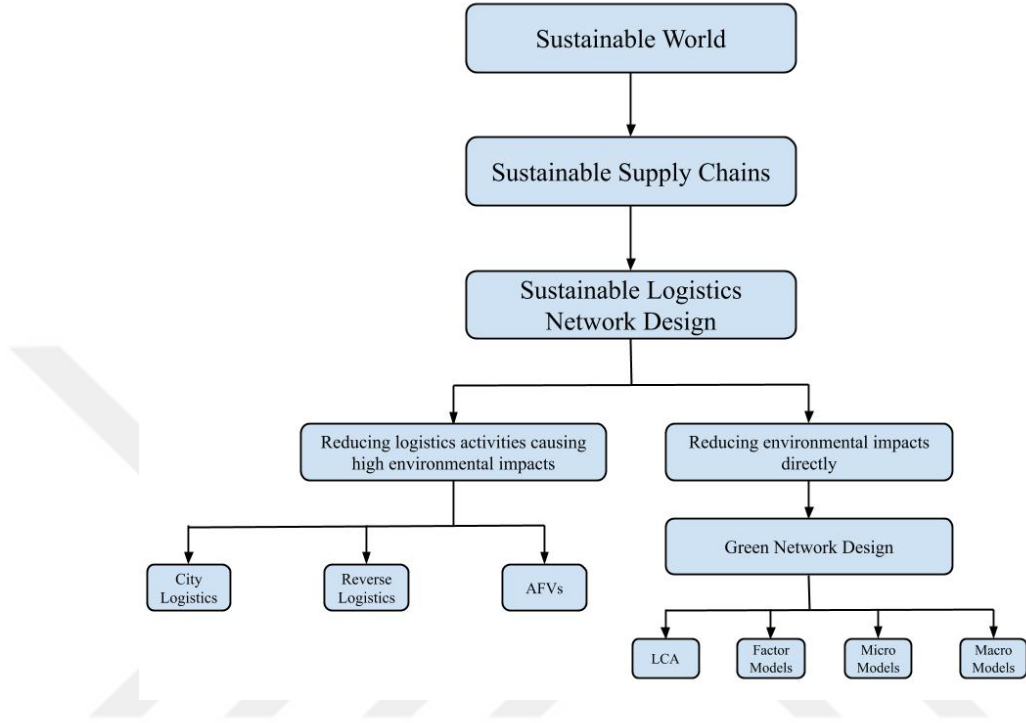


Figure 1.1: Classification for the design of the sustainable logistics networks

namely those focusing on reducing the type or amount of logistics activities with negative environmental impacts and reducing the negative environmental impact directly (Figure 1.1). The first category makes use of concepts such as city logistics, reverse logistics and alternate fuel vehicles (AFVs), which aim to reduce logistics activities that have environmental impact. In particular, city logistics reduces the environmental impacts of urban freight transportation within city boundaries with due consideration to economical and social impacts. The environmental effects within a city can be reduced by minimizing the number of freight vehicles traveling within the city and by optimizing the usage of these vehicles. City logistics uses two fundamental concepts to achieve this: the consolidation of loads in warehouses and the coordination of freight transportation activities. A more detailed discussion on city logistics can be found in [2]. Reverse logistics comprises the reuse, recycling and disposal of waste products and packaging by arranging transportation activities as it is described in [3]. Reverse logistics allows companies to reduce emissions by transporting recycled products

instead of producing or supplying them. In some studies, both forward and reverse logistics are considered simultaneously, giving rise to what is now known as a Closed Loop Supply Chain. For comprehensive surveys on reverse logistics and closed loop supply chains, we refer the reader to the studies by [4], [5], [6] and [7]. Finally, in [8], AFVs are described as vehicles that run on alternative, environment friendly source of fuel such as biodiesel, electricity, hydrogen, methanol, ethanol, and propane rather than petroleum-based fuels. AFVs produce lower emissions compared to fuel-based vehicles. A detailed discussion on AFVs can be found in [9] and references therein.

The second main category shown in Figure 1.1, which we refer to as Green Network Design, is a class of planning problems with an aim to reduce the environmental impacts of logistics activities. One of the prominent environmental impacts of logistics operations is the emission of Greenhouse Gases (GHGs), due to their detrimental effect on both human health and the environment. GHGs are described as gases that “emit and absorb radiation at specific wave-lengths within the spectrum of thermal infrared radiation emitted by the earth’s surface, the atmosphere itself and by clouds” as defined in the Glossary of IPCC’s 2007 Synthesis Report [10]. The primary GHGs include carbon dioxide (CO_2) that has been linked to global warming, nitrous oxide (N_2O), methane (CH_4), water vapor (H_2O), ozone (O_3). Burning fossil fuels such as oil, natural gas and coal emit GHG and CO_2 .

Estimating or quantifying emissions of transportation activities is not straightforward. For instance, minimizing the travel distance of a vehicle does not necessarily result in minimizing fuel (or energy) consumption as the latter depends on other factors, such as speed and load (see, for example, [11]). Such environmental factors would therefore have to be explicitly included in the estimation of emissions. Environmental impacts such as emissions have been calculated using different types of principles and models in the literature. These models include the Life Cycle Assessment (LCA) method, factor models, and macroscopic and microscopic fuel consumption models (see, [11]). LCA is a method used to evaluate the environmental impacts of a product from its raw material form until recycle. Although LCA does not directly model the emissions or the

fuel requirements, it proposes a simple and systematic method of calculating the environmental impact of a process such as production, transportation or disposal. This methodology consists of four stages; goal definition and scoping, inventory analysis, impact assessment and interpretation. The goal definition and scoping stage entails the definition of the product, process and activities and the identification of boundaries and environmental impacts. In the inventory analysis stage, resource usage and environmental releases are characterized and quantified, both of which are assessed during the impact assessment stage. The Eco-indicator 99, a damage oriented method for life cycle impact assessment, is often used during this stage. Finally, the interpretation stage evaluates the results obtained during second and third stages. A more detailed explanation of the LCA method can be found in [12] and [13]. In contrast to the LCA method, the other models focus solely on transportation related activities. In factor models, the data for travel distance or fuel consumption is collected and multiplied by certain coefficients (e.g., the emission factor), mainly used to estimate the CO₂ emissions. Several of such factor models are proposed in [14]. On the other hand, macroscopic and microscopic models consider other factors that influence fuel consumption and CO₂ emissions, such as vehicle weight, vehicle speed, payload, etc., in order to provide more accurate estimation of fuel consumption, and in turn CO₂ emissions which are directly proportional (see, [11]). Macroscopic models estimate fuel consumption and CO₂ emission using average aggregate network parameters, whereas microscopic models include detailed parameters using instantaneous (e.g., second by second) measurements. Network design problems have been studied with an explicit goal of reducing fuel or energy consumption in the freight transportation sector using these types of models, an aspect to which we will refer to as green.

In this dissertation, we present four new green network design problems that consider location and routing decisions. First, we introduce the Green Location-Routing Problem where location and routing decisions are incorporated to a freight transportation problem in which the fuel consumption (emissions) of trucks is explicitly calculated and minimized. Second, we describe the Green Hub Location Problem where we consider the fuel consumption (emission) minimization of trucks on a hub network. Third, we study the integration of trucks

and drones in a freight transportation problem called the Drone Delivery Problem where drones make the last-mile delivery. In this problem, since drones are powered by batteries, instead of a fuel consumption model, we use an energy consumption model to estimate the amount of energy consumed by a drone. The aim of this problem is to minimize the energy consumption of drones while respecting drone range and time bound limitations. Fourth, we present an extension of the Drone Delivery Problem, called the Stochastic Drone Delivery Problem in which we consider the effects of uncertain wind on drone speed which has an impact on energy consumption, drone range and time bound.

The rest of this thesis is presented as follows. Section 2 presents an extensive literature review on green network design problems, provides mathematical formulations and describes applications where relevant. As our focus is on green network design problems, we do not provide a detailed coverage of others that have looked at sustainable network design problems such as AFVs, city logistics, and reverse logistics and closed loop supply chains. However, we do include pioneering works and surveys in our review that relate to both green network design and reverse logistics.

Chapter 3 introduces the Green Location-Routing Problem extending the Location-Routing Problem by including fuel consumption and CO₂ emissions explicitly. In this section, the problem is described and is formulated as a mixed integer program. The section also includes two heuristic algorithms; one of which is an integer programming-based algorithm (matheuristic) and the other one is an iterated local search algorithm. Computational results on parametric analysis and also on the performance of the proposed solution approaches are discussed. Also, a case study in Istanbul, Turkey is described. Furthermore, Chapter 3 presents some optimal solution characterizations for the special cases of the Green Location-Routing Problem.

Chapter 4 presents the Green Hub Location Problem that finds the best locations for hubs, assignments of demand nodes to these hubs and speed of trucks/flights so as to route the demand between any origin-destination pair. The aim is to minimize the total amount of emissions that depends on vehicle

speed and payload while having the deliveries within a predetermined service time limit. We first propose a nonlinear model for this problem, which is then reformulated as a second order cone programming model. We strengthen the new formulation by using perspective reformulation approach. An extensive computational study on the traditionally used datasets demonstrates the benefits of incorporating green transportation service activities to the classic hub location problem. We also present managerial insights for the service providers by analyzing the solutions with different discount factors, service time limits and number of hubs.

Chapter 5 introduces the Drone Delivery Problem in which drones are used to make deliveries to a number of customers and the drones themselves are transported by traditional vehicles that act as launch points. The problem consists of selecting the launch points from a potential set of sites from where drones will take off to serve a number of customers, assignments of customers to the launch points, and the speed at which drones are to travel between the customers and the launch points. We present a nonlinear model, which minimizes the total operational cost including an explicit calculation of the energy consumption of the drone as a function of the drone speed, that is limited by both a service time bound and the range of the drone. The model is reformulated using second order cone programming, and subsequently strengthened by perspective cuts, that allows the use of off-the-shelf optimization software to solve the problem. Computational results are presented on a realistic data set that quantifies the effect of various parameters on location, assignment and speed decisions.

Chapter 6 presents an extension of the Drone Delivery Problem that is called the Stochastic Drone Delivery Problem where uncertainty of the wind speed and its effect on the drone speed are considered. Similar to the deterministic version, the problem again decides the location of launch points, customer assignments to drones and the drone speed. The objective is to minimize a total cost function including operational cost of trucks and the expected energy consumption cost. Initially, the model is formulated as a two-stage nonlinear program and then it is reformulated by using deterministic equivalent problem and second order cone programming approaches. We also propose a scenario decomposition algorithm

to solve instances with higher number of scenarios. Computational analyses are carried out over a real data set to evaluate the performance of the algorithm and the impact of stochastic optimization.

The concluding remarks and some possible future extensions to the proposed problems are given in Chapter 7.



Chapter 2

Literature Review

In this chapter, we provide an overview and a classification of Green Network Design Problems. Section 2.1 presents previous survey papers related to green and sustainable supply chain and network design problems. In Section 2.2, we analyze the existing literature on Green Network Design Problems arising at different levels of decision making, from operational to strategic, and will present definitions, optimization models and practical applications for some of the key problems in this category. In Section 2.3, we provide some concluding remarks and possible future research directions on green network design problems.

This chapter is published as a book chapter [15] in the book called Sustainable Transportation and Smart Logistics.

2.1 Previous Survey Papers

The sudden rise of the popularity of sustainable and green supply chain and network design problems has lead to several review articles being published in the literature (Table 2.1). One of the earlier such review papers on green supply chain management is by [16], which classifies the literature as those discussing the importance of the green supply chain management, green design and green

operations. The survey covers the papers until 2006, a period of time during which the relevant research focused more on reverse logistics. In [17], green logistics is introduced as a new concept and it is combined with some combinatorial optimization problems, in particular reverse logistics, waste management and vehicle routing and scheduling problems. In [18], a comprehensive review on green logistics problems is presented within Operations Research, classified into those relevant to transportation, product (inventory) and facility location. In [19], a literature review on sustainable supply chain management and performance measures is provided, with a particular focus on the latter. In [20], a survey on green Vehicle Routing Problems (VRPs) is presented by first classifying the classical VRP, then by categorizing green VRPs, Pollution-Routing Problems and those arising in Reverse Logistics. The authors describe green VRPs as problems that minimize energy consumption and Pollution-Routing Problems as those that minimize GHG (particularly CO₂) emissions. The review by [11] is exclusively on green road freight transportation, where the authors identify and explain the factors that affect fuel consumption, and review the relevant fuel consumption models. They specifically focus on routing problems but also mention papers related to location problems. In [21], a literature review on sustainable supply chain management is provided, which also covers studies that deal with network design. However, they do not consider routing problems with environmental concerns. The review paper by [22] is the one on sustainable supply chain network design, with a particular focus on optimization problems arising within this area. The authors review various studies relating to economic, environmental or social impacts. The authors do not consider the papers that include any routing decisions.

Table 2.1 summarizes previous survey papers related to green network design problems and compares them with our study based on the following factors: which sustainability tool is considered; (i) city logistics, (ii) reverse logistics, (iii) alternative fuel vehicles, and (iv) green network design, which decisions are considered; (v) location, and (vi) routing, and (vii) the number of common references.

As Table 2.1 shows, there does not seem to be a review that fully covers the green network design literature where both location and routing decisions are

Table 2.1: Features of Existing Survey Papers

<i>Reference</i>	Sustainability Tool				Decision		Number of Common References
	CL	RL	AFVs	GND	Location	Routing	
[16]	×	●	×	○	○	×	1
[17]	×	●	×	○	×	○	0
[18]	×	○	×	○	○	○	13
[19]	×	○	×	○	○	×	3
[20]	×	●	○	○	×	●	12
[11]	×	×	×	●	○	●	30
[21]	×	○	×	○	○	×	3
[22]	×	○	×	●	●	×	19
Our Study	×	○	×	●	●	●	-

CL: City Logistics, RL: Reverse Logistics, GND: Green Network Design

×: Not covered, ○: Partially Covered, ●: Fully Covered

included, which is the aim of this chapter. Here, we review 107 articles in detail. The last column of Table 2.1 reports the number of the common references cited in the reviews above and in this review. [11] and [22] are the two review papers that have the highest number of shared references with our study, 30 and 19, respectively. However, in [11], the main focus is on routing problems whereas in [22], only problems that include location decisions are reviewed.

2.2 Green Network Design Problems

The ensuing review is based on a categorization of the relevant studies based on the three classical levels of decision-making, namely operational, tactical and strategic, as depicted in Figure 2.1, along with the number of references in each category. Operational decisions are mainly those related to routing. Tactical decisions consist of location-routing and allocation problems. Strategic decisions include studies that look at location-allocation problems. We present the relevant studies in the three main sections below.

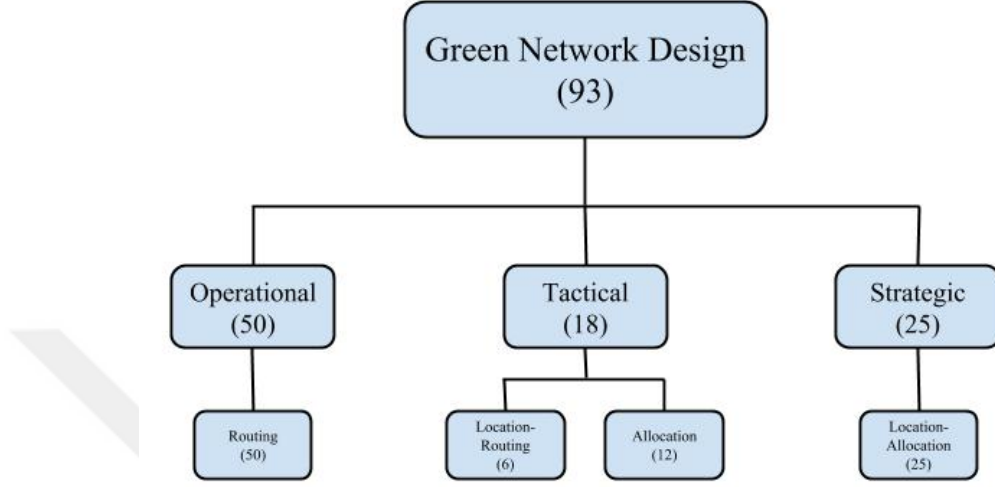


Figure 2.1: Categorization of green network design problems

2.2.1 Operational decision making

Most papers in this category involve routing decisions. The Energy Minimizing Vehicle Routing Problem (EMVRP) by [23] and the Pollution Routing Problem (PRP) by [24] are the two pioneering works that consider the minimization of fuel consumption in vehicle routing problems. In the following sections, we describe these two problems with the proposed mathematical formulations and those studies that extend these two problems.

2.2.1.1 The energy minimizing vehicle routing problem

In [23], the EMVRP is introduced as an extension of the classical VRP where the objective is to minimize a distance-weighted load function in order to minimize the total energy consumption. The EMVRP is defined on a network $G = (N, A)$ where $N = \{1, \dots, n\}$ is the set of nodes and node 0 is the depot. The customer set is denoted by $N_0 = \{1, 2, \dots, n\}$ and $A = \{(i, j) : i, j \in N, i \neq j\}$ denotes the set of arcs. The distance on arc $(i, j) \in A$ is denoted by d_{ij} . A fleet of m vehicles, each with a carrying capacity Q and a tare weight Q_0 is available to serve customers, each of which has a nonnegative weight (demand) q_i , $i \in N$.

The problem is to find a set of routes for the vehicles that all start from and end at the depot such that the total energy as modeled by the distance-weighted load function is minimized. The integer programming formulation proposed by [23] to solve the EMVRP uses a binary variable x_{ij} that equals 1 if a vehicle travels on arc $(i, j) \in A$, and 0 otherwise. A continuous nonnegative variable y_{ij} represents the total weight of the vehicle (including tare weight) on arc $(i, j) \in A$. The proposed mathematical model is as follows:

$$\text{Minimize } \sum_{i \in N} \sum_{j \in N \setminus \{i\}} d_{ij} y_{ij} \quad (2.1)$$

subject to

$$\sum_{i \in N_0} x_{0i} = m \quad (2.2)$$

$$\sum_{i \in N_0} x_{i0} = m \quad (2.3)$$

$$\sum_{i \in N} x_{ij} = 1 \quad \forall j \in N_0 \quad (2.4)$$

$$\sum_{j \in N} x_{ij} = 1 \quad \forall i \in N_0 \quad (2.5)$$

$$\sum_{j \in N} y_{ij} - \sum_{j \in N} y_{ji} = q_i \quad \forall i \in N_0 \quad (2.6)$$

$$y_{0i} = Q_0 x_{0i} \quad \forall i \in N_0 \quad (2.7)$$

$$y_{ij} \leq (Q + Q_0 - q_j) x_{ij} \quad \forall (i, j) \in A \quad (2.8)$$

$$y_{ij} \geq (Q_0 + q_i) x_{ij} \quad \forall (i, j) \in A \quad (2.9)$$

$$x_{ij} \in \{0, 1\} \quad \forall (i, j) \in A. \quad (2.10)$$

The objective function (2.1) minimizes a cost function that depends on the total weight of the vehicle and the total distance traversed. Constraints (2.2) and (2.3) set the number of vehicles to m . Constraints (2.4) and (2.5) ensure that a

vehicle arrives and leaves each node. Constraints (2.6) are the flow conservation between nodes. Constraints (2.7) ensure that the weight of the vehicle while leaving the depot equals the tare weight. Constraints (2.8) set an upper bound on the flows and serves as the vehicle capacity constraints. Similarly, Constraints (2.9) set a lower bound on the weight variable. Finally, Constraints (2.10) are domain constraints on the variable.

Different versions of the EMVRP have been studied in the literature, as shown in Table 2.2, the first column of which shows the reference and the following four columns indicate the general features of the problem studied, namely the network type (single or multi-echelon), the number of objectives (single or multiple), solution methods (exact “E” or heuristic “H”) and whether an application is presented or not. The next four columns represent the specifications of the proposed models, namely time window (TW), time-dependency (TD), simultaneous pickup & delivery (P&D) and uncertainty (U), respectively. The last four columns are relevant to fuel consumption, the first of which shows the type of the emission model (factor, macroscopic or microscopic) used. The remaining three columns show whether distance (Dis), load (Loa) and Speed (Spe) is considered as a parameter “P” or decision “D” within the respective models.

Table 2.2: Studies related to the EMVRP

References	General				Model Specifications				Fuel Consumption			
	Net.	Obj.	Sol.	A. Case	TW	TD	P&D	U	Emission	Dis	Loa	Spe
[23]	Single	Single	E						Factor	P	D	-
[25]	Single	Single	E & H						Factor	P	D	-
[26]	Single	Single	E						Factor	P	D	-
[27]	Single	Single	H				✓		Factor	P	D	-
[28]	Single	Single	H		✓		✓		Micro	P	D	P
[29]	Single	Single	E		✓		✓	✓	Micro	P	D	P
[30]	Single	Single	H						Factor	P	D	-
[31]	Single	Single	E						Factor	P	D	-
[32]	Single	Single	E & H		✓	✓			Micro & Macro	P, D	D	-
[33]	Single	Single	H			✓			Macro	P, D	D	-
[34]	Single	Multi	H		✓	✓			Micro	P	D	P
[35]	Single	Single	E & H			✓		✓	Micro	P	D	P
[36]	Single	Single	E		✓				Factor	P	P	P
[37]	Single	Single	E & H						Factor	P	D	-
[38]	Single	Single	H	✓			✓		Factor	P	P	-
[39]	Single	Single	H	✓					Micro	P	D	P
[40]	Multi	Single	H	✓	✓				Factor	P	D	P
[41]	Single	Multi	H						Factor	P	D	-

Some of the problems shown in Table 2.2 are very similar to the EMVRP. For example, in [25], the authors consider minimizing fuel consumption in the capacitated vehicle routing problem where the fuel consumption rate is load dependent, but the way in which it is calculated is more complex. Similarly, in [26], the cost is modeled over each arc as the product of the arc length and the weight of the vehicle including payload and curb weight. The authors presented two new mixed-integer programming formulations, namely an arc-load formulation and a set partitioning formulation, where the latter is solved by a branch-cut-and-price algorithm.

Incorporating backhauling or simultaneous pick-up and delivery options in vehicle routing may further reductions in the environmental impacts of vehicle routing, given the flexibility afforded by such options in eliminating some of the transportation activities that cause CO₂ emissions. One such study is by [27], which focuses on load-dependent vehicle routing problem similar to the EMVRP but extended to take into account simultaneous pick-up and delivery. This is modeled by assuming, for each customer $i \in N$, a delivery request d_i and pick-up request p_i . Two nonnegative continuous variable D_{ij} and P_{ij} are defined to represent the delivery and pickup load carried on arc $(i, j) \in A$. The model of this problem follows that of the EMVRP, where Constraints (6)–(9) are replaced by the following:

$$\sum_{j \in N} P_{ij} - \sum_{j \in N} P_{ji} = p_i \quad \forall i \in N_0 \quad (2.11)$$

$$\sum_{j \in N} D_{ij} - \sum_{j \in N} D_{ji} = d_i \quad \forall i \in N_0 \quad (2.12)$$

$$d_j x_{ij} \leq D_{ij} \leq (Q - d_i) x_{ij} \quad \forall (i, j) \in A \quad (2.13)$$

$$p_i x_{ij} \leq P_{ij} \leq (Q - p_j) x_{ij} \quad \forall (i, j) \in A \quad (2.14)$$

$$D_{ij} + P_{ij} \leq (Q - \max\{0, p_j - d_j, p_i - d_i\}) x_{ij} \quad \forall (i, j) \in A. \quad (2.15)$$

Constraints (2.11) and (2.12) model flow conservation for both pick-up and delivery. Constraints (2.13)–(2.15) provide stronger lower and upper bounds on

the flow variables to satisfy vehicle capacity constraints. Local search algorithms and a branch-and-cut method are proposed for the problem. Other relevant studies are by [28] and [29] that consider a VRP with backhauling or simultaneous pick-up and delivery options.

The references mentioned above all assume the use of a homogeneous fleet of vehicles, i.e., all vehicles are identical. In contrast, one can assume a heterogeneous set of vehicles with varying characteristics. [30], for example, is one such study that looks at the use of a carbon trading mechanism within the problem. In [31], a similar problem, namely the Emission Minimization Vehicle Routing Problem with Vehicle Categories is studied, but without the use of a carbon trading mechanism.

The studies mentioned above also assume that vehicles travel at constant speed whilst traversing an arc, which may not be a realistic assumption, given that traffic conditions such as congestion are known to affect vehicle speed. One way to tackle this would be to assume that vehicle speeds vary with time, giving rise to routing problems where travel times are time-dependent. One such study is by [32], which extends the Green Vehicle Routing and Scheduling Problem (GVRSP) proposed by [42] with the inclusion of time-dependent travel times, time window constraints, the effect of weight on fuel consumption and a heterogeneous fleet of vehicles. They also allow vehicles to stop on arcs at any time, which breaks away from similar studies that consider time-varying congestion. To solve the problem, the authors propose a hybrid algorithm that uses partial-mixed integer programming and iterated neighborhood search. The same authors study a heterogeneous fleet GVRSP with tardiness objective in [33] for which they propose a hybrid algorithm that combines a genetic algorithm and the exact dynamic programming solution technique. The other two studies that consider time-dependent travel times are [34] and [35]. Some variants of the EMVRP incorporate additional time related constraints such as time windows in [36] or a limit on tour length in [37].

One application of the EMVRP can be found in the paper by [38], which presents a case study for Eroski, a food distribution company, operating in the

Navarre region of Northern Spain. The distribution network consists of one depot, 15 customers and 25 suppliers. Backhauling is used to fill stocks from the suppliers after serving the customers. The authors describe a nearest neighbor insertion algorithm to solve the case study. The results indicate a savings of 14.9% in CO₂ emissions for a week of distribution activities. In [39], one application of the inventory routing problem for a petrochemical company operating in South-Eastern Europe is described. The company operates on a network that consists of one depot, and seven regions including 45 filling stations (customers) in 27 cities. A mathematical formulation for the problem is presented, and when it is solved with a single objective function that only minimizes economic impacts, a 15.97% saving is achieved over a year. When environmental impacts are included in the objective function, an additional saving of 1.35% is achieved. In [40], a two-echelon time-constrained vehicle routing problem is proposed. The authors develop a two-stage heuristic algorithm and present a real-life application for two trucking companies operated in Shandong province of China, one with 23 city distribution centers serving 1008 customers, and the other with 10 city distribution centers serving 818 customers. The paper by [41] does not present a real-life problem, but considers users' viewpoint while calculating fuel consumption for a routing problem called a practical PRP.

2.2.1.2 The pollution-routing problem

The second main study that considers environmental impacts in the VRP is the Pollution-Routing Problem (PRP) proposed by [24], where the objective function minimizes the total cost including the driver cost and the fuel consumption and CO₂ emissions cost. The fuel consumption is estimated using the Comprehensive Modal Emission Model (CMEM) proposed by [43], [44] and [45]. In the PRP, all parameters of the emission model on a given segment of road (e.g., arc) are assumed to be constant except for load and speed, which are considered as decision variables in order to calculate emissions more accurately. One of the assumptions in this work is that vehicles travel with a speed of at least 40 km/hr that is typically applicable to intercity routes, i.e., urban areas and congestion speeds are

not considered.

The PRP is defined on the same graph $G = (N, A)$ as the EMVRP, where, additionally, there are time windows $[a_i, b_i]$ for each customer $i \in N_0$, with the service time at this customer denoted by t_i . Also, α_{ij} is an arc specific constant and β is a vehicle specific constant. An integer linear programming formulation is described for the PRP, where the main routing variable x_{ij} is the same as the one defined for the EMVRP. In addition, the continuous nonnegative variables f_{ij} and v_{ij} represent the total weight of the vehicle (excluding tare weight) and speed of the vehicle on arc $(i, j) \in A$, respectively. The start time of service at node $j \in N_0$ is denoted by y_j . The total time spent on a route in which node $j \in N_0$ is the last visited node is denoted by s_j . As the speed variables v_{ij} result in a nonlinear term in the objective function and the constraints, the speed is discretized into a set of levels $R = \{0, 1, 2, \dots, r\}$ and v_r represents the average vehicle speed for a speed level $r \in R$. A new binary variable z_{ij}^r is defined which equals 1 if a vehicle travels with a speed level $r \in R$ on arc $(i, j) \in A$, and 0 otherwise. The corresponding mathematical formulation is as follows:

$$\text{Minimize } \sum_{(i,j) \in A} (c_f + e)\alpha_{ij}d_{ij}Q_0x_{ij} \quad (2.16)$$

$$\sum_{(i,j) \in A} (c_f + e)\alpha_{ij}d_{ij}f_{ij} \quad (2.17)$$

$$\sum_{(i,j) \in A} (c_f + e)\beta d_{ij} \left(\sum_{r \in R} (v^r)^2 z_{ij}^r \right) \quad (2.18)$$

$$\sum_{j \in N_0} p s_j \quad (2.19)$$

subject to (2.2), (2.4)-(2.5), (2.10)

$$\sum_{j \in N} f_{ji} - \sum_{j \in N} f_{ij} = q_i \quad \forall i \in N_0 \quad (2.20)$$

$$q_j x_{ij} \leq f_{ij} \leq (Q - q_i) x_{ij} \quad \forall (i, j) \in A \quad (2.21)$$

$$y_i - y_j + t_i + \sum_{r \in R} \left(\frac{d_{ij}}{v^r} \right) z_{ij}^r \leq M_{ij}(1 - x_{ij}) \quad \forall i \in N, j \in N_0 : i \neq j \quad (2.22)$$

$$a_i \leq y_i \leq b_i \quad \forall i \in N_0 \quad (2.23)$$

$$y_i - s_j + t_j + \sum_{r \in R} \left(\frac{d_{j0}}{v^r} \right) z_{j0}^r \leq L(1 - x_{j0}) \quad \forall j \in N_0 \quad (2.24)$$

$$\sum_{r \in R} z_{ij}^r = x_{ij} \quad \forall (i, j) \in A \quad (2.25)$$

$$f_{ij} \geq 0 \quad \forall (i, j) \in A \quad (2.26)$$

$$z_{ij}^r \in \{0, 1\} \quad \forall (i, j) \in A, r \in R. \quad (2.27)$$

The objective function consists of two components, the first of which is the cost of fuel consumption and CO₂ emission represented by (2.16)–(2.18), and the second is the cost of drivers shown by (2.19). Constraints (2.20) ensure flow conservation between nodes. Constraints (2.21) impose lower and upper bounds on the flow variables and serve as vehicle capacity constraints. Constraints (2.22) compute the service start time for each node. The time window restrictions for each customer are modeled through Constraints (2.23). The total time spent on each route is calculated by Constraints (2.24). Finally, Constraints (2.25) ensure that only one level of speed chosen on each arc of the graph that is traversed by a vehicle. Constraints (2.26) and (2.27) are the domain constraints.

We now present a review of studies that are in the spirit of the PRP. These studies are summarized in Table 2.3. Initially, we focus on the studies that focus on the original version of the PRP. In [46], the PRP is studied where the vehicles to travel slower than 40 km/h is allowed. They develop a heuristic algorithm in which the VRP with time windows is solved by an adaptive large neighborhood search, following which a speed optimization algorithm finds the optimal speed for each arc of route identified for each vehicle. In [47], the bi-objective variant of the PRP is studied, where the two (conflicting) objectives are to minimize fuel consumption and to minimize driving time. Pareto solutions are identified by using the heuristic as a search engine, in conjunction with four a posteriori

methods, namely a weighting method, a weighting method with normalization, the ϵ -constraint method and a new hybrid method that combines the adaptive weighting and the ϵ -constraint method. The results indicate that the hybrid one outperforms the others. One other metaheuristic for the PRP is described by [48], which combines iterated local search with speed optimization procedures and integer programming optimization over a set partitioning formulation.

Table 2.3: Studies related to the PRP

References	General				Model Specifications				Fuel Consumption				
	Net.	Obj.	Sol.	A. Case	TW	TD	P&D	Unc	Emis.	M.	Dis	Loa	Spe
[24]	Single	Single	E		✓				Micro	P	D	D	
[46]	Single	Single	E & H		✓				Micro	P	D	D	
[47]	Single	Multi	H		✓				Micro	P	D	D	
[48]	Single	Single	H		✓				Micro	P	D	D	
[49]	Single	Single	E		✓				Micro	P	D	D	
[50]	Single	Single	E		✓				Micro	P	D	D	
[51]	Single	Single	E		✓	✓			Micro	P	D	D	
[52]	Single	Single	H			✓		✓	Micro	P	D	P	
[53]	Single	Single	H		✓	✓			Micro	P	D	D	
[54]	Single	Single	H		✓				Micro	P	D	D	
[55]	Single	Single	H		✓				Micro	P	D	D	
[56]	Single	Multi	H		✓				Micro	P	D	D	
[57]	Single	Single	E		✓			✓	Micro	P	D	D	
[58]	Single	Single	H		✓		✓		Micro	P	D	D	
[59]	Single	Single	E	✓				✓	Micro	P	D	P	
[60]	Multi	Single	E	✓		✓			Micro	P	D	P	
[61]	Single	Single	E	✓				✓	Micro	P	D	P	
[62]	Single	Single	H	✓		✓			Macro	P	D	D	

As for the exact methods on the PRP, in [49], the authors use disjunctive convex programming to develop two mixed-integer convex optimization models where the speed is kept as a continuous variable. They also develop a set of valid inequalities. On the other hand, the study by [50] describes a branch-and-price algorithm to solve a variant of the PRP where the speed along all arcs of a given route is assumed to be constant. In the algorithm, the master problem is of a set-partitioning type, where the pricing is performed through solving a speed and start-time elementary shortest path problem with resource constraints using a tailored labeling algorithm.

Fuel consumption is known to be affected by congestion, particularly with the low speeds that vehicles travel at under heavy traffic conditions. In [51], such considerations are incorporated within the PRP, in particular time-dependent

travel times, where it is assumed that there is an initial period of congestion followed by free-flow traffic conditions, and look at optimal policies around departure time. The authors also advocate for idle waiting both before and after service to avoid congestion. The mathematical formulation they describe without any congestion is also valid for the PRP, which is shown to perform better than that of [24]. The authors also study a special case where there is only one vehicle and a fixed sequence of customers and propose a specified algorithm for this problem. An adaptive large neighborhood search for this problem can be found in [53]. In urban areas, the conditions around vehicle speeds are different than those of intercity travel. One way to calculate vehicle speed on a path between two customers is an arc-averaging method described by [63]. A time-dependent vehicle routing problem in urban areas is described and solved in [52].

The choice of vehicles in the fleet also impacts fuel consumption, as each type of vehicle has own specific parameters such as curb weight, engine friction factor, engine speed, etc. The study by [54] considers the extent to which the fleet choice matters by introducing and solving the Fleet Size and Mix PRP, where a heterogeneous vehicle fleet is used. In [55], the PRP with a heterogeneous fleet of vehicles is studied. Instead of time windows, however, the proposed problem assumes that there are deadlines associated to each customer request.

Several studies apply different variants of the PRP to real or realistic problem instances. For instance, in [59], an application based on distribution of fresh tomato is presented for a company operating in the Western Turkey, where the distribution network has one distribution center and 11 supermarkets (customers). The authors solve an inventory routing problem for perishable items by considering environmental factors and demand uncertainty. The results show that using consideration of perishability of items and fuel consumption reduces total amount of emissions by 2%, but this leads a 25.2% increase on the total cost. In [60], a case study is conducted for the distribution network of a supermarket chain operating in the Netherlands, where the distribution network consists of one depot, two satellites and 16 customers. For this application, the authors extend the problem setting of [24] to a time-dependent, two-echelon capacitated vehicle routing problem formulation with environmental considerations. The results

indicate that using a fuel-minimizing objective function provides an average reduction of 2.5% on fuel consumption, but this comes at the expense of a 10.8% increase on cost. The study of [61] presents an extension to [59] by considering multiple products and multiple suppliers where horizontal collaboration is assumed between suppliers. The authors present a practical application for two suppliers, one of which distributes figs and the other cherries to five wholesale market halls (customers) using a third-party logistics company. The numerical evidence suggests that through horizontal collaboration a reduction of 17.1% and 29.3% can be achieved, on the total cost and the total amount of emissions, respectively. The final application we present here is by [62] that is for a distribution operation of dairy products in the city of Esfahan in Iran, which includes one depot, 28 customers and three vehicles. The case study is then formulated as a time-dependent vehicle routing problem with the objective of reducing fuel consumption. The authors present numerical results suggesting that savings of around 21% can be reaped on fuel consumption.

2.2.1.3 Other routing problems

This section discusses other types of routing problems that explicitly incorporate environmental considerations. A list of the studies reviewed in this section is provided in Table 2.4.

One of the first studies that addresses CO₂ emissions within the VRP is [64], which investigates the effects of congestion on CO₂ emissions. In [65], a VRP with time-dependent travel times is studied for which the author develops a method to calculate fuel consumption and solves the problem using a simulated annealing algorithm. In [66], an emissions minimizing VRP is described, which incorporates time-dependent travel speeds and time windows, for which a single objective and a hierarchical multi-objective formulations are presented. The author describes heuristic algorithms for both versions of the problem. Along similar lines, a time-dependent VRP that minimizes emissions is described in [67]. A tabu search method using a nearest neighbor heuristic as a construction algorithm is proposed to solve the problem. In [68], a multi-product multi-period inventory routing

Table 2.4: Other green routing problems

References	General				Model Specifications				Fuel Consumption				
	Net.	Obj.	Sol.	A. Case	TW	TD	P&D	Unc	Emis.	M.	Dis	Loa	Spe
[64]	Single	Single	H		✓	✓			Micro	P	P	P	D
[65]	Single	Single	H			✓			Factor	P	P	P	P
[66]	Single	Multi	E & H		✓	✓			Macro	P	-	P	P
[67]	Single	Single	H			✓			Macro	P	-	D	D
[68]	Single	Single	H						Factor	P	-	-	-
[42]	Single	Multi	E & H		✓	✓			Factor	P	-	-	-
[63]	Single	Single	H			✓		✓	Macro	P	P	P	P
[69]	Single	Single	H			✓		✓	Macro	P	-	P	P
[70]	Single	Single	H	✓	✓	✓			Macro	P	-	P	P
[71]	Single	Multi	H	✓	✓	✓			Macro	P	-	D	D
[72]	Single	Single	H	✓	✓	✓			Macro	P	-	D	D
[73]	Single	Single	H	✓		✓			Macro	P	-	P	P
[74]	Single	Single	H	✓					LCA	-	-	-	-
[75]	Single	Single	E & H	✓	✓		✓		Factor	-	-	P	P

problem with a heterogeneous fleet of vehicles is presented where greenhouse gas emissions are limited by a constraint. The authors propose a mixed-integer linear programming formulation to solve the proposed problem. In [42], the Green Vehicle Routing and Scheduling Problem is introduced, which includes time-dependent travel times and time window constraints. The authors develop a MILP formulation of the problem and a three-stage solution approach for the solution with hierarchical objectives. They also describe a simulated annealing algorithm to solve large-size problem instances. The study by [63] investigates the effects of speed variability in relation to minimizing emissions on paths in urban areas. The authors assume that vehicles travel at traffic speed, using which they develop two data-driven approaches to find shortest paths that minimize fuel consumption, namely path and arc-averaging methods. A similar problem is studied in [69] by considering stochastic vehicle speeds and a different macroscopic emission model.

Other applications reported for routing problems with an explicit consideration to minimize negative environmental impacts are as follows. In [70], a case study is described for the distribution system of an electric goods wholesaler operated in the South West of the UK, for deliveries made over nine days and where the number of customers visited ranges between 40 and 64 each day. A heuristic

algorithm based on tabu search is used to solve the problem. Through a computational study, the authors report around 7% savings on CO₂ emissions. In [71], the same problem introduced in [66] is studied by analyzing CO₂ emissions for different levels of congestion and time-definite customer demands. The author also carries out a case study in Portland, USA. An algorithm that consists of a route construction and a route improvement phase is described to solve the problem, using which the author analyzes the impact of different speed levels and different depot locations on emissions. The study by [72] focuses on a problem that finds paths with the least fuel consumption where vehicle speeds are time-dependent. The authors also conduct a case study with 14 customers and one depot located in Bristol, UK. They describe a time-increment-based dynamic programming algorithm and a new heuristic method consisting of a route selection and a speed adjustment stage. The application of the algorithms leads to about 6-7% savings in emissions. In [73], a distribution system operating over a pharmaceutical warehouse and 15 pharmacies in Ankara, Turkey is studied. The application of a simulation based restricted dynamic programming algorithm as a solution approach indicates that if the vehicles avoid heavily congested period to serve the pharmacies, then savings of 2.3% can be achieved on the total amount of emissions. Other application based studies are [74] and [75].

2.2.2 Tactical decision making

This section reviews studies concerning tactical decisions such as location-routing and allocation problems.

2.2.2.1 Location-routing problems

The first class of problems we review here are those that consider a joint treatment of location and routing decisions. The literature on such problems is still in its infancy when an explicit consideration of environmental performance of the transportation activities is concerned. Table 2.5 provides a summary of the

existing papers.

Table 2.5: Tabulated summary of location-routing problems incorporating environmental concerns

References	General				Model Specifications				Fuel Consumption						
	Net.	Obj.	Sol.	A.	Case	TW	TD	P&D	Unc	Emis.	M.	Dis	Loa	Spe	
[76]	Multi	Single	E			✓				Factor	P	-	-		
[77]	Multi	Multi	H								Factor	-	-	-	
[78]	Single	Single	E & H								Micro	P	D	P	
[79]	Single	Multi	E								Macro	P	D	P	
[80]	Multi	Multi	H		✓				✓	Micro	P	D	-		
[81]	Single	Multi	E & H		✓					Factor	P	D	-		

The first two of the studies listed in Table 2.5 address the location and routing decisions as part of a green network design problem. In particular, in [76], a retail store supply chain problem is described by considering CO₂ emissions, where the objective is to minimize the transportation cost, which includes costs relevant to operating vehicles, fuel consumption and emissions, and space (store) cost. A two-echelon network is considered with a warehouse, retailers and customers. To replenish the inventories, retailers travel to warehouses, which is formulated as a Traveling Salesman Problem, whereas the distribution problem for the customer is modeled as continuous version of p-median problem, to which inventory decisions are linked. The problem compares small local shops and big retailers with regards to this objective. The second study is by [77], who describe a two-echelon location-routing problem with time windows for a perishable food supply chain network with manufacturers, distribution centers and retailers. The model consists of two objective functions; to minimize the total cost and minimize the total environmental impact. The authors describe a multi-objective hybrid approach to solve that problem that combines two multi-objective algorithms, namely a multi-objective particle swarm optimization and a multi-objective variable neighborhood search.

The study by [78] analyzes the impact of location, fleet composition and routing on emissions in urban freight transportation. In this study, speed is not considered to be a decision variable but rather determined on the basis of different speed zones that cities are assumed to be divided into. The authors describe a location-routing problem with heterogeneous fleet of vehicles in a city logistics

concept. The problem is solved by means of an adaptive large neighbourhood search algorithm. On the basis of randomly generated but structured instances, the findings suggest that the depot locations are generally selected to be farther away from city centres even if this increases the distance, mainly due to being able to drive faster than the slow speeds assumed in city centres. In [79], a bi-objective green capacitated location-routing problem is presented where the two objective functions minimize the operational cost and fuel consumption and CO₂ emission, respectively. The ϵ -constraint method is used to solve the corresponding bi-objective mathematical model.

A real-life application is studied in [80] that is based on a supply chain of LCD and LED televisions assuming a two-echelon network. The network consists of 20 cities of Iran, each of which is a demand point, seven candidate depot locations and two suppliers. For this application, the authors introduce a sustainable closed-loop location-routing-inventory problem under mixed uncertainty where the objectives are to (i) minimize the total cost, (ii) minimize the environmental impact of CO₂ emissions, fuel consumption and wasted energy and (iii) maximize the social impact of the closed-loop supply chain. The authors present a stochastic-possibilistic programming formulation of the problem that treats some of the uncertainty through the use of fuzzy parameters, and propose a new hybrid two-stage solution algorithm. The last study we review in this section is the one by [81] which describes a green city hub location routing problem which is an extension of the location-routing problem with heterogeneous fleet with two objectives; to minimize the total cost and minimize CO₂ emissions. Solutions are obtained by decomposition that first generates vehicle routes which are fed into a set covering model solved by using a bi-objective branch-and-bound algorithm. The authors test their algorithm on instances obtained from industrial partners in Austria that include of 22 hubs, 898 or 1635 customers, and two or seven vehicle types. The authors conclude by suggesting that investing in facilities reduces pollution by showing trade-offs with cost.

2.2.2.2 Allocation problems

Problems arising at a tactical level of decision making also include those of allocation, in which decisions concern the assignment of customers to facilities (or depots) at given locations. In multi-echelon networks, allocation decisions are made at each echelon. For example, in a two-echelon network with suppliers, distribution centers and retailers, the allocation decisions include the assignment of distribution centers to the suppliers and the retailers to the distribution centers. Table 2.6 presents an overview of the studies of such problems with an explicit aim of reducing negative environmental impacts of transportation activities.

Table 2.6: Allocation problems with environmental concerns

References	General				Model Specifications				Fuel Consumption				
	Net.	Obj.	Sol.	A. Case	TW	TD	P&D	Unc	Emis.	M.	Dis	Loa	Spe
[82]	Multi	Single	E						Macro		P	-	D
[83]	Multi	Multi	E	✓					Factor		P	D	-
[84]	Multi	Multi	E	✓					LCA		-	D	-
[85]	Multi	Multi	H	✓					LCA		-	D	-
[86]	Multi	Single	E	✓					Factor		P	D	-
[87]	Single	Multi	H	✓					Macro		P	D	P
[88]	Single	Single	E	✓					Macro		P	D	P
[89]	Multi	Single	E	✓					Macro		P	D	P
[90]	Single	Single	E	✓					Factor		P	D	-
[91]	Single	Single	E & H	✓	✓			✓	Micro		-	D	-
[92]	Multi	Multi	E						Factor		-	D	-
[93]	Multi	Multi	E						Factor		-	D	-

Each study shown in Table 2.6 gives rise to a different formulation of the relevant problem. Rather than presenting the individual formulations, we provide below a general representative model that serves as a framework of allocation problems where environmental indicators are represented in an objective function using cost measures. The problem is defined on a directed graph where N is the set of nodes consisting of set of suppliers, distribution centers and retailers with the corresponding nodes denoted by the sets S , D and R , respectively. Each distribution center $j \in D$ has a storage capacity C_j and each retailer $k \in R$ has demand D_k . The unit transportation and CO₂ emissions cost per a unit distance are denoted by c_t and c_{co} , respectively, where d_{ij} represent the distances between two different nodes i and j . The decision variables of the formulation are defined as follows: Nonnegative continuous variables f_{ij} and g_{ij} represent the amount of

commodity carried between a supplier $i \in S$ and a distribution center $j \in D$, and a distribution center $j \in D$ and a retailer $k \in R$, respectively. A generic formulation for a basic allocation problem is as follows:

$$\text{Minimize } \sum_{i \in P} \sum_{j \in D} f_{ij} d_{ij} (c_{co} + c_t) + \sum_{j \in D} \sum_{k \in R} g_{jk} d_{jk} (c_{co} + c_t) \quad (2.28)$$

subject to

$$\sum_{i \in P} f_{ij} \leq C_j \quad \forall j \in D \quad (2.29)$$

$$\sum_{j \in D} g_{jk} = D_k \quad \forall k \in R \quad (2.30)$$

$$\sum_{i \in P} f_{ij} - \sum_{k \in R} g_{jk} = 0 \quad \forall j \in D \quad (2.31)$$

$$f_{ij} \geq 0 \quad \forall i \in P, j \in D \quad (2.32)$$

$$g_{jk} \geq 0 \quad \forall j \in D, k \in R. \quad (2.33)$$

The objective function (2.28) minimizes the total transportation and CO₂ emissions cost. Constraints (2.29) impose capacity limits on the distribution centers. Constraints (2.30) ensure that demand of each customer is fully met. Constraints (2.31) guarantee that all demand sent to a distribution center will be distributed to the customers allocated to that distribution center. Constraints (2.32) and (2.33) are the non-negativity restrictions on the decision variables.

Several studies look at allocation problems on variations or extensions of the formulation above. For example, in [82], a supply chain network design problem is studied that minimizes the costs relevant to transportation, noise pollution, CO₂ emissions and fuel consumption. The authors present an integer non-linear programming formulation of the problem. The study by [83] considers a food logistics network design problem for which the authors present a multi-objective linear programming model. The objectives are to minimize the total logistics cost and to minimize the total GHG emissions. The authors use the ϵ -constraint

method to identify the Pareto frontier, and present a real-life application for a beef logistics network in Brazil exporting products to the European Union.

Some studies include reverse logistics activities in the green network design problems. In such settings, end-of-life facilities are explicitly represented in the network, at which points the products are recycled and sent onwards to the suppliers. The study by [84] looks at design and evaluation of sustainable logistics network structures using a multi-objective optimization model in which the objectives relate to minimizing cost and environmental impacts. The authors describe a new technique to evaluate the efficiency of existing networks that exploits the similarities between data envelopment analysis and multi-objective programming. The European pulp and paper industry is used as a case study. A similar problem is studied by [85] where the authors propose a two-phase heuristic algorithm to find an approximation to the Pareto frontier, using a recycling logistics network in Germany as a real-life application of the problem. In [86], a sustainable reverse logistic network design problem is described for a multi-level network with multiple products, using a case study arising in the separation of plastic waste operations in the Netherlands.

Within the context of tactical level planning problems, there are studies that assume the use of different transportation modes on more complex networks where each mode of transportation has its own set of parameters, such as capacity and emissions. For example, in [87], a bi-objective design problem on a multimodal hub and spoke network is studied where the objectives are to minimize transport cost and CO₂ emissions and solved using the ϵ -constraint method. The authors apply the method to a problem arising in real-life freight distribution network connecting the ports of Rotterdam in the Netherlands and Gdansk in Poland. One other such study is by [88] on designing an intermodal freight network. The authors describe a large-scale integer linear programming formulation of the problem, and apply it on an intermodal network operating over Austria, the Czech Republic and Poland. [89], [90] and [91] are the other studies that consider different transportation modes.

Some studies on these problems apply game theoretic models. In [92], for

example, a transportation network design problem arising in a supply chain is considered with two objectives, one maximizing profit and the other minimizing emissions. The authors derive optimality and equilibrium conditions for the problem. The study of [93] describes a supply chain network design problem to which corporate social responsibility considerations are incorporated.

2.2.3 Strategic decision making

This section analyzes the studies in which long-term strategic decisions are made, such as those concerning facility location, with explicit environmental concerns in mind. Table 2.7 presents an overview of the relevant studies in this area on single echelon networks, which we describe in further detail below.

Table 2.7: Strategic location problems with environmental concerns defined on single echelon networks

References	General				Model Specifications				Fuel Consumption				
	Net.	Obj.	Sol.	A. Case	TW	TD	P&D	Unc	Emis.	M.	Dis	Loa	Spe
[94]	Single	Single	E	✓					Factor	-	D	-	
[95]	Single	Multi	H						Factor	P	P	-	
[96]	Single	Single	E & H	✓					Factor	P	D	-	
[97]	Single	Multi	E & H						Factor	P	-	-	
[98]	Single	Single	E		✓	✓			Micro	P	P	D	
[99]	Single	Multi	E & H					✓	Micro	P	D	P	
[100]	Single	Multi	H		✓				Micro	P	P	D	

In [94], a facility location problem with market competition is studied in which market prices and production costs are decided based on economic equilibrium. The authors impose a limit on emissions by considering a carbon trading mechanism. The study by [95] presents a multi-objective uncapacitated facility location problem where the objective functions are to minimize cost, to minimize CO₂ emissions and to maximize minimum service reliability. The problem is solved by a heuristic hybrid algorithm that uses the ϵ -constraint method. In [96], two problems, namely the p-median and the warehouse location problems, are described, where environmental and economic impacts of transportation activities are minimized. In [97], a capacitated facility location-allocation problem is presented by using multi-objective optimization where the objective functions are to minimize

the total cost and to minimize the CO₂ emissions. Solutions are obtained using a mixed integer linear programming formulation and a heuristic that combines a multi-objective evolutionary algorithm for the location decisions and Lagrangian relaxation for the allocation decisions. A green Weber problem and its time-dependent version are described in [98], where the decisions concern the location of a single facility, as well as speeds of the vehicles sent to customers, so that the total amount of CO₂ emissions is minimized. Second order cone programming formulations are used for both problems.

There are a couple of studies that look at environmental considerations within hub location problems. In particular, the study by [99] describes a sustainable hub location problem with three objectives, namely to minimize transportation costs, to minimize the total cost of noise pollution and to minimize the fuel consumption on arcs and at hubs. Another study that consider hub network is [100] which presents a bi-objective hub location problem assuming collaboration between a holding company and multiple carriers. The objective function maximizes the profits for both the company and the carriers. Fuel consumption and CO₂ emissions are modeled as tax for carriers in the objective function.

As for other strategic location(-allocation) problems that appear in the literature on multi-echelon networks, we present a summary in Table 2.8 and discuss these references in further detail below.

In [101], a supply chain network design problem is studied with the consideration of LCA principles and using multiple objective functions. The objectives are to maximize the net present value and to minimize the environmental impact. The authors propose a multi-objective mixed integer linear programming formulation and use the ϵ -constraint method to find the efficient frontier. In [102], environmental investment decisions are considered for facilities with two objective functions; to minimize the total cost and minimize CO₂ emissions from facilities and transportation activities. The study of [103] presents a two-echelon supply chain network design problem, where the objective is to minimize the costs of installation, handling, transportation and CO₂ emissions. The solution algorithm combines Lagrangian relaxation with a heuristic. In [104], a supply chain network

Table 2.8: Strategic location problems with environmental concerns defined on multi-echelon networks

References	General				Model Specifications				Fuel Consumption				
	Net.	Obj.	Sol.	A. Case	TW	TD	P&D	Unc	Emis.	M.	Dis	Loa	Spe
[101]	Multi	Multi	E	✓					LCA	P	-	-	
[102]	Multi	Multi	E	✓					Factor	P	D	-	
[103]	Multi	Single	H						Factor	P	D	P	
[104]	Multi	Multi	E	✓					Factor	-	D	-	
[105]	Multi	Multi	E & H	✓					Factor	-	D	-	
[106]	Multi	Multi	E	✓					Factor	-	D	-	
[107]	Multi	Multi	E	✓				✓	LCA	-	D	-	
[108]	Multi	Multi	E	✓					LCA	-	D	-	
[109]	Multi	Multi	E	✓					Factor	P	D	-	
[110]	Multi	Single	E	✓					LCA	P	D	-	
[111]	Multi	Multi	E						LCA	-	D	-	
[112]	Multi	Single	E					✓	Factor	-	D	-	
[113]	Multi	Single	E	✓				✓	Factor	-	D	-	
[114]	Multi	Multi	E	✓				✓	LCA	P	D	-	
[115]	Multi	Multi	E	✓					LCA	P	-	-	
[116]	Multi	Multi	E	✓					LCA	-	D	-	
[117]	Multi	Multi	E	✓					LCA	P	-	-	
[118]	Multi	Multi	E	✓					LCA	P	D	-	

design problem is studied in which the decisions concern the selection of the port of entry and transportation mode, and where the authors analyze the impact of using dedicated and shared warehouses on cost and emissions on a real-life application in the South-East Europe. The study of [105] revisits a case study that was looked at in [104], by casting the problem as a multi-objective green supply chain problem. The objectives separately minimize the total cost, total amount of CO₂ emissions and the total amount of Particulate Matters emitted. In addition to using exact methods such as the weighted sum and ϵ -constraint scalarization, the authors apply two well-known multi-objective evolutionary algorithms, namely SPEA2 and NSGA-II and devise an interactive solution mechanism that incorporates the indirect preferences of a decision maker. In [106], a multi-objective sustainable supply chain network design problem is studied where the objective is to minimize the economic, environmental and social impacts of the supply chain for a top wine company in Australia. The authors develop a customized model solved by an augmented ϵ -constraint method. Other similar studies are due to [107] and [108].

Similar to those discussed in previous sections, some studies make use of a carbon trading mechanism to minimize emissions. One of such studies is [109], which uses goal programming to solve a bi-objective network design problem minimizing total cost and the total amount of CO₂ emissions are minimized. In [110], a carbon-sensitive supply chain problem using green procurement strategies is proposed, where a single objective function minimizes the sum of the fixed costs, distribution costs, procurement costs and emissions cost related to the carbon trading mechanism. In [111], a bi-objective sustainable supply chain network design problem under an emission trading mechanism is presented that also includes reverse logistics activities. Other studies that consider a carbon trading mechanism are [112] and [113], both of which study green network design problems under uncertainty.

A number of studies have a particular focus on the design chemical supply chains with environmental consideration. For example, the study of [114] describes a sustainable chemical supply chain design problem where the objectives are to maximize the net present value and minimize the environmental impacts based on LCA principles. The authors formulated the problem as a bi-criterion stochastic mixed integer nonlinear programming model, which is then reformulated as a parametric mixed integer nonlinear programming model. Other similar studies are due to [115], [116], [117] and [118].

2.2.4 Other studies

In conducting this review, a number of papers were identified that did not necessarily focus on decision (optimization) problems arising in logistics network planning, but rather provided broader discussions and insights into green applications. For this reason, we review them here separately as opposed to being part of the three-level classification of decision-making. For example, some studies discuss the use of computerized routing and scheduling as well as vehicle telematics for reducing emissions (see, e.g., [119] and [120]). Others discuss the need to use geographical information system software in vehicle routing such as GIS, ArcGIS

and GPS (see, e.g., [121],[122],[123],[124],[125],[126]). In [127] and [128] the effect of innovative ideas, strategies or structural changes on environment is evaluated. In [129], a transit network design problem is proposed with green vehicles that produce lower emissions. Since the number of green vehicles is limited, they are only assigned to specific routes.

The use of other types of methods within green network design are discussed in various references, such as simulation (see, [130]), Analytic Network Process (see, [131]), constant factor approximation algorithms (see, [132]) and fuzzy-based approaches (see, [133] and [134]).

2.3 Conclusion and Further Research Directions

Given the increasing concerns on impacts of transportation, logistics and supply chain activities on the environment, the existing body of research is continually developing and expanding at a significant pace. This review has identified most of these studies to be on operational aspects, such as vehicle routing and scheduling, which are short-term plans for such activities. The work on integrating environmental concerns, although growing, is less developed at tactical and strategic levels of decision making, and as such it will be important to understand the implications of longer term decisions, such as facility location, customer allocation and transport mode choice, on the environment as well as on the economic viability of the underlying logistics system.

This review has highlighted that a good portion of the relevant OR literature in this field makes use of multi-objective optimization tools in formulating, solving and analyzing green network design problems. This is not entirely surprising given the ability of multi-objective optimization tools allowing for separate treatment of various objectives that are not all necessarily commensurable (e.g., cost in monetary units versus emissions in grams). This is all the more important as

not all environmental considerations can be measured in monetary units. Such tools also allow identifying the trade-offs between what seem to be conflicting objectives, although in some cases there may be win-win situations.

A common way in dealing with green network design problems seems to be an explicit integration of the environmental factors, such as emissions, noise pollution, carbon trading mechanisms and energy usage, into the existing models of such problems. This typically manifests itself in the form of an augmented (and often more complicated) objective function(s), where the aim is often to minimize the environmental consequences along with the traditional operational cost measures. The one aspect that comes across clearly from a methodological point of view is that, such integrations give rise to problem extensions that are often as challenging, if not more difficult, to solve. Most of the solution algorithms, which have been described for the solution of such problems, seem to be modifications of the existing ones.

The explicit goal of reducing emissions assumes the availability of models that adequately capture the type of factors affecting fuel consumption that is inherently linked to emissions, the degree to which such factors affect fuel usage and the accuracy of estimations. Whilst there is good body of work on this aspect, offering models that range from macroscopic to microscopic, from factor models and wide-area assessment tools, there is still some room for studies that offer empirical evidence as to the accuracy of such models. These models are generally used for operational activities. The consideration of higher-level design problems such as facility location require a good understanding of the emissions caused by the processes within such entities (e.g., energy use within manufacturing facilities or container ports), which also need further investigation.

Finally, we mention the importance of the choice of transport mode in designing distribution networks, given the unique characteristics and environmental performance of each individual mode of transport. Modal shift, a term that has long been known and discussed within logistics to reduce the environmental externalities, can be captured at sufficient levels of detail within strategic and tactical decision making problems discussed above, which would allow for assessing

the trade-offs associated with shifting of freight on economic and environmental measures of performance.

In this literature review, we observe that some of the well-known network design problems such as location-routing and hub location problems are not studied in detail with an explicit consideration of fuel consumption models to measure environmental impacts. Therefore, we first present two problems in which vehicle payload and vehicle speed are considered as decisions since both of these terms have a direct impact on fuel consumption. Then, in order to fill the gap in the literature related to the problems with more than one transportation mode and to adapt new technological developments into the freight transportation, we propose a new delivery problem, in which trucks and drones are used together to make deliveries to customers and we also present an extension to that problem, where uncertainty of wind speed and its impact on drones is analyzed. In both versions of the problem, drone speed is considered as a decision, which directly affects energy consumption and range of a drone and also delivery time to customers.

Chapter 3

Green Location-Routing Problem

In this chapter, we introduce the Green Location-Routing Problem (GLRP), an extension of the Location-Routing Problem that explicitly accounts for fuel consumption and CO₂ emissions, the amount of which is measured by a widely used emission model, that is the CMEM. The GLRP consists of locating depots on a subset of a discrete set of points, from where vehicles of limited capacity will be dispatched to serve a number of customers with service requirements, and routing the vehicles by determining the order of customers served by each vehicle and the speeds on each leg of the journey, such that customers are served within their respective time windows and vehicle capacities are respected. The objective is to minimize a total cost function comprising location, fuel and emission costs. As for the network, we assume a single echelon structure including the depot(s) and the customers.

The structure of this chapter is as follows: Section 3.1 provides motivations to work on this study by providing different application areas. Section 3.2 formally defines the GLRP, provides a mixed integer linear programming formulation for the GLRP along with a set of preprocessing rules and valid inequalities to strengthen the formulation. Section 3.3 presents two solution algorithms; one is to solve small-sized GLRP instances in reasonable times to near-optimality, and the other to efficiently solve large-sized GLRP instances. Section 3.4 presents

extensive computational analyses on the GLRP to quantify the benefit of the location decisions on internal (operational) and external (environmental) costs, and to evaluate the performance of the heuristic algorithms. Section 3.5 describes a case study based on the GLRP in Istanbul, Turkey. Section 3.6 presents an extension in which we study optimal solution characterizations for the special cases of the GLRP. Conclusions are given in Section 3.7.

The results of this chapter are published in *Computers & Operations Research* [135].

3.1 Introduction and Motivation

The Location-Routing Problem (LRP) is a generalization of the vehicle routing problem that exploits the interdependency between the location decisions of facilities and routing decisions of vehicles, as it has been shown in [136] that making the two decisions independently can result in suboptimal solutions. The basic LRP involves locating facilities and routing a fleet of vehicles from the facilities to serve a given set of customers, with the aim of minimizing the cost of location and routing [see, e.g., 137, 138, for comprehensive surveys].

Although not many scientific studies yet exist on the LRP with an explicit consideration of fuel consumption and emissions as it can be seen in Section 2.2.2.1, recent developments in practice suggest that this is a growing area of attention, particularly in cargo and fast-moving consumer goods (FMCG) industries. Unilever, for example, who operates in the FMCG industry, has adopted a new Transport Management System since 2012, which optimizes transport flows between suppliers, factories, warehouses and retailers, using a new network structure. Increasing transport and fuel efficiency and reducing emissions are the main drivers behind this system (see, [139]). Similar initiatives have been put in place by other companies, such as UPS who achieved a reduction of 25,000 metric tonnes of CO₂ through optimizing their network in 2015 (see, [140]), and FedEx

who invested in an EarthSmart program since 2010 to reduce transportation related emissions by optimizing vehicle loads and routes (see, [141]). FedEx also ask their drivers to apply idle reduction and speed control techniques to reduce fuel consumption (see, [142]). DHL opened a new logistics center in Milan to reduce emissions as part of network design in the GoGreen environmental protection program. This new center, which is located in a strategic region of Milan that can be combined with air and sea transportation, uses 120 trucks to deliver 810,000 tons of goods per year. A recent press release in [143] indicates that the new DHL center has resulted in an “estimated reduction of facility and transport CO₂ emissions of 18 per cent at the new site. 13 per cent of which can be traced back to an improved road network and a reduction of both transit time and the average fuel consumption”. Recently, DHL has made another significant investment by opening a logistics hub in Milan Malpensa Airport which transports 60% of Italian goods and is the sixth largest cargo airport in Europe. One of the company executives emphasizes that the company will focus on the environmental sustainability for this new hub, which requires an investment of €350M over the next five years (see, [144]).

Another application area of the GLRP has emerged due to recent developments in on-road vehicle technologies. One example where this is being put in practice is a European Commission research project known as Sartre - Safe Road Trains for the Environment. In this application, a lead vehicle (usually a truck) travels ahead of a platoon formed by other semi-autonomous vehicles, which all follow and travel at the same speed as the lead vehicle. The ability to maintain a constant speed allows to achieve reductions in congestion, fuel consumption and accidents. Trials of the road train technology were successfully held in Sweden (see, [145]) and Spain (see, [146]). Another more recent practice is the use of autonomous vehicles. These type of vehicles also maintain a relatively constant speed on the road compared to conventional vehicles. Recently, Daimler AG, an automotive corporation that owns Mercedes-Benz, launched two autonomous trucks; Mercedes-Benz Future Truck 2025 (see, [147]) and Freightliner Inspiration Truck (see, [148]). Although these vehicles are still being trialled, they are expected to be driven on the roads in the near future (see, [149]). Consequently,

most of the leading cargo companies have started to consider using such new technologies in their delivery operations; DHL published a report in [150] on self-driving vehicles in logistics based on its benefits and applications, US Postal Service is planning to make deliveries using self-driving mail trucks within seven years (see, [151]), FedEx is also interested in autonomous vehicles and is collaborating with the manufacturers, Daimler and Volvo (see, [152]), and Amazon formed a team to study self-driving vehicles (see, [153]).

These recent initiatives and applications serve to illustrate the growing importance of the need to optimize the network structure to be able to reduce environmental externalities, which include decisions concerning routing and location.

3.2 Problem Description and Formulation

The GLRP is defined on a complete directed graph $G = (N, A)$ where $N = \{1, \dots, n\}$ denotes the set of nodes representing both the set of customers and the potential sites for a total of p depots to be located, and $A = \{(i, j) : i, j \in N, i \neq j\}$ is the set of arcs. The fixed cost of operating a depot at node $i \in N$ is denoted by c_i . A fleet of m identical vehicles, each with capacity C serves the customers across the p depot(s). The distance on arc $(i, j) \in A$ is denoted by d_{ij} . Each customer i has a nonnegative demand q_i . The service time and time windows at node $i \in N$ are denoted by s_i and $[l_i, u_i]$, respectively. If a vehicle arrives at customer i before l_i , it waits until l_i and then service starts. The minimum and maximum speed limits for vehicles are denoted by v^l and v^u , respectively. The unit combined fuel consumption and emission cost is denoted by e .

3.2.1 Calculating fuel consumption and emissions

The CMEM was proposed by [43], [44], [45] in order to estimate fuel consumption for heavy-goods vehicles. Since emissions are directly related to fuel consumption,

one can easily calculate the amount of emissions when the fuel consumption is known. Compared to other microscopic emission models in the literature, it requires more detailed vehicle specific parameters such as the engine friction coefficient and the vehicle engine speed.

Based on the CMEM, the fuel consumption rate, F_r (in g/s) can be calculated as,

$$F_r = \xi(K\Upsilon V + P/\eta)/\kappa,$$

where ξ is the fuel-to-air mass ratio, K is the engine friction factor (in kJ/rev.L), Υ is the engine speed (in rev/s), V is the engine displacement (in L), η is the efficiency parameter for diesel engines and κ is the heating value of a typical diesel fuel (in kJ/g). Finally, P is the second-by-second engine power output (in kW) and can be calculated as follows:

$$P = P_{tract}/n_{tf} + P_{acc},$$

where n_{tf} is the vehicle drive train efficiency and P_{acc} is the engine power demand associated with running losses of the engine and the operation of vehicle accessories such as air conditioning usage (assumed to be zero). P_{tract} is the total tractive power requirement (in kW) and can be calculated as follows:

$$P_{tract} = (Ma + Mg \sin \theta + 0.5C_d \rho S v^2 + MgC_r \cos \theta)v/1000,$$

where M is the total weight of the vehicle (in kg) including the empty vehicle weight ω and payload, a is the instantaneous acceleration (in m/s²), g is the gravitational constant (in m/s²), θ is the road angle, C_d is the coefficient of aerodynamic drag, ρ is the air density (in kg/m³), S is the frontal surface area (in m²), v is the vehicle speed (in m/s) and C_r is the coefficient of rolling resistance.

To simplify the above formulation, some new parameters are used as follows: $\lambda = \xi/\kappa\psi$ where ψ is the conversion factor of fuel from g/s to L/s, $\gamma = 1/1000n_{tf}\eta$, $\delta = a + g\sin\theta + gC_r\cos\theta$ is a vehicle-arc specific constant and $\beta = 0.5C_d\rho S$ is a vehicle-specific constant. By using the new parameters, the total fuel consumption $F(v, M)$ (in L) of a vehicle traversing a road segment of d units (in m) as a function of speed v and total weight M , can be given as follows:

$$F_r d/v = F(v, M) = \alpha\lambda\gamma dM + \lambda\gamma\beta dv^2 + \lambda K\Upsilon V d/v.$$

As it can be seen from the expression above, the CMEM consists of three modules, namely the weight module (shown by $\alpha\lambda\gamma dM$), the speed module (defined by $\lambda\gamma\beta dv^2$) and the engine module (expressed by $\lambda K\Upsilon V d/v$). These three modules are explicitly included in the objective function of the mathematical model in the following section.

Similar to other routing problems (see, e.g., [24], [46], [47]) that use CMEM as the emission model, we also treat speed and load as decision variables in order to estimate the emissions more accurately. This makes our study different than other studies that consider a location-routing problem with environmental concerns.

3.2.2 An integrated model of location, routing, fuel consumption and emissions

In this section, we propose a mixed integer programming formulation for the GLRP which is based on the model developed by [24]. The decision variables are defined as follows: A binary variable x_{ij}^k equals 1 if a vehicle that is assigned to depot $k \in N$ travels on arc $(i, j) \in A$, and 0 otherwise. If the customer at node $i \in N$ is assigned to a depot at node $k \in N$, then a binary variable y_{ik} equals 1, and 0 otherwise. The service start time at node $j \in N$ is denoted by a continuous nonnegative variable t_j . Similarly, a continuous nonnegative variable f_{ij} represents the total amount of flow on arc $(i, j) \in A$.

As the vehicle speed is a decision variable, some of the objective function components and constraints of the formulation will have non-linear terms due to the emission function used. To linearize these terms, we adapt the discretization technique applied for the PRP by [24]. To that end, a finite set $R = \{1, \dots, r, \dots\}$ of speed levels is defined where $r \in R$ corresponds to a fixed speed v^r . In order to include the speed decision into the model, a new binary variable, w_{ij}^{kr} , is introduced which takes the value of 1, if a vehicle allocated to depot $k \in N$ travels with a speed level $r \in R$ on arc $(i, j) \in A$, and 0 otherwise. A mathematical model of the GLRP is as follows:

$$\text{Minimize } \sum_{k \in N} c_k y_{kk} \quad (3.1)$$

$$+ e \sum_{(i,j) \in A} \left[(\alpha \gamma \lambda d_{ij} \omega \sum_{k \in N} x_{ij}^k) \right] \quad (3.2.1)$$

$$+ (\alpha \gamma \lambda d_{ij} f_{ij}) \quad (3.2.2)$$

$$+ (\beta \gamma \lambda d_{ij} \sum_{k \in N} \sum_{r \in R} (v^r)^2 w_{ij}^{kr}) \quad (3.2.3)$$

$$+ (K \Upsilon V \lambda d_{ij} \sum_{k \in N} \sum_{r \in R} \frac{w_{ij}^{kr}}{v^r}) \quad (3.2.4)$$

subject to

$$\sum_{k \in N} y_{ik} = 1 \quad \forall i \in N \quad (3.3)$$

$$y_{ik} \leq y_{kk} \quad \forall i, k \in N \quad (3.4)$$

$$\sum_{k \in N} y_{kk} = p \quad (3.5)$$

$$\sum_{k \in N} \sum_{j \in N \setminus \{k\}} x_{kj}^k \leq m \quad (3.6)$$

$$\sum_{j \in N \setminus \{i\}} x_{ij}^k = y_{ik} \quad \forall i, k \in N : k \neq i \quad (3.7)$$

$$\sum_{j \in N \setminus \{i\}} x_{ji}^k = y_{ik} \quad \forall i, k \in N : k \neq i \quad (3.8)$$

$$\sum_{j \in N \setminus \{k\}} x_{jk}^k = \sum_{j \in N \setminus \{k\}} x_{kj}^k \quad \forall k \in N \quad (3.9)$$

$$\sum_{r \in R} \left(\frac{d_{kj}}{v^r} \right) w_{kj}^{kr} \leq t_j \quad \forall j, k \in N : k \neq j \quad (3.10)$$

$$t_i + s_i + \sum_{r \in R} \left(\frac{d_{ij}}{v^r} \right) w_{ij}^{kr} - (u_i + s_i)(1 - x_{ij}^k) \leq t_j \quad \forall (i, j) \in A, k \in N : k \neq i, j \quad (3.11)$$

$$\sum_{r \in R} w_{ij}^{kr} = x_{ij}^k \quad \forall (i, j) \in A, k \in N \quad (3.12)$$

$$l_j(1 - y_{jj}) \leq t_j \quad \forall j \in N \quad (3.13)$$

$$t_j \leq u_j(1 - y_{jj}) \quad \forall j \in N \quad (3.14)$$

$$\sum_{j \in N \setminus \{i\}} f_{ji} \leq \sum_{j \in N \setminus \{i\}} f_{ij} - q_i(1 - y_{ii}) + \sum_{k \in N} q_k y_{ii} \quad \forall i \in N \quad (3.15)$$

$$\sum_{j \in N \setminus \{i\}} f_{ij} \leq C(1 - y_{ii}) \quad \forall i \in N \quad (3.16)$$

$$f_{ij} \leq C \sum_{k \in N} x_{ij}^k \quad \forall (i, j) \in A \quad (3.17)$$

$$x_{ij}^k \in \{0, 1\} \quad \forall (i, j) \in A, k \in N \quad (3.18)$$

$$y_{ik} \in \{0, 1\} \quad \forall i, k \in N \quad (3.19)$$

$$w_{ij}^{kr} \in \{0, 1\} \quad \forall (i, j) \in A, k \in N, r \in R \quad (3.20)$$

$$t_j \geq 0 \quad \forall j \in N \quad (3.21)$$

$$f_{ij} \geq 0 \quad \forall (i, j) \in A. \quad (3.22)$$

The objective function consists of two components. The first, shown by (3.1), minimizes the fixed cost of operating depots. The second part shown collectively

by (3.2.1)–(3.2.4) minimizes the total cost of fuel consumption and emissions estimated by the CMEM described in Section 3.2.1. In particular, the first two components (3.2.1) and (3.2.2) represent the weight module of the emission model in which (i) the empty vehicle weight ω is represented by the load-independent component (3.2.1), and (ii) the weight of the load carried associated to the load-dependent component (3.2.2) is represented by the flow variable f . Components (3.2.3) and (3.2.4) calculate the fuel consumption and emissions due to the speed and engine modules of the CMEM, respectively. Constraints (3.3) ensure that every customer is assigned to exactly one depot. Constraints (3.4) stipulate that if a depot is not opened at a node, then none of the customers can be assigned to the depot at that node. Constraint (3.5) sets the number of depots to be opened equal to p . Constraint (3.6) guarantees that at most m vehicles can be used to serve the customers. With Constraints (3.7) and (3.8), it is ensured that if a customer is assigned to a specific depot, then a vehicle visits this customer before and after two other customers which are also assigned to this depot or just depot. Constraints (3.9) ensure that the number of vehicles that leave and that arrive at the depot is the same. Constraints (3.10)–(3.14) are related to time and speed. Constraints (3.10) calculate the arrival time of a vehicle at the first customer visited after leaving the depot. Constraints (3.11) calculate the arrival times of a vehicle at customers assigned to the same depot as the vehicle. Constraints (3.11) are an adaptation of the well known subtour elimination constraints proposed by [154] and prohibit the formation of tours solely within customer nodes. With Constraint (3.12), vehicles can use only one of the specified speed levels over an arc. Constraints (3.13) and (3.14) model the time window constraints for customers. These constraints also stipulate that, if a depot is located at a node j (i.e., $y_{jj} = 1$), then $t_j = 0$, indicating that the customer at node j is served immediately. Constraints (3.15) provide flow conservation between nodes except where a depot is opened. In particular, f_{ij} is the total amount of demand in the route until, but excluding, customer j , and where a customer at node k is not taken into account if k is selected as a depot. Constraints (3.16) and (3.17) collectively enforce the vehicle capacity constraints on the flow on each arc. Finally, Constraints (3.18)–(3.22) are the domain constraints on the variables.

3.2.3 Preprocessing and valid inequalities

This section describes some preprocessing rules and valid inequalities to strengthen the formulation presented in the previous section, and to potentially reduce solution times to optimality.

We first present a couple of variable fixing rules for w_{ij}^{kr} variables, which we implement prior to solving the formulation:

- If $l_i + s_i + \frac{d_{ij}}{v^r} > u_j$, then $w_{ij}^{kr} = 0$
- If $\frac{d_{kj}}{v^r} > u_j$, then $w_{kj}^{kr} = 0$.

The first rule dictates that if the sum of the lower time limit l_i at node i , the travel time $\frac{d_{ij}}{v^r}$ between nodes i and j and the service time s_i at node i is greater than the upper time limit u_j at node j , then w_{ij}^{kr} is set equal to zero. The second preprocessing rule is a special case of the first one where j is the first customer after the depot.

Next, we describe several valid inequalities in order to strengthen the linear programming (LP) relaxation of the mathematical formulation in the expectation of reducing the CPU times. These inequalities narrow the solution space by eliminating some fractional solutions and can provide stronger lower bounds for the problem.

First, we consider two-node subtour breaking constraint proposed by [155] in order to eliminate cycles between two customers and develop two different valid inequalities as shown below:

$$x_{ij}^k + x_{ji}^k \leq y_{ik} \quad \forall (i, j) \in A, k \in N : k \neq i, j \quad (\text{VI 3.1.1})$$

$$\sum_{k \in N \setminus \{i, j\}} (x_{ij}^k + x_{ji}^k) \leq \sum_{k \in N \setminus \{i, j\}} y_{ik} \quad \forall (i, j) \in A. \quad (\text{VI 3.1.2})$$

Valid inequalities (VI 3.1.1) and (VI 3.1.2) ensure that if a customer is assigned

to a specific depot, then this customer and any other customer assigned to the same depot can have a link between them in only one direction.

Second, we develop a flow based valid inequality (VI 3.2), which ensures that the amount of flow on arc $(i, j) \in A$ is larger than the demand q_i of node $i \in N$, unless node i is selected as a depot.

$$q_i \left(\sum_{k \in N} x_{ij}^k - y_{ii} \right) \leq f_{ij} \quad \forall (i, j) \in A. \quad (\text{VI } 3.2)$$

The valid inequality we propose next (VI 3.3) provides a lower bound on the number of vehicles required, which is derived from the ratio of the demand of all customers (excluding depots) to the vehicle capacity.

$$\frac{\sum_{k \in N} q_k (1 - y_{kk})}{C} \leq \sum_{k \in N} \sum_{j \in N \setminus \{k\}} x_{kj}^k. \quad (\text{VI } 3.3)$$

Similar inequalities to (VI 3.3) were first proposed by [156] for a vehicle routing problem, and later adapted for a location-routing problem by [157]. The last sets of inequalities are stronger versions of the time window constraints (3.13) and (3.14). These inequalities are the adapted versions of [24] proposed for the PRP.

$$l_j (1 - y_{jj}) + \sum_{i \in N \setminus \{j\}} \sum_{k \in N \setminus \{i, j\}} \sum_{r \in R} \max(0, l_i - l_j + s_i + \frac{d_{ij}}{v^r}) w_{ij}^{kr} \leq t_j \quad \forall j \in N \quad (\text{VI } 3.4.1)$$

$$t_j \leq u_j (1 - y_{jj}) - \sum_{i \in N \setminus \{j\}} \sum_{k \in N \setminus \{i, j\}} \sum_{r \in R} \max(0, u_j - u_i + s_j + \frac{d_{ji}}{v^r}) w_{ji}^{kr} \quad \forall j \in N. \quad (\text{VI } 3.4.2)$$

Valid inequality (VI 3.4.1) implies that service of a customer at node $j \in N$ starts after either the customer's lower time limit (l_j) or the sum of the lower time limit (l_i) and service time (s_i) of a customer at node $i \in N$ that proceeds it, and the travel time ($\frac{d_{ij}}{v^r}$) between these two customers. Similarly, valid inequality (VI 3.4.2) guarantees that service of a customer at node $j \in N$ starts before either the customer's upper time limit (u_j) or the time that ensures that the next customer's $i \in N$ service starts before its upper time limit (u_i) at worst.

3.3 Heuristic Algorithms for the GLRP

In this section, we present two heuristic algorithms to solve the GLRP. Both algorithms first divide the GLRP into subproblems; namely, the Cumulative Location Routing Problem (CumLRP) and the Speed Optimization Problem (SOP), and solve each in a hierarchical manner. In particular, once the CumLRP is solved, the location of the depots and the routes of the vehicles are determined. The SOP is then solved using the routes of the vehicles in order to identify the optimum speeds for the vehicles. The solutions found by the algorithms are feasible for the GLRP since they satisfy all the constraints imposed by the GLRP formulation. We describe the two heuristic algorithms in more detail below.

3.3.1 Cumulative location-routing and speed optimization algorithm (CLRSOA)

The Cumulative location-routing and speed optimization algorithm (CLRSOA) works as follows; first, one of the CumLRP formulations that will be introduced in Section 3.3.1.1 is solved to optimality. During the optimization process, some feasible solutions are stored in the “solution pool”. Based on the depot locations and vehicle routes, the SOP is solved by the Speed Optimization Algorithm (SOA) explained in Section 3.3.1.2 for each of the solutions in the pool. Then, a feasible solution with the lowest objective function value is selected as the solution of the CLRSOA.

Next, we will present the mathematical formulations and solution techniques for the two subproblems.

3.3.1.1 Cumulative location-routing problem

The Cumulative Location-Routing Problem (CumLRP) is a special case of the GLRP where the time window constraints are relaxed and where the speed-induced fuel consumption cost is not included in the objective function. In other words, the objective function only minimizes the weight-induced fuel consumption cost. In [158], the Cumulative Vehicle Routing Problem is introduced, where only routing decisions are made and where a factor model is used to estimate fuel consumption instead of a microscopic emission model as in the CumLRP. To the best of our knowledge, the CumLRP has not yet been defined in the literature. The main difference between the CumLRP and the classical LRP is the objective function. The classical LRP minimizes the operational cost that is a function of the total distance traveled. In the CumLRP, the operational cost depends on both the distance traveled and the load of the vehicle.

An integer programming formulation of the CumLRP can be derived by removing the speed related objective function components (3.2.3–3.2.4), as well as the speed and time related decision variables and constraints from the GLRP formulation (Constraints 3.10–3.14). The mathematical model of the CumLRP is as follows:

$$\text{Minimize } (3.1) + (3.2.1) + (3.2.2)$$

subject to

$$(3.3)-(3.9), (3.15)-(3.19), (3.22).$$

In addition to the above CumLRP formulation, we also propose a different version of the CumLRP formulation called CumLRP' to diversify the solutions in the “solution pool”. In the CumLRP', we assume that the vehicles travel at the optimal speed v^* on each arc of the network, calculated as follows. The fuel consumption function $F(v, f)$, which depends on speed v and load f , can be written as:

$$F(v, f) = (\alpha\gamma\lambda dw) + (\alpha\gamma\lambda df) + (\beta\gamma\lambda dv^2) + (K\Upsilon V\lambda d/v),$$

from which $v^* = \sqrt[3]{\frac{K\Upsilon V}{2\beta\gamma}}$ is obtained as the global minimizer. The objective function of the CumLRP' formulation is the same as that of GLRP when $v^r = v^*$ for all $r \in R$.

The main difference between the CumLRP and the CumLRP' formulations is that in the latter, we add the cost components (3.2.3)–(3.2.4) in the objective function with the assumption that the vehicles travel at the optimal speed v^* , which makes the optimal value of the CumLRP' formulation a valid lower bound for the corresponding GLRP.

To solve the CumLRP or CumLRP' formulations within the CLRSOA, we use three different solution strategies of the solver CPLEX to diversify the solutions in the “solution pool”. The first one is the default “dynamic search”, the second is “traditional branch and cut” without the cuts (pure branch and bound algorithm), and third, a cut-and-branch method using the second technique with some of the valid inequalities presented in Section 3.2.3 added at the root node.

3.3.1.2 Speed optimization problem

Once the location of depots and route of vehicles are known, the only remaining decision is the speed to be used over each arc so that time windows will be obeyed and the total ‘cost’, which is composed of speed-induced fuel consumption will be optimized. The speed optimization problem is introduced by [46] for road transportation. Given a route and time windows for each customer, the problem decides the vehicle speed on each arc of the route while minimizing the total cost including fuel consumption and driver cost. As the estimation of fuel consumption is non-linear, the authors presented a non-linear formulation.

Since we do not consider driver cost in the GLRP, we only minimize the fuel consumption in our version of the speed optimization problem. In addition, we do not need to decide on the vehicle speed for the arc between the last customer

visited before the depot and the depot itself since the vehicles travel at the optimal speed v^* on this arc because there is no time related constraint for returning the depot. Based on these differences between the formulation proposed by [46] and our version, we reformulate the corresponding speed optimization problem.

Speed optimization algorithm

In order to solve the SOP, we use the speed optimization algorithm (SOA) which is first proposed by [159] and [160] for maritime transportation. The algorithm is first adapted by [46] for ground transportation. The authors state that the algorithm finds the optimal solution due to convexity of the objective function. We adapt the algorithm proposed by [46] to our problem. The pseudo-code of the algorithm is presented in Appendix A.1. The main difference of our algorithm compared to the one proposed by [160] is while calculating the vehicle speeds we consider the time windows, the minimum and maximum speed limits and the optimal speed (v^*).

In [161], a speed and departure time optimization algorithm is developed, which is very similar to the algorithm proposed by [46]. They reformulate the speed optimization problem and prove the optimality of their algorithm by using the necessary and sufficient Karush-Kuhn-Tucker optimality conditions of the reformulated version of the speed optimization problem. Their proof can easily be adapted to prove our version of the speed optimization algorithm.

We note here that the proposed algorithm gives the exact value of vehicle speed that minimizes the fuel consumption, rather than a discretized speed level as in the green location routing problem formulation. Therefore, it provides a more accurate estimation for fuel consumption.

3.3.2 Iterated local search algorithm

We also develop an Iterated Local Search (ILS) algorithm for the GLRP. The ILS approach is first proposed by [162]. The ILS algorithm has already been applied

to several vehicle routing problems along with some location-routing problems in the literature (see, for example, [163] and [164]).

The main structure of the proposed algorithm is shown in Algorithm 3.1.

Algorithm 3.1 Iterated Local Search

```

1:  $Iter \leftarrow 1, f(s^*) \leftarrow \infty$ 
2: for  $Iter \leftarrow 1$  to  $MaxIter$  do
3:   Generate an initial solution  $s$ 
4:    $\bar{s} \leftarrow s, Iter_{NI} \leftarrow 0$ 
5:   while  $Iter_{NI} < MaxIter_{NI}$  do
6:      $s' \leftarrow Local\ Search(s)$ 
7:     if  $f(s') < f(\bar{s})$  then
8:        $\bar{s} \leftarrow s'$ 
9:        $Iter_{NI} \leftarrow 0$ 
10:    end if
11:     $s \leftarrow Perturbation(\bar{s})$ 
12:     $Iter_{NI} \leftarrow Iter_{NI} + 1$ 
13:  end while
14:  if  $f(\bar{s}) < f(s^*)$  then
15:     $s^* \leftarrow \bar{s}$ 
16:  end if
17: end for
18: return  $s^*$  and  $f(s^*)$ 

```

The proposed ILS algorithm consists of three main components; initial solution, local search and perturbation. At each iteration $Iter$, the algorithm first generates an initial feasible solution s , which is also assigned as the incumbent solution $\bar{s}$ (lines 3 to 4). Then, a local search procedure is applied to this initial solution to find a new solution s' (line 6). If the objective function value of this new solution $f(s')$ is less than that of the incumbent solution $f(\bar{s})$, then this new solution s' becomes the incumbent solution $\bar{s}$ (lines 7 to 8). To escape from a local optimum solution, the algorithm perturbs the incumbent solution $\bar{s}$ and generates a new starting solution s (line 11). These local search and perturbation procedures repeat until a certain number $MaxIter_{NI}$ of iterations without improvement is reached (lines 5 to 13). Finally, if the objective function of the incumbent solution $f(\bar{s})$ is less than the that of the global best solution $f(s^*)$, then the incumbent solution $\bar{s}$ replaces the global best solution s^* (lines 14 to 15).

The algorithm continues until a certain number $MaxIter$ of iterations is reached (lines 2 to 17).

3.3.2.1 Initial Solution

Initial feasible solutions to the GLRP are generated by first locating the depots and then assigning the customers to the located depots. The depot decisions are made in two different ways. In the first iteration of the algorithm ($Iter = 1$), we select the first p depots that have the lowest average distances to the customers. In the subsequent iterations ($Iter > 1$), we identify a larger set of $p + k$ candidate depot locations that have the lowest average distances to the customers, where $k > 1$ is an integer, and randomly locate p depots from within this set. Once the depot locations are fixed, customers are assigned to their nearest depots in the first $\delta\%$ of the total number $MaxIter$ of iterations of the algorithm. In the rest of the algorithm, the assignments of customers to depots are done randomly. The effect of such random assignments on the algorithm's performance is numerically investigated in later sections.

To construct the routes, we use the savings algorithm proposed by [165]. At the beginning of the savings algorithm, vehicles serve only one customer, which means after visiting a customer, the vehicle returns the depot directly without visiting any other customers. After constructing the tours in this manner, the algorithm calculates the potential savings to be gained if two different tours are combined. Then, starting from the maximum savings combination, the algorithm combines tours until there is no savings combinations left. While combining the tours, our version of this algorithm also respects vehicle capacity and customer time window constraints. After constructing the tours, the SOA is applied to find the optimal vehicle speeds.

3.3.2.2 Local Search

For the local search procedure, initially, the algorithm uses removal and insertion operations between the tours. Initially, two tours are selected; one from which a customer will be removed and the other to which the removed customer will be inserted. The selection of tours are random except for single-customer tours. In this case, a customer from the tour with the highest number of customers is removed and inserted into a single-customer tour.

The selection of the customer that will be removed and the selection of the position into which that customer will be inserted are decided as follows. First, the cost of a customer is calculated as the difference of total distance of the tour with and without that customer. The customer with the highest cost on tour is selected to be removed from the former tour. Then, the position that removed customer will be inserted is selected based on its impact on the latter tour. The algorithm selects the position with the lowest impact on the tour in terms of distance and then it inserts the removed customer into that position.

After the removal and insertion operators, the well-known two-opt algorithm proposed by [166] is used where two edges from a tour are removed and then two resulting paths are reconnected in a different way. In our algorithm, for each tour in the solution, all possible two-opt moves are applied. After these moves, if an improvement is achieved, the same two-opt procedure is applied to the new improved solution until there is no improvement in the solution. Any two-opt move that violates the time window constraints are not allowed in this algorithm. After each two-opt move, the SOA is also applied to the tours to find the optimal vehicle speeds.

3.3.2.3 Perturbation Search

In the perturbation stage, the algorithm again uses removal and insertion operations between the tours. The tour selection is the same as the one in local search. However, the selection of the customer that will be removed and the selection

of the position into which that customer will be inserted are made randomly. Any move that cause an infeasible solution due to the capacity or time window constraints are not allowed in the algorithm.

3.4 Computational Results

In this section, we present extensive computational results and analyses on the GLRP and also the performance of the solution approaches. The aim of the computational analysis is three-fold. First, we test the formulation proposed for the GLRP and the effect of the valid inequalities on its performance. Second, we conduct a detailed analysis on the GLRP by numerically assessing the effect of a number of parameters, such as depot cost, fuel consumption and emission cost, time windows, depot locations and vehicle speed. Third, we compare three solution approaches for the GLRP, namely to use the GLRP formulation and two heuristic methods.

The computational experiments were carried out on a server using 4 AMD Opteron Interlagos 6282 SE and with 96 GB of RAM. All mathematical models and algorithms were implemented in Java. The IBM ILOG CPLEX Optimization Studio version 12.6.1.0 was used as the solver. The time limit was set as two hours for any instance.

3.4.1 Description of the data set

The instances tested here are from the PRP Library of [46]. The data set in this library consists of randomly selected cities of the United Kingdom with real road distances, but where demands, time windows and service time are randomly generated. As the library does not include any information on the cost of a depot, the fixed operating cost of a depot is modeled to be proportional to the distance to the customers. To determine this value, for each depot, the average of the distances from other demand nodes to that depot is calculated, bearing

in mind that any demand node can be a depot. Here, we assume that being closer to customers means a more centrally located depot, which can reduce the operational cost of a depot.

The set of speeds are defined from 55 km/h to 90 km/h in 5 km/h increments, resulting in $R = \{55, 60, 65, 70, 75, 80, 85, 90\}$. We do not consider any speed level less than 55 km/h based on the results of [47] who showed that the optimal vehicle speed to minimize the amount of emission is around 55 km/h for given specific parameter values, irrespective of the vehicle being empty or loaded, and when there are no time related constraints. This assumption is justified by the fact that the vehicles can wait at nodes before the service starts. Therefore, any solution using speed values less than 55 km/h would be dominated.

All other values used for the emission model parameters can be found in Appendix A.2 (see, [46] and [47]).

3.4.2 Performance of the valid inequalities

This section reports the results of detailed experiments on the performance of the proposed valid inequalities. We use the first four of the 20-node instances from the PRP Library with three different (m, p) pairs as $(3, 1)$, $(3, 2)$, $(3, 3)$, resulting in a total of 12 instances tested here.

The valid inequalities are used in combination to find the best configuration. We do not consider any combinations that include Valid inequalities (3.1.1) and (3.1.2) together, as they both are subtour breaking constraints. A total of 24 combinations are tested, where each combination is appended to the formulation and solved with CPLEX. We normalize the CPU times against the base case, shown in the first row of the table, in which no valid inequalities are used.

The average results over the 12 instances are presented in Table 3.1, where the columns titled “Comb.” show the various combinations of Valid inequalities (3.1.1), (3.1.2), (3.2), (3.3) and (3.4) including (3.4.1) and (3.4.2). In this

table, we present only the average values; the average solution time under column “Av.CPU” as well as the average normalized solution time under column “Av.N.CPU”. Detailed results are given in Appendix A.3.

Table 3.1: Performance of the valid inequalities

Comb.	Av.CPU	Av.N.CPU	Comb.	Av.CPU	Av.N.CPU	Comb.	Av.CPU	Av.N.CPU
Base	1763.42	1.00	3.1.1-3.4	2489.45	2.04	3.1.1-3.2-3.4	1795.16	2.00
3.1.1	2044.12	1.71	3.1.2-3.2	1736.87	1.64	3.1.1-3.3-3.4	1077.80	1.01
3.1.2	1705.05	1.28	3.1.2-3.3	782.14	0.61	3.1.2-3.2-3.3	1250.60	1.21
3.2	2623.29	2.44	3.1.2-3.4	2317.37	1.83	3.1.2-3.2-3.4	2639.75	2.43
3.3	1426.74	0.92	3.2-3.3	1753.66	1.68	3.1.2-3.3-3.4	1045.26	0.93
3.4	2529.33	2.16	3.2-3.4	2997.97	2.86	3.2-3.3-3.4	1841.75	1.52
3.1.1-3.2	1272.73	1.71	3.3-3.4	2138.74	1.76	3.1.1-3.2-3.3-3.4	1259.45	1.25
3.1.1-3.3	920.89	0.78	3.1.1-3.2-3.3	859.12	0.62	3.1.2-3.2-3.3-3.4	2061.90	2.16

The results in Table 3.1 indicate that the combinations 3.1.2-3.3 and 3.1.1-3.2-3.3 both provide the two lowest average normalized CPU times equal to 0.61 and 0.62, respectively. In terms of the average solution time, however, the combination 3.1.2-3.3 with 782.14s performs better than the combination of 3.1.1-3.2-3.3 with 859.12s, for which reason the former combination will be used in the rest of the experiments.

3.4.3 Analysis of the GLRP solutions

We conduct a comprehensive analysis on the GLRP, to test the sensitivity of the solutions against changes in the input parameters, such as the number of depots p , the fixed cost c_k and time windows $[l_i, u_i]$. For this purpose, we generate a larger set of problem instances with $|N| = 10, 15, 20$ and $p = 1, 2, 3$, where, for each pair (N, p) , m is decided as follows; starting from $m = 2$, m value is increased by one until a feasible solution is found. Four instances for each (N, p, m) are generated, resulting in a total of 36 instances altogether. Details of the instances as well as the experiments are given in Appendix A.4.

We first present a summary of the results for the new instances in Table 3.2, which presents the average values over four instances for each combination of (N, p) , averages for each N , and averages across all instances in the last row. The columns titled “Total Cost”, “Depot Cost” and “Fuel Consumption” stand for the

optimal objective value, the total cost (in pounds), the fixed cost of depot location (in pounds) and the amount of fuel consumed (in L), separately for weight and speed-induced amounts, respectively. In the last three columns, “Average Speed”, “Distance” and “CPU” represent the average vehicle speed (in km/h), the total distance traversed (in km) and finally the CPU time (in s), respectively.

Table 3.2: Summary of the computational results for the GLRP

$ N $	p	Total Cost (£)	Depot Cost (£)	Fuel Consumption			Avg. Speed (km/h)	Distance (km)	CPU (s)
				Weight (L)	Speed (L)	Total (L)			
10	1	243.52	140.30	28.07	45.66	73.73	56.02	457.19	6.59
10	2	381.67	288.11	25.69	41.14	66.83	56.25	411.39	8.09
10	3	533.43	442.89	24.87	39.81	64.67	56.39	398.04	7.59
10		386.21	290.43	26.21	42.20	68.41	56.22	422.21	7.42
15	1	294.62	152.37	39.09	62.52	101.61	62.42	599.40	809.93
15	2	435.27	302.02	36.76	58.41	95.18	60.50	568.73	405.52
15	3	587.33	468.44	32.71	52.20	84.92	57.23	520.13	331.86
15		439.07	307.61	36.19	57.71	93.90	60.05	562.75	515.77
20	1	288.76	136.86	42.47	66.03	108.50	56.65	659.87	796.17
20	2	419.98	281.17	38.61	60.55	99.15	56.25	605.96	592.01
20	3	560.12	424.66	37.62	59.14	96.76	56.50	591.71	958.23
20		422.95	280.89	39.56	61.91	101.47	56.47	619.18	782.14
Average		416.08	292.98	33.99	53.94	87.93	57.58	534.71	435.11

As it can be seen from the table, as the value of p is increased, the total cost and the total fixed cost of operating depots also increase by £142.33 and £151.08 on average, respectively. In contrast, increasing the value of p reduces the total amount of fuel consumed by 6.25 L on average, and by 2.41 L and 3.84 L for the weight and speed-induced consumption, respectively. Increasing the number of opening depots reduces the number of customers to be served in the network, leading to less load on the vehicles and the total distance traveled. The average CPU times for 10, 15 and 20 nodes instances are 7.42, 515.77 and 782.14 s, respectively, which shows the expected increase on the CPU time as the instance sizes increase.

3.4.3.1 The effect of the depot cost

To assess the effect of depot location decisions on fuel consumption and emissions, we use two different types of depot costs. In the first, depot costs are assigned as being inversely proportional to the average distance to other demand nodes. In the second, depot costs are generated randomly. In Table 3.3, we present the comparison results for 10, 15 and 20 node problem instances.

Table 3.3: Different depot cost analysis

N	Base (Directly Proportional)			Inversely Proportional			Random		
	Fuel Cons. (L)	A. Speed (km/h)	Distance (km)	Fuel Cons. (L)	A. Speed (km/h)	Distance (km)	Fuel Cons. (L)	A. Speed (km/h)	Distance (km)
10	68.41	56.22	422.21	65.60	57.94	397.72	64.74	57.13	398.99
15	93.90	60.05	562.75	98.06	57.28	595.24	92.44	58.41	556.71
20	101.47	56.47	619.18	109.63	56.06	666.30	102.10	57.54	619.31
Average	87.93	57.58	534.71	91.10	57.09	553.09	86.43	57.70	525.00

The results indicate that using inversely proportional depot costs yields different results in terms of the depot location or vehicle routes than directly proportional depot costs in all 36 problem instances. As for the GLRP with randomly generated depot cost, the solution change in 35 problem instances, suggesting that location decisions do play a crucial role on fuel consumption and emissions.

Based on the average values shown in the last row of Table 3.3, using inversely proportional depot costs change depot location and vehicle routes for all instances, resulting in a 3.17 L (3.60%) increase in fuel consumption due to a 18.38 km (3.44%) increase in the total distance traveled. Since the cost of the depot located near to the customers is more expensive, an increase in the total distance traveled and in the fuel consumed is expected. In contrast, using randomly generated depot costs provides a 1.50 L (1.71%) reduction in fuel consumption due to a 9.71 km (1.82%) decrease in the total distance traveled. No matter how depot costs are generated, the problem yields very similar results in terms of average vehicle speed.

3.4.3.2 The effect of the fuel consumption and emission cost

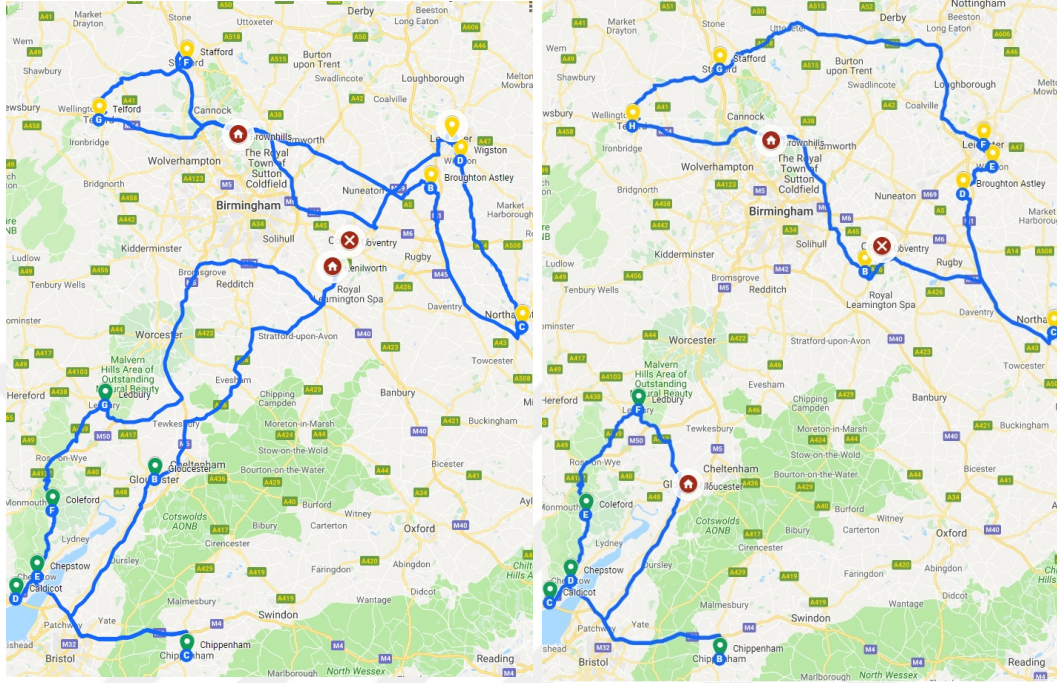
The results shown in the previous section suggest that the cost of fuel consumption and emissions has a marginal effect on the location decisions, as compared to the fixed depot costs. The cost of fuel consumption can be volatile in practice. In this section, we conduct additional experiments to analyze the sensitivity of the resulting solutions on the changes in the unit fuel cost. First, we test minor (up to $\pm 5\%$) and major (up to $\pm 50\%$) changes in the fuel cost. A summary of the results can be found in Table 3.4, the columns of which show the number of instances (out of 36) in which the solution has changed in terms of depot location and/or vehicle route, average total depot cost, average fuel consumption, average vehicle speed and average total distance traveled.

Table 3.4: The effect of increase and decrease on the fuel consumption and emission cost

Change	Fuel Cost (£)	# of instances changed	Depot Cost (£)	Fuel Consumption (L)	Speed (km/h)	Distance (km)
-50%	0.7	5	291.51	89.17	57.73	541.62
-10%	1.26	2	292.11	88.59	57.74	538.20
-5%	1.33	0	292.98	87.93	57.58	534.71
0	1.4	0	292.98	87.93	57.58	534.71
5%	1.47	0	292.98	87.93	57.58	534.71
10%	1.54	1	293.24	87.75	57.38	534.71
50%	2.1	3	293.68	87.52	57.31	533.52

The results in Table 3.4 indicate that modest and realistic changes of about 5% in the unit fuel consumption and emission cost do not significantly alter the solutions obtained. More extreme variations, however, may result in more observable differences in the solutions obtained. Figures 3.1a and 3.1b serve to illustrate this point, and show two solutions for an instance with 15 nodes, three potential depots and up to two vehicles, with a 50% decrease and increase, respectively, on the unit fuel and emission cost. In both figures, the opened depots which are actively used to serve other customers are represented by houses and the ones do not serve any other customers (except itself) are represented by X marks.

The solution shown in Figure 3.1a uses 107.05 L of fuel, traverses a total



(a) Solution obtained with $e = £0.7/L$ (b) Solution obtained with $e = £2.1/L$

Figure 3.1: Two GLRP solutions on the instance 15_3.2_3

distance of 656.53 km and with an average speed equal to 56.43 km/h. The same statistics for the solution shown in Figure 3.1b are 86.35 L, 529.95 km and 55 km/h, respectively. Whereas the solution in Figure 3.1a has a total cost equal to £673.11 of which fuel and emissions account for 11%, the solution in Figure 3.1b has a total cost equal to £806.58 of which 22% is for fuel and emissions.

3.4.3.3 The effect of time windows

The results in Table 3.2 suggest that speed may have a more significant effect on fuel consumption as compared to that of weight. One of the constraints that affects speed is time windows. To serve customers within the predetermined time windows, in some cases, vehicles have to increase their speed even if it leads to a higher fuel requirements, and consequently emissions. To analyze the effects of time windows on the amount of emissions, we generate new time windows values by narrowing down the original values by 10%, 20%, 30%, 40% and 50%. The

results are shown in Table 3.5.

Table 3.5: Comparisons between the different time windows

	Fuel Consumption						
	Total Cost (£)	Fixed Cost (£)	Weight (L)	Speed (L)	Total (L)	A. Speed (km/h)	Distance (km)
Base	413.00	292.54	32.95	53.09	86.04	56.30	530.45
10%	414.19	292.54	33.10	53.79	86.89	57.16	532.64
20%	415.94	292.34	33.45	54.83	88.29	58.16	540.56
30%	418.86	292.26	33.96	56.22	90.18	57.97	553.70
40%	422.41	292.36	34.72	58.17	92.89	58.71	569.78
50%	429.09	292.87	36.23	61.07	97.30	58.65	610.35

The average results reported in Table 3.5 suggest that narrowing down the time windows by up to 20% does not have a significant impact on the solutions. While the increase on the total cost and the total amount of emission is less than 1% and 3%, respectively, in only two out of 36 instances, the depot locations change. However, for the cases when time windows are narrowed down by more than 30%, there is a significant change on the solutions in terms of vehicle routes and depot locations. The increase on the total amount of emission is 7.97% and 13.09%, when the time windows are narrowed further down by 40% and 50%, respectively. In this case, the increase in the total distance traveled, 7.41% and 13.37%, causes the increase in the total amount of emissions. While the average vehicle speed increases in general, for some cases, it remains low for tighter time windows as can be seen from Table 3.5. The main reason for this unexpected situation is that with the increase in vehicle speed some of the vehicle routes became too costly when time windows are too tight that forces vehicles use alternative routes traveling at lower speeds. These new routes, however, eventually increase the total amount of distance traveled and consequently the total amount of emissions.

3.4.3.4 The effect of the depot location decision

In order to evaluate the impact of the depot location decisions, the GLRP is compared with a version of the problem where the depots are fixed a priori and cannot be changed. For this purpose, the instances in the PRP Library [46]

with $p = 1$ are used, where the location of the depot is as described therein. In this case, the number of nodes is increased by one due to one additional node on which the depot is located. The comparison results are given in Table 3.6. Detailed results are given in Appendix A.5.

Table 3.6: Comparison between the GLRP with and without a fixed depot location

	GLRP							PRP (GLRP with a known depot location)						
N			Fuel Consumption							Fuel Consumption				
			Weight	Speed	Total	A. Speed	Distance			Weight	Speed	Total	A. Speed	Distance
	Total Cost (£)	Depot Cost (£)	(L)	(L)	(L)	(km/h)	(km)	Total Cost (£)	Depot Cost (£)	(L)	(L)	(L)	(km/h)	(km)
11	242.37	134.67	30.06	46.87	76.93	56.46	469.45	256.20	147.37	30.09	47.65	77.74	56.56	477.40
16	290.60	148.07	38.65	63.15	101.80	58.37	616.35	327.67	173.69	42.62	67.37	109.99	57.27	671.78
21	291.68	134.90	44.09	67.89	111.98	56.41	679.78	322.69	157.55	46.32	71.63	117.96	55.82	718.28
Average	274.88	139.21	37.60	59.30	96.91	57.08	588.53	302.19	159.53	39.68	62.22	101.89	56.55	622.49

The results indicate that in 10 out of 12 instances, the two problems provide different results with respect to the depot location and vehicle routes. For eight out of these 10 instances, the GLRP results in a reduction in fuel consumption by 4.98 L (4.89%), on average (Table 3.6). The reduction on the amount of weight and speed-induced consumption is 2.08 and 2.92 L, respectively. The average speed for the GLRP is nearly the same as the fixed depot case, but the total travel distance is reduced by 33.96 km (5.46%) and the total cost by 9.04% in the former.

3.4.3.5 The effect of the vehicle speed decision

This section presents an analysis on the impact of considering vehicle speed as a decision. Here, we consider a variant of the GLRP in which it is assumed that vehicle speed on all arcs is set to a fixed value. The fixed vehicle speed values are taken from the set $R = \{55, 60, 65, 70, 75, 80, 85, 90\}$ and also the average vehicle speed obtained by solving the GLRP over all arcs and all instances, which is 57.58 km/h, is also considered. Table 3.7 presents average results over 36 instances and reports the deviation values in percentages from the optimal solutions obtained by solving the GLRP where vehicle speed is a decision.

Results indicate that using a fixed vehicle speed does not cause an infeasible solution in all instances and all vehicle speed values except only one instance

Table 3.7: The average deviation values for fixed vehicle speed

Fixed Speed (km/h)	Total Cost (%)	Emission (%)	Depot Cost (%)	Distance (%)
55	1.21	3.04	0.24	4.03
57.58	0.95	2.04	0.43	2.96
60	0.83	2.12	0.16	2.72
65	0.72	2.06	0.02	0.88
70	1.18	3.35	0.08	0.36
75	1.99	5.82	0.14	-0.16
80	2.74	8.58	-0.04	-0.56
85	3.95	12.27	-0.04	-0.65
90	5.25	16.33	-0.06	-0.85

when the vehicle speed is fixed to 55 km/h.

As it is mentioned earlier, the optimal vehicle speed is around 55 km/h when there are no time related constraints. Therefore, we assume that using this optimal speed as the fixed speed could be a good start to evaluate the impact of vehicle speed decisions. However, we observe that fixing vehicle speed to 55 km/h increases the total cost and the total amount of emissions by 1.21% and 3.04% compared to the GLRP, respectively. In order to make deliveries within time windows, the depot locations and vehicle routes change resulting with 0.24% and 4.03% increases in depot cost and total distance traveled, respectively. The results indicate that using the average optimal vehicle speed (57.58 km/h) as the fixed speed for all arcs provides the least deviation amount in terms of emissions (2.04%), but it also leads to the most deviation amount in terms of depot cost (0.43%) resulting with a 0.95% deviation amount in the total cost. When the fixed vehicle speed value is increased to 60 and 65 km/h, we notice that there is a decrease in deviations from the optimal results in terms of the total cost, in particular setting fixed speed value to 65 km/h leads to a 0.72% increase in the total cost. After 65 km/h, we observe increases in deviation values in terms of both the total cost and the emission amount, for instance a 16.33% increase in the total amount of emissions when vehicles travel at a speed of 90 km/h on all arcs. Here we also note that increasing fixed vehicle speed value generally causes less total depot cost and total distance traveled compared to the optimal results

obtained by the GLRP.

3.4.4 Performance of the solution algorithms

In this section, we present computational results on the performance of the CLR-SOA and the ILS algorithm in terms of solution quality and computational time compared to solving the GLRP formulation. For this purpose, four 20-node problem instances with $p = 1, 2, 3$ from PRP data set are used.

For the CLR-SOA, preliminary analysis indicates that for some problem instances the optimization process of solving a CumLRP formulation takes too much time. In order to reduce the solution times, we stop the optimization process of the CumLRP formulations after a predetermined time limit and use the resulting incumbent solutions in the “solution pool” for the SOA. The time limit for the optimization process of the CumLRP is set as 10 minutes.

The parameters of the ILS algorithm are chosen after a set of preliminary fine-tuning experiments and are set as follows: $MaxIter = 25$, $MaxIter_{NI} = 50$, $k = 2$ and $\delta = 40\%$. Since the ILS algorithm contains some random aspects, instances are run five times and the best, average and worst results are reported.

3.4.4.1 Computational experiments of the solution algorithms

This section presents the results obtained by solving the GLRP formulation and two heuristic algorithms for small sized instances and provides a comparison between the solutions and computational time of the aforementioned solution methods with the results of the GLRP formulation which solves 20-node GLRP instances to optimality. We present the comparison results separately for each of the two heuristic algorithms.

The results obtained with the two variants of the CLR-SOA are given in Tables

3.8 & 3.9, one using the CumLRP and the other using the CumLRP' formulation, respectively. The first three columns show the problem parameters; the number of nodes ($|N|$), instance number (I) and the number (p) of depots to be located, respectively. The columns titled "Obj. Func." and "S. Time" represent the objective function value (in £) and the solution time (in s) of the corresponding strategy; namely, Dynamic Search (DS), Branch & Bound (BB) and Cut & Branch (CB), respectively. We also report the gap (in %) calculated as $(z^{CLRSOA} - z^{GLRP}) \times 100 / z^{GLRP}$, where z^{GLRP} and z^{CLRSOA} are the objective function values of the GLRP formulation and the CLRSOA, respectively. As all 20-node problem instances are solved to optimality with the GLRP formulation, the gaps correspond to the deviations from the optimal values.

Table 3.8: Results of the CLRSOA with the CumLRP formulation for 20-node instances

$ N $	I	p	GLRP Formulation		DS			BB			CB		
			Obj Func. (£)	S. Time (s)	Obj Func. (£)	S. Time (s)	Gap (%)	Obj Func. (£)	S. Time (s)	Gap (%)	Obj Func. (£)	S. Time (s)	Gap (%)
20	1	1	346.34	2864.73	348.46	70.28	0.61	348.46	82.84	0.61	348.46	90.65	0.61
20	1	2	506.47	746.82	512.88	94.19	1.26	512.99	113.72	1.29	512.99	127.25	1.29
20	1	3	673.49	904.23	675.60	59.47	0.31	675.60	105.74	0.31	675.53	53.78	0.30
20	2	1	306.33	67.51	306.30	16.45	-0.01	306.30	16.90	-0.01	306.30	13.96	-0.01
20	2	2	446.75	114.01	446.72	14.06	-0.01	446.72	17.45	-0.01	446.72	25.89	-0.01
20	2	3	600.98	147.81	600.95	16.20	0.00	600.95	22.64	0.00	600.95	39.68	0.00
20	3	1	206.05	100.60	206.04	23.20	-0.01	206.04	37.00	-0.01	206.04	36.24	-0.01
20	3	2	309.15	657.89	309.82	78.70	0.22	309.82	106.65	0.22	309.82	72.98	0.22
20	3	3	412.67	642.50	412.63	69.95	-0.01	412.66	59.38	0.00	413.37	59.30	0.17
20	4	1	296.31	151.82	296.31	61.22	0.00	296.31	45.07	0.00	296.31	44.31	0.00
20	4	2	413.80	189.00	414.36	16.87	0.14	415.78	32.99	0.48	413.81	40.03	0.00
20	4	3	546.22	120.29	546.23	14.04	0.00	546.23	25.32	0.00	546.84	33.57	0.11
Average				558.93		44.55	0.21		55.48	0.24		53.14	0.22

Table 3.9: Results of the CLRSOA with the CumLRP' formulation for 20-node instances

$ N $	I	p	GLRP Formulation		DS			BB			CB		
			Obj Func. (£)	S. Time (s)	Obj Func. (£)	S. Time (s)	Gap (%)	Obj Func. (£)	S. Time (s)	Gap (%)	Obj Func. (£)	S. Time (s)	Gap (%)
20	1	1	346.34	2864.73	356.09	601.03	2.81	346.48	111.70	0.04	346.57	74.91	0.07
20	1	2	506.47	746.82	506.37	326.74	-0.02	506.37	204.16	-0.02	506.37	130.41	-0.02
20	1	3	673.49	904.23	673.81	163.58	0.05	682.69	252.93	1.36	673.41	80.07	-0.01
20	2	1	306.33	67.51	306.30	19.92	-0.01	306.30	33.21	-0.01	306.30	33.70	-0.01
20	2	2	446.75	114.01	446.72	72.89	-0.01	446.72	63.85	-0.01	446.72	52.94	-0.01
20	2	3	600.98	147.81	601.81	96.13	0.14	601.81	55.51	0.14	600.95	64.03	0.00
20	3	1	206.05	100.60	206.04	75.55	-0.01	206.04	58.66	-0.01	206.04	64.43	-0.01
20	3	2	309.15	657.89	309.11	150.53	-0.01	309.11	153.38	-0.01	309.11	117.05	-0.01
20	3	3	412.67	642.50	412.63	106.51	-0.01	412.63	80.83	-0.01	413.37	127.90	0.17
20	4	1	296.31	151.82	296.31	120.55	0.00	296.31	50.31	0.00	296.31	54.64	0.00
20	4	2	413.80	189.00	413.80	68.43	0.00	413.80	78.24	0.00	413.80	80.47	0.00
20	4	3	546.22	120.29	546.22	31.68	0.00	31.09	159.44	0.00	546.22	63.38	0.00
Average				558.93		152.79	0.24		97.82	0.12		78.66	0.01

In Tables 3.8 & 3.9, some negative gaps are observed. This is due to the SOP being solved exactly within the CLRSOA but with discretized values in the GLRP formulation. The results on Tables 3.8 & 3.9 show that all versions of the CLRSOA provide optimal or near optimal solutions in similar amounts of time. Among these six versions, CumLRP' formulation with the CB strategy provides the best results. The average gap and the average solution time for CumLRP' with CB version is 0.01% and 78.66 seconds, respectively.

We report the results of the ILS algorithm in Table 3.10. Each instance is run five times and the table provides the best, average and worst results of these five runs.

Table 3.10: Results of the ILS algorithm for 20-node instances

			GLRP Formulation		ILS								
					Best			Average			Worst		
$ N $	I	p	Obj. F. (£)	S. Time (s)	Obj. F. (£)	S. Time (s)	Gap (%)	Obj. F. (£)	S. Time (s)	Gap (%)	Obj. F. (£)	S. Time (s)	Gap (%)
20	1	1	346.34	2864.73	346.27	5.15	-0.02	346.27	5.34	-0.02	346.27	5.71	-0.02
20	1	2	506.47	746.82	510.99	6.09	0.89	511.49	6.45	0.99	513.18	6.09	1.32
20	1	3	673.49	904.23	676.59	5.58	0.46	677.93	5.07	0.66	678.27	5.22	0.71
20	2	1	306.33	67.51	308.17	5.91	0.60	308.17	6.23	0.60	308.17	6.38	0.60
20	2	2	446.75	114.01	446.72	8.99	-0.01	451.54	7.76	1.07	460.49	6.81	3.08
20	2	3	600.98	147.81	601.94	6.06	0.16	608.45	6.71	1.24	619.87	5.52	3.14
20	3	1	206.05	100.60	206.04	5.44	-0.01	206.04	5.75	-0.01	206.04	6.20	-0.01
20	3	2	309.15	657.89	309.12	7.65	-0.01	310.61	7.46	0.47	313.67	6.88	1.46
20	3	3	412.67	642.50	415.94	5.54	0.79	418.19	6.19	1.34	421.61	6.54	2.17
20	4	1	296.31	151.82	302.37	5.72	2.05	302.37	6.26	2.05	302.37	6.69	2.05
20	4	2	413.80	189.00	413.80	4.78	0.00	413.80	5.29	0.00	413.80	5.83	0.00
20	4	3	546.22	120.29	546.22	4.59	0.00	546.22	4.85	0.00	546.22	5.13	0.00
Average			558.93		5.96 0.41			6.11 0.70			6.08 1.21		

Similar to results of the CLRSOA, since the SOP is solved exactly within the ILS algorithm, negative gaps can be observed in Table 3.10. Table 3.10 indicates that the ILS algorithm generally provides very good results in terms of solution quality and computational time. The average optimality gap and the average solution time of the ILS in the best case scenario is 0.41% and 5.96 seconds and 1.21% and 6.08 seconds in the worst case scenario.

In order to explore different solution and escape possible local optimal solution, we increase the effects of randomness on the algorithm. Therefore, we conduct experiments with higher *MaxIter* and lower δ values. In addition to (25, 40%) combination of *MaxIter* and δ values for which the results are reported in Table

3.11, we also report the summary results for the combinations; (50, 20%) and (100, 10%).

Table 3.11: $(MaxIter, \delta)$ analysis for ILS algorithm

Combination	Best		Average		Worst	
	S. Time (s)	Gap (%)	S. Time (s)	Gap (%)	S. Time (s)	Gap (%)
(25, 40%)	5.96	0.41	6.11	0.70	6.08	1.21
(50, 20%)	12.58	0.37	12.71	0.79	12.84	1.19
(100, 10%)	26.75	0.28	27.49	0.50	27.84	0.71

The results on Table 3.11 indicate that increasing number of iterations results with higher solution times, but better solutions. With 50 iterations, the average optimality gap in the best case scenario is 0.37% and with 100 iterations it becomes 0.28%. On average of five experiments, the average optimality gaps are 0.79% with 50 iterations and 0.50% with 100 iterations. The solution times are approximately 12 and 25 seconds for 50 and 100 iterations, respectively. Since solution times up to 25 seconds can be acceptable, we propose to use the algorithm with the 100-iteration version.

In conclusion, compared to the CLRSOA, the solutions found by the ILS algorithm are not as good as the ones obtained by the CLRSOA, but in terms of solution time the ILS algorithm performs better than the CLRSOA. So, for small sized instances, the CLRSOA is very efficient alternative to solve the GLRP.

3.4.5 Computational analysis for large sized instances

We also conduct computational analysis on four different 100-node problem instances with three different p values as 5, 7, 10. Due to computational times required, we do not use the CLRSOA to solve large sized problem instances, and only conduct the experiments with the ILS algorithm using the (100, 10%) combination for the $(MaxIter, \delta)$ setting. The results can be found in Table 3.12.

As it can be seen from Table 3.12, increasing the value of p leads to an increase in the total cost and the total fixed cost of operating depots. In contrast, as the

Table 3.12: Results of the ILS algorithm for 100-node instances

$ N $	I	p	Total Cost (£)	Depot Cost (£)	Fuel Consumption			Avg. Speed (km/h)	Distance (km)	S. Time (s)
					Weight (L)	Speed (L)	Total (L)			
100	1	5	1407.89	848.78	157.93	241.44	399.36	55.84	2417.27	820.04
100	1	7	1748.75	1184.16	159.43	243.85	403.27	55.85	2441.51	952.13
100	1	10	2234.23	1715.62	147.00	223.44	370.44	56.20	2225.54	1050.34
100	2	5	1395.32	851.00	155.40	233.40	388.80	55.42	2343.09	963.34
100	2	7	1728.97	1191.50	152.48	231.43	383.91	55.20	2324.25	1295.47
100	2	10	2228.81	1714.27	145.90	221.63	367.53	55.19	2225.86	1190.75
100	3	5	1047.81	618.20	121.41	185.45	306.86	55.49	1860.54	1118.73
100	3	7	1288.65	871.05	118.03	180.25	298.29	55.49	1808.33	1003.43
100	3	10	1667.98	1251.96	117.74	179.42	297.16	55.50	1780.32	1122.83
100	4	5	1230.91	715.77	146.85	221.11	367.96	55.19	2220.62	839.01
100	4	7	1510.00	1002.33	143.59	219.03	362.62	55.19	2199.74	1089.31
100	4	10	1917.73	1456.52	129.79	199.65	329.44	55.19	2005.07	1308.53

value of p is increased, the total amount of fuel consumed and the total distance traveled generally reduces. The difference between average vehicle speeds for different p values can be considered as insignificant, suggesting that the vehicle speed remains stable. In addition, increasing the value of p generally increases the required solution time.

3.5 A Case Study

We now present a case study to show the importance of the fuel consumption and emission cost while deciding the location of the depots and the routes of the vehicles. For this study, we consider a fast-moving consumer goods (FMCG) company that distributes cold drinks to high schools and universities located in Istanbul, Turkey.

The schools considered in this study are located in the west (European) side of the Istanbul. Initially, we detect the type of schools in those counties; high schools and universities and we find 365 schools in total consisting of 329 high schools and 36 university campuses with their actual coordinates. While deciding the candidate depot location, we search the location of the depots that are used for the distribution purposes for an FMCG company located in the west side

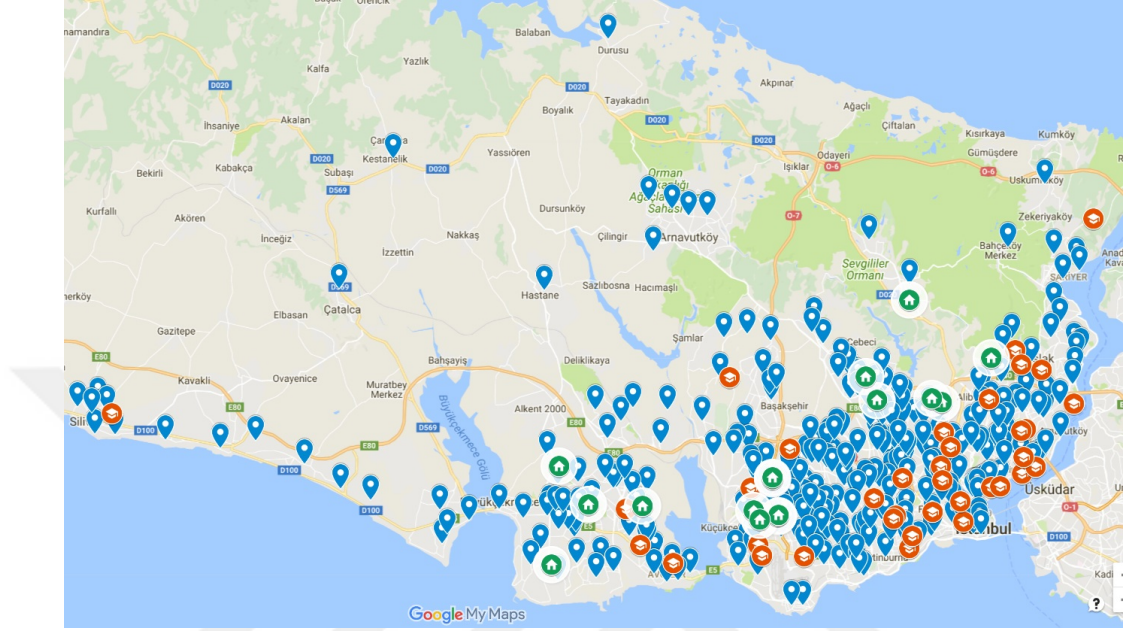


Figure 3.2: The locations of schools and candidate depots on Istanbul map

of Istanbul. We find 16 candidate depot locations with their actual coordinates. Figure 3.2 shows the locations of the schools (blue points) and universities (orange graduation caps) and possible depot locations (green houses) on Istanbul map.

The distance between each candidate depot location and schools is calculated by the help of Google Maps via a visual basic code in [167]. Each type of school has different working hours and thus time windows are generated accordingly (Table 3.13). It is assumed that the delivery trucks can leave the depot(s) at 06:00 am at earliest. Also, demand values are randomly generated for each type of school based on the number of students that will probably consume that type of drink (Table 3.13). The service time for each school is assumed to be directly proportional to the demand of that school.

Table 3.13: Uniform distribution for time windows and demands for each type of school

	High School	University
Lower Time Bound	[8 am, 10 am]	[7 am, 10 am]
Upper Time Bound	[1 pm, 3 pm]	[2 pm, 5 pm]
Demand	[300, 500]	[600, 800]

Based on the settings explained above, we apply the ILS algorithm proposed in Section 3.3.2 to solve the problem raised by this case study. We conduct computational experiments with four different p values as 3, 5, 7, 10. The results can be found in Table 3.14.

Table 3.14: Results of the case study

p	Fuel Consumption				Depot Cost (£)	# of Vehicles	Distance (km)	Avg. Speed (km/h)
	Total Cost (£)	Weight (L)	Speed (L)	Total (L)				
3	777.62	121.98	180.24	302.22	354.52	45	1810.21	55.19
5	1000.48	120.44	177.28	297.72	583.68	45	1780.39	55.19
7	1243.82	122.59	180.66	303.26	819.26	46	1814.40	55.19
10	1533.20	97.93	145.35	243.28	1192.61	45	1459.73	55.19

The results indicate that increasing the number of depots generally reduces the total amount of emission along with total distance traveled. An interesting conclusion is that the vehicle travels at the optimal speed on each arc of the tours which means that time windows does not affect the vehicle speed and so the total amount of emission. Also, on average, there are approximately nine schools in a tour and a solution consists of approximately 45 tours. The results also show that generally trucks visit universities at the beginning or at the end of the tours and trucks visit more than one university (two or three) in a tour.

3.6 Optimal Solution Characterizations for the Special Cases of the GLRP

In this subsection, we investigate optimal solution characterizations for the special cases of the GLRP by considering different network topologies such as complete and star networks and different special cases such as equal demands and equal distances.

Definition 3.1. *Let us consider a network with $|N|$ nodes where $c_i = c, \forall i \in N$; $C = \infty$ and $[l_i, u_i] = [0, \infty], \forall i \in N$. First, let consider a solution, in which node i is selected as the depot and the tour is as follows: $T_1 = (i - j - P_1 -$*

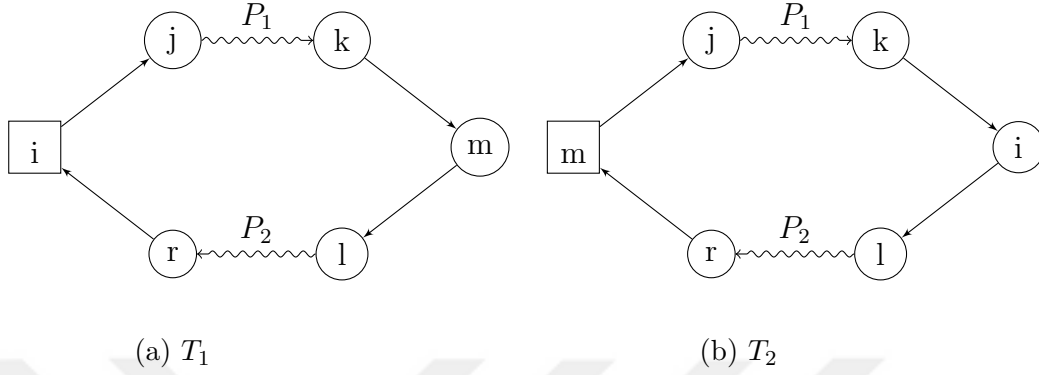


Figure 3.3: Representation of tours T_1 and T_2

$k - m - l - P_2 - r - i$) where P_1 and P_2 are two paths with the total of a and b nodes, respectively. Now, let consider a second solution where an arbitrary node m on T_1 is selected as the depot and nodes i and m are swapped in the first tour and the resulting tour is as follows $T_2 = (m - j - P_1 - k - i - l - P_2 - r - m)$. Then, $\Delta_{LD} = LD(T_1) - LD(T_2)$ and $\Delta_D = D(T_1) - D(T_2)$ where $LD(T)$ and $D(T)$ represent the total load based distance and the total distance of tour T , respectively. So, based on tours T_1 and T_2 depicted in Figure 3.3, we have the followings;

$$LD(T_1) = (q_j + q_{P_1})d_{P_1} + (q_j + q_{P_1} + q_k)d_{km} + (q_j + q_{P_1} + q_k + q_m)d_{ml} + (q_j + q_{P_1} + q_k + q_m + q_l + q_{P_2})d_{P_2} + (q_j + q_{P_1} + q_k + q_m + q_l + q_{P_2} + q_r)d_{ri},$$

$$LD(T_2) = (q_j + q_{P_1})d_{P_1} + (q_j + q_{P_1} + q_k)d_{ki} + (q_j + q_{P_1} + q_k + q_i)d_{il} + (q_j + q_{P_1} + q_k + q_i + q_l + q_{P_2})d_{P_2} + (q_j + q_{P_1} + q_k + q_i + q_l + q_{P_2} + q_r)d_{rm},$$

$$D(T_1) = d_{ij} + d_{P_1} + d_{km} + d_{ml} + d_{P_2} + d_{ri},$$

$$D(T_2) = d_{mj} + d_{P_1} + d_{ki} + d_{il} + d_{P_2} + d_{rm}.$$

For ease of description of Δ_{LD} and Δ_D we define the notations in Table 3.15.

Observation 3.1. Based on the information in Definition 3.1 and the notations in Table 3.15, $\Delta_{LD} = Q_1(D_1 - D_2) + Q_2(D_3 - D_4) + q_m D_5 - q_i D_6$ and $\Delta_D = D_7 - D_8$.

Proof. In both of these solutions, vehicle travels without any load on the first

Table 3.15: Notations

Notations	Explanation	Value
Q_1	The total demand of customers located in between nodes i and m in tour T_1	$q_j + q_{P_1} + q_k$
Q_2	The total demand of customers located in between nodes m and i in tour T_1	$q_l + q_{P_2} + q_r$
D_1	The total distance in tour T_1 , which will be affected by the swap except the distance between the depot and and first customer	$d_{km} + d_{ml} + d_{ri}$
D_2	The total distance in tour T_2 , which is affected by the swap after except the distance between the depot and and first customer	$d_{ki} + d_{il} + d_{rm}$
D_3	The distance between the last customer visited and the depot in tour T_1	d_{ri}
D_4	The distance between the last customer visited and the depot in tour T_2	d_{rm}
D_5	The total distance between nodes m and i in tour T_1	$d_{ml} + d_{P_2} + d_{ri}$
D_6	The total distance between nodes i and m in tour T_2	$d_{il} + d_{P_2} + d_{rm}$
D_7	The total distance in tour T_1 , which will be affected by the swap	$d_{ij} + d_{km} + d_{ml} + d_{ri}$
D_8	The total distance in tour T_2 , which is affected by the swap after	$d_{mj} + d_{ki} + d_{il} + d_{rm}$

arc of the tour, so the first arc $((i, j)$ in T_1 and (m, j) in T_2) does not affect the total load based distance. Between nodes j and k and nodes l and r , vehicle travels on the same paths P_1 and P_2 , respectively for both solutions. Thus, $\Delta_{LD} = LD(T_1) - LD(T_2)$ will be determined by the following arcs of T_1 ; namely, (k, m) , (m, l) and (r, i) and the following arcs of T_2 ; namely, (k, i) , (i, l) and (r, m) . $\Delta_{LD} = LD(T_1) - LD(T_2) = (q_j + q_{P_1} + q_k)((d_{km} + d_{ml} + d_{ri}) - (d_{ki} + d_{il} + d_{rm})) + (q_l + q_{P_2} + q_r)(d_{ri} - d_{rm}) + q_m(d_{ml} + d_{P_2} + d_{ri}) - q_i(d_{il} + d_{P_2} + d_{rm})$. By definitions in Definition 3.1 and the notations in Table 3.15, $\Delta_{LD} = Q_1(D_1 - D_2) + Q_2(D_3 - D_4) + q_m D_5 - q_i D_6$

Similarly, for Δ_D , the difference between T_1 and T_2 is the following arcs; (i, j) , (k, m) , (m, l) and (r, i) for T_1 and (m, j) , (k, i) , (i, l) and (r, m) for T_2 . $\Delta_D = D(T_1) - D(T_2) = (d_{ij} + d_{km} + d_{ml} + d_{ri}) - (d_{mj} + d_{ki} + d_{il} + d_{rm})$. By definitions in Definition 3.1 and the notations in Table 3.15, $\Delta_D = D_7 - D_8$. $\square$

Theorem 3.1. *If $\exists$ a node i such that $\Delta_{LD} \leq 0$ and $\Delta_D \leq 0$ (except the case $\Delta_{LD} = \Delta_D = 0$) $\forall m \in N \setminus \{i\}, \forall j, k, l, r \in N \setminus \{i, m\}$, then node i must be selected as the depot.*

Proof. $\Delta_{LD} \leq 0$ and $\Delta_D \leq 0$ means that $LD(T_1) \leq LD(T_2)$ and $D(T_1) \leq D(T_2)$, for every possible choice of m , respectively. Therefore, tour T_1 yields smaller amount of total load based distance and also total distance than T_2 does, which means tour T_1 causes smaller amount of emission compared to tour T_2 .

Since these two conditions depend on some specific nodes, which are nodes m ,

j, k, l and r , we can conclude that node i must be selected as the depot if these two conditions hold $\forall m \in N \setminus \{i\}, \forall j, k, l, r \in N \setminus \{i, m\}$. $\square$

Theorem 3.2. *If $\exists$ a node i such that $\Delta_{LD} \geq 0$ and $\Delta_D \geq 0$ (except the case $\Delta_{LD} = \Delta_D = 0$) $\forall m \in N \setminus \{i\}, \forall j, k, l, r \in N \setminus \{i, m\}$, then node i cannot be selected as the depot.*

Proof. Similar to the proof of Theorem 3.1, $\Delta_{LD} \geq 0$ and $\Delta_D \geq 0$ means that $LD(T_1) \geq LD(T_2)$ and $D(T_1) \geq D(T_2)$, for every possible choice of m , respectively. Therefore, tour T_1 yields higher amount of total load based distance and also total distance than T_2 does, which means tour T_1 causes higher amount of emission compared to tour T_2 . $\square$

3.6.1 Complete network

Lemma 3.1. *Let us consider a complete network with equal demand for each customer ($q_{ij} = q, \forall i, j \in N$) and equal distance between each node ($d_{ij} = d, \forall i, j \in N$). Then, any node can be selected as the depot.*

Proof. Since distance between each node is equal to each other and demand of each customer is the same, Δ_{LD} and Δ_D will be equal to 0. Since this situation is valid for any node, by utilizing Theorem 3.1, we can conclude that any node can be selected as the depot. $\square$

Lemma 3.2. *Let us consider a complete network with equal distance between each node ($d_{ij} = d, \forall i, j \in N$). The node with the highest demand must be selected as the depot.*

Proof. Since distance between each node is equal to each other, Δ_{LD} will be equal to $(q_m - q_i)(b + 3)d$ and Δ_D will be equal to 0. By utilizing Theorem 3.1, if $\exists$ a node i such that $q_m \leq q_i \forall m \in N \setminus \{i\}$ then node i must be selected as the depot, which means that the node with the highest demand must be selected as the depot. $\square$

3.6.2 Star network

Next, we consider a star network as the underlying transportation network depicted in Figure 3.4, in which node i is the center node of the network and to travel from one leaf node to another, the vehicle must go to node i first. Therefore, distance between any two leaf nodes equals to the total distance between leaf nodes and the center node; e.g. $d_{jk} = d_{ji} + d_{ik}$.

Theorem 3.3. *In a star network, if the center node is not selected as the depot, it must be the last customer visited before the depot.*

Proof. Let us consider a tour where the center node is not the last customer visited before the depot and let assume that the tour is the optimal. Let say the tour is constructed as follows; $T = (m - k - i - l - j - m)$ where node m is the depot and node i is the center node. Then, $LD(T) = q_k(d_{ki}) + (q_k + q_i)d_{il} + (q_k + q_i + q_l)(d_{li} + d_{ij}) + (q_k + q_i + q_l + q_j)(d_{ji} + d_{im})$ and $D(T) = d_{mi} + d_{ik} + d_{ki} + d_{il} + d_{li} + d_{ij} + d_{ji} + d_{im}$. Now, let consider another tour in which the center node (node i) is the last visited customer. The new tour is $S = (m - k - l - j - i - m)$ resulting with $LD(S) = q_k(d_{ki} + d_{il}) + (q_k + q_l)(d_{li} + d_{ij}) + (q_k + q_l + q_j)d_{ji} + (q_k + q_i + q_j + q_i)d_{im}$ and $D(S) = d_{mi} + d_{ik} + d_{ki} + d_{il} + d_{li} + d_{ij} + d_{ji} + d_{im}$. $D(T)$ and $D(S)$ are equal to each other. But, $LD(T) - LD(S) = q_i(d_{il} + d_{li} + d_{ij} + d_{ji})$. Since tour T is the optimal solution, $LD(T) - LD(S)$ should be less than or equal to zero. However, since demands and distances are positive, this contradicts that tour T is the optimal. $\square$

Next, we focus on the tours in Figure 3.4, which are; $T_3 = (i - j - P_1 - k - i - m - i - l - P_2 - r - i)$ and $T_4 = (m - i - j - P_1 - k - i - l - P_2 - r - i - m)$

Based on the definitions in Definition 3.1 and Figure 3.4, we redefine $LD(T)$ and $D(T)$ as follows;

$$LD(T_3) = (q_j + q_{P_1})d_{P_1} + (q_j + q_{P_1} + q_k)(d_{ki} + d_{im}) + (q_j + q_{P_1} + q_k + q_m)(d_{mi} + d_{il}) + (q_j + q_{P_1} + q_k + q_m + q_l + q_{P_2})d_{P_2} + (q_j + q_{P_1} + q_k + q_m + q_l + q_{P_2} + q_r)d_{ri},$$

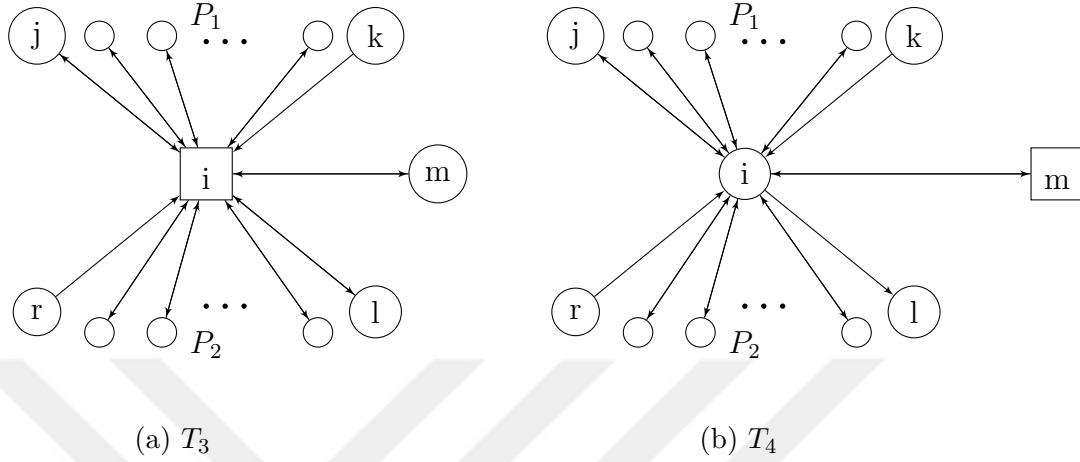


Figure 3.4: Representation of tours T_3 and T_4

$$LD(T_4) = (q_j + q_{P_1})d_{P_1} + (q_j + q_{P_1} + q_k)(d_{ki} + d_{il}) + (q_j + q_{P_1} + q_k + q_l + q_{P_2})d_{P_2} + (q_j + q_{P_1} + q_k + q_l + q_{P_2} + q_r)d_{ri} + (q_j + q_{P_1} + q_k + q_l + q_{P_2} + q_r + q_i)d_{im}.$$

$$D(T_3) = d_{ij} + d_{P_1} + d_{ki} + d_{im} + d_{mi} + d_{il} + d_{P_2} + d_{ri},$$

$$D(T_4) = d_{mi} + d_{ij} + d_{P_1} + d_{ki} + d_{il} + d_{P_2} + d_{ri} + d_{im}.$$

For ease of notation we also define the followings: D_9 represents the total distance in tour T_3 after node m excluding d_{mi} ($D_9 = d_{il} + d_{P_2} + d_{ri}$).

Observation 3.2. For star networks, $\Delta_{LD} = (Q_1 + q_m)d_{mi} + q_mD_9 - (Q_2 + q_i)d_{im}$ and $\Delta_D = 0$.

Proof. In the first tour (T_3), vehicle travels without any load on the first arc of the tour ((i, j) in T_3), and in the second tour (T_4), vehicle travels without any load on the first two arcs of the tour ((m, i) & (i, j) in T_4) so these arcs do not affect the total load based distance. Thus, $\Delta_{LD} = LD(T_3) - LD(T_4) = (q_j + q_{P_1} + q_k + q_m)d_{mi} + q_m(d_{il} + d_{P_2} + d_{ri}) - (q_l + q_{P_2} + q_r + q_i)d_{im}$. By the definitions and the notations, $\Delta_{LD} = (Q_1 + q_m)d_{mi} + q_mD_9 - (Q_2 + q_i)d_{im}$.

It can easily be observed that $D(T_3) = D(T_4)$. Therefore, $\Delta_D = 0$. □

Lemma 3.3. Let us consider a star network with symmetric distances. Take any arbitrary node m , if $\exists$ an ordering of nodes such that $j, k, \dots, m, l, r, \dots, i$ with

total demand of nodes until node m (including node m) being higher than the total demand of nodes after node m , then the center node cannot be selected as the depot.

Proof. Since distances are symmetric, $d_{im} = d_{mi}$. Then, $\Delta_{LD} = (Q_1 + q_m - (Q_2 + q_i))d_{mi} + q_m D_9$. Since if $q_j + q_{P_1} + q_k + q_m \geq q_l + q_{P_2} + q_r + q_i$, then $\Delta_{LD} \geq 0$, by utilizing Theorem 3.2, the center node cannot be a depot. $\square$

Lemma 3.4. *Let us consider a star network with equal distance between each node, say $d_{ij} = d$, $\forall i, j \in N$. Take any arbitrary node m , if $\exists$ an ordering of nodes such that $j, k, \dots, m, l, r, \dots, i$ with total demand of nodes until node m (including node m) being higher than the total demand of nodes after node m , then the center node cannot be selected as the depot.*

Proof. The proof follows the proof of Lemma 3.3. $\square$

Lemma 3.5. *Let us consider a star network with equal demand for each customer, say $q_{ij} = q$, $\forall i, j \in N$ and distances are symmetric. If $\exists$ a partitioning of nodes into P_1 and P_2 such that the number of nodes in path P_1 is higher than the ones in path P_2 , then the center node cannot be selected as the depot.*

Proof. Since distances are symmetric and demands are equal to each other, $\Delta_{LD} = (aq - bq)d_{mi} + qD_9$. By utilizing Theorem 3.2, if $\exists$ a center node i such that $a \geq b$, then the center node cannot be selected as the depot. $\square$

Lemma 3.6. *Let us consider a star network with equal demand for each customer and equal distance between each node. In this network, the center node cannot be selected as the depot.*

Proof. Since distances and demands are equal to each other, $\Delta_{LD} = (aq - bq)d + q(b + 3)d = (a + 3)qd$. By utilizing Theorem 3.2, since $(a + 3)qd$ is a positive number, the center node cannot be selected as the depot. $\square$

3.7 Conclusions and Managerial Implications

In this chapter, we introduce the GLRP as a combination of the traditional LRP and the more recently studied PRP, in which fuel consumption and CO₂ emissions are explicitly considered. We develop a mixed integer programming formulation for the GLRP, and describe a group of preprocessing rules and valid inequalities to strengthen the formulation. Additionally, we propose two heuristic algorithms to solve small and larger sized instances in reasonable times. For the computational study of the GLRP, we conduct different sensitivity analyses by changing some key parameters such as the number of depots to be opened, the fixed cost of operating depots and the fuel consumption and emission cost. We also evaluate the impacts of time windows, and depot location and vehicle speed decisions on fuel consumption. Additionally, we compare the GLRP formulation and the proposed heuristic approaches in terms of solution quality and time. This chapter also describes a case study for an FMCG company in Istanbul, Turkey and presents the computational analysis. Finally, we present an extension, where optimal solution characterizations for the special cases of the GLRP are investigated on different networks and cases.

The overall results show that including the “green” aspect in the objective function through fuel consumption and emissions does affect the optimal solutions. It is possible to draw a number of managerial insights from the results given in the previous section. First, depot locations must be explicitly considered in combination with the routing decisions for reductions not only in cost, but also in fuel consumption, resulting in lesser environmental impact. In particular, it may seem attractive to locate depots where it is cheaper to do so, but this may have a knock-on effect on the weight and speed-induced fuel consumption, resulting in a more expensive solution overall. Second, any opportunity that will allow to use looser time windows in making deliveries should be explored by operators, given that such constraints are generally seen to increase speed and distance, along with the associated fuel consumption. Finally, the results suggest that it may be beneficial to locate depots to areas for which heavy deliveries are to be regularly made.

Finally, the performance of the heuristic algorithms indicate that while the CLRSOA is a very effective approach to solve the GLRP for small sized instances, the ILS algorithm can be used to solve larger sized instances in reasonable solution times compared to both the GLRP formulation and the CLRSOA.



Chapter 4

Green Hub Location Problem

This chapter introduces the Green Hub Location Problem (GHLP) that extends the Hub Location Problem by considering CO₂ emissions explicitly. The problem decides locations for hubs, assignments of demand nodes to these hubs and vehicle speed to route the demand between any origin-destination pairs. The objective is to minimize the total amount of CO₂ emissions that depends on vehicle speed and payload while making all deliveries within a predetermined service time limit. In this study, first a nonlinear model is proposed for this problem, which is then reformulated as a second order cone programming formulation strengthened by using perspective cuts. An extensive computational study on two well-known datasets is conducted to show the benefits of including environmental impacts into the classic hub location problems. Analyses on the solutions with different discount factors, service time limits and number of hubs provide managerial insights for the carrier companies.

The structure of this chapter is as follows: Section 4.1 presents a general introduction to the hub location problem. Section 4.2 formally defines the GHLP and provides a mixed integer nonlinear programming formulation for the GHLP. Section 4.3 presents a second order cone programming reformulation of the model and perspective cuts to strengthen the formulation. Section 4.4 presents extensive computational analyses on the GHLP by changing some key parameters of the

problem. Conclusions and some managerial insights are given in Section 4.5.

The results of this chapter are published in Transportation Research Part E: Logistics and Transportation Review [168].

4.1 Introduction

Hubs are special facilities which are used to consolidate and disseminate flow in many-to-many distribution systems. These facilities are largely employed in transportation, city-logistics and telecommunication systems to route demand between each origin-destination (OD) pair. Instead of providing direct connections between each OD pair, consolidating flows at hubs enables us to discount routing cost between hub facilities and use fewer links and vehicles in the network.

The aim of the basic hub location problem is to find the best locations for hubs and assignment of demand nodes to these hubs. Assigning a demand node to its nearest hub does not necessarily provide the optimal solutions although it does in the classical location problems. Therefore, the optimal assignment of demand nodes to the hubs must also be determined in the hub location problems as it is explained in [169]. The pioneering works of [170], [171], [172] introduce the hub location problem and present an integer programming formulation with a quadratic objective function, which is another main difference of hub location problems from the classical location problems. Later, in [173], the hub location problem is classified into four categories with respect to their objectives: p -hub median, the uncapacitated hub location, p -hub center and hub covering problems, and presents linear formulations for each of them. The first two problems have economic objectives and their aim is to minimize the total cost whereas the last two can be considered as having service level objectives. The p -hub center problem minimizes the maximum service level between any OD pair and the hub covering problem minimizes the number of hub locations while maintaining a predetermined service level for each pair.

Survey papers by [174] and [175] on hub location problems show that the majority of the literature is devoted to the first two problems. However, due to today's competitive environment, in recent years, companies pay more attention to their service levels. Travel distances or travel times can be used to measure companies' service levels and 24-hour or 48-hour delivery times are also offered to consumers by cargo companies (see, [176]). Thus, some recent studies consider both economic and service level objectives. In [177], the objective is to minimize total transportation cost and determine the fleet size while meeting the predetermined service commitment of carriers. The study by [178] finds locations of hubs and minimizes total transportation cost under distance-dependent service level constraints for truck transportation. In [179], a cost minimization problem is considered with a service time bound for a hierarchical hub network with single assignment. The study by [180] also considers a cost minimization problem for a rail-road intermodal hub network under service time requirements. In [176], a hierarchical multimodal hub location problem is studied with time-definite deliveries over a hub network that contains airline and road segments. In [181], routing and scheduling decisions are added to the same problem discussed in [176].

As it can be seen in Section 2.2.3, there are only two studies [99] and [100] that consider environmental impacts of transportation activities in a hub location problem and to the best of our knowledge, this is the first study that consider a hub location problem with a service time bound in which fuel consumption and CO₂ emissions are explicitly included. As discussed before, due to competitive environment, carrier companies pay attention to their service level objectives and aim to decrease the required time of routing flows. To decrease their delivery times, companies may prefer to increase vehicle speeds. Since vehicle speed and payload affect fuel consumption significantly, we consider them as decisions of the CMEM to estimate fuel consumption amount accurately. Thus, including them as decisions could provide insights to the carrier companies that consider environmental impacts of their transportation activities.

4.2 Problem Definition and Formulation

We define the green hub location problem as designing a hub network that finds locations for hubs, assignments of demand nodes to these hubs, the flow (payload) carried between nodes and the speed at which vehicles travel on spoke (non-hub to hub) and hub arcs. The aim of the problem is to minimize total amount of emission which is explicitly calculated by an emission model while guaranteeing a predetermined service time bound between each OD pair. The same emission model (CMEM) described in Section 3.2.1 is used to estimate fuel consumption in the GHLP.

4.2.1 Model development of GHLP

The GHLP is defined on a directed complete graph $G = (N, A)$ where N denotes the demand nodes, $A = \{(i, j) : i, j \in N, i \neq j\}$ denotes the set of arcs and H represents the possible hub locations ($H \subseteq N$). The parameters and decision variables of the mathematical model can be found in Table 4.1. For the sake of tractability, the parameters of the emission model are given in Appendix A.2. We note that, in order to calculate emissions during the transportation correctly, we differentiate vehicle speeds on hub arcs (v_{km}^h) and spoke arcs (v_{ik}^d). To incorporate the effects of a hub network, we assume that the vehicles used between hubs will have different specifications that can affect the amount of fuel consumed and travel time. Therefore, we use two different discount factors, α_c and α_t for discounting travel cost (emissions) and travel time, respectively similar to the studies in the hub location literature.

The mixed-integer nonlinear programming formulation (GHLP-0) for the GHLP is as follows:

(GHLP-0)

$$\text{Minimize } z_1 + z_2 + z_3 + z_4 \tag{4.1}$$

Table 4.1: Nomenclature

Parameters	
w_{ij}	demand originated from node $i \in N$ and destined to node $j \in N$
O_i	total amount of flow originated at node $i \in N$, $O_i = \sum_{j \in N} w_{ij}$
D_i	total amount of flow destined to node $i \in N$, $D_i = \sum_{j \in N} w_{ji}$
d_{ij}	distance from node $i \in N$ to node $j \in N$
α_c	hub-to-hub discount factor for the travel cost
α_t	hub-to-hub discount factor for the travel time
p	number of hubs
v_{min}	minimum travel speed
v_{max}	maximum travel speed
T	maximum service time for each OD pair
Decision Variables	
x_{ik}	1 if node $i \in N$ is allocated to hub $k \in H$, and 0 otherwise
y_i^{km}	flow originated at node $i \in N$ and routed from hub $k \in H$ to hub $m \in H$
r_k	maximum time between hub $k \in H$ and the nodes allocated to that hub
v_{ik}^d	travel speed from node $i \in N$ to hub $k \in N$
v_{km}^h	travel speed from hub $k \in N$ to hub $m \in N$

subject to

$$z_1 = \sum_{i \in N} \sum_{k \in H} \delta \gamma \lambda d_{ik} (2\omega + O_i + D_i) x_{ik} \quad (4.2)$$

$$z_2 = \sum_{k \in H} \sum_{m \in H} \alpha_c \delta \gamma \lambda d_{km} (\omega x_{kk} x_{mm} + \sum_{i \in N} y_i^{km}) \quad (4.3)$$

$$z_3 = \sum_{i \in N} \sum_{k \in H} 2\lambda d_{ik} (\beta \gamma (v_{ik}^d)^2 + K \Upsilon V \frac{1}{v_{ik}^d}) x_{ik} \quad (4.4)$$

$$z_4 = \sum_{k \in H} \sum_{m \in H} \alpha_c \lambda d_{km} (\beta \gamma (v_{km}^h)^2 + K \Upsilon V \frac{1}{v_{km}^h}) x_{kk} x_{mm} \quad (4.5)$$

$$\sum_{k \in H} x_{ik} = 1 \quad \forall i \in N \quad (4.6)$$

$$x_{ik} \leq x_{kk} \quad \forall i \in N, k \in H \quad (4.7)$$

$$\sum_{k \in H} x_{kk} = p \quad (4.8)$$

$$\sum_{m \in H} y_i^{km} - \sum_{m \in H} y_i^{mk} = O_i x_{ik} - \sum_{j \in N} w_{ij} x_{jk} \quad \forall i \in N, k \in H \quad (4.9)$$

$$\sum_{m \in H \setminus \{k\}} y_i^{km} \leq O_i x_{ik} \quad \forall i \in N, k \in H \quad (4.10)$$

$$\frac{d_{ik}}{v_{ik}^d} x_{ik} \leq r_k \quad \forall i \in N, k \in H \quad (4.11)$$

$$r_k + r_m + \alpha_t \frac{d_{km}}{v_{km}^h} x_{kk} x_{mm} \leq T \quad \forall k, m \in H \quad (4.12)$$

$$v_{min} \leq v_{ik}^d \leq v_{max} \quad \forall i \in N, k \in H \quad (4.13)$$

$$v_{min} \leq v_{km}^h \leq v_{max} \quad \forall k, m \in H \quad (4.14)$$

$$x_{ik} \in \{0, 1\} \quad \forall i \in N, k \in H \quad (4.15)$$

$$y_i^{km} \geq 0 \quad \forall i \in N, k, m \in H \quad (4.16)$$

$$v_{ik}^d \geq 0 \quad \forall i \in N, k \in H \quad (4.17)$$

$$v_{km}^h \geq 0 \quad \forall k, m \in H \quad (4.18)$$

Objective function (4.1) minimizes the total amount of emissions calculated by the emission model described in Section 3.2.1 consisting of four terms; weight induced emissions on spoke (z_1) and hub arcs (z_2), and speed induced emissions on spoke (z_3) and hub arcs (z_4) represented by equations (4.2)–(4.5), respectively. Constraints (4.6) guarantee that each node is assigned to a single hub and Constraints (4.7) ensure that a hub is opened at a node if a node is assigned to that hub. Constraint (4.8) satisfies that exactly p hubs are opened. Constraints (4.9) guarantee flow balance at each node and Constraints (4.10) provide a link between the decision variables related to flow and assignment. Constraints (4.11) calculate the maximum time between a hub and the nodes that are allocated to that hub. Constraints (4.12) guarantee that the service time for each OD pair cannot exceed a predetermined service level, T . For service time limitations, we utilize *radius of hubs* concept by [182] and [183] in Constraints (4.11) and (4.12).

Constraints (4.13) and (4.14) limit travel speed on the arcs between demand node and hub, and between hubs, respectively. Constraints (4.15)–(4.18) are the domain constraints.

We remark here that, in this study, we only concentrate on total amount of emissions to show and discuss benefits of incorporating green transportation service to the hub location problem. If one aims to minimize the total cost that includes fixed, transportation and emission costs, our model can be easily adapted by only adding the costs of them to the objective function.

The proposed GHLP-0 is a mixed-integer nonlinear programming model since objective function components (4.3)–(4.5) and Constraints (4.11) and (4.12) have non-linear terms. To solve the problem, we first reformulate it as a second order cone programming (SOCP) model.

4.3 Reformulation of GHLP as a SOCP

The standard form of the Second Order Cone Programming (SOCP) is represented by [184] as follows:

$$\text{Minimize } f^T x$$

subject to

$$\|A_i x + b_i\|_2 \leq c_i^T x + d_i, \quad i = 1, \dots, m \quad (4.19)$$

$$Fx = g$$

where $f \in \mathbb{R}^n$, $A_i \in \mathbb{R}^{n_i \times n}$, $b_i \in \mathbb{R}^{n_i}$, $c_i \in \mathbb{R}^n$, $d_i \in \mathbb{R}$, $F \in \mathbb{R}^{p \times n}$, $g \in \mathbb{R}^p$ and $\|\cdot\|_2$ is Euclidean norm. Different types of inequalities such as linear, quadratic, hyperbolic, etc. can be represented as a second order cone constraint (4.19). For applications of the SOCP problems, we refer the reader to the studies by [184] and [185].

Below, we reformulate GHLP-0 as a SOCP model. We first linearize the multiplication of two binary decision variables x_{kk} and x_{mm} by defining a new auxiliary decision variable, a_{km} . We replace $x_{kk}x_{mm}$ in the objective function components (4.3) and (4.5) and in Constraints (4.12) with a_{km} and add the following constraints to the GHLP-0:

$$a_{km} \leq x_{kk} \quad \forall k, m \in H \quad (4.20)$$

$$a_{km} \leq x_{mm} \quad \forall k, m \in H \quad (4.21)$$

$$a_{km} \geq x_{kk} + x_{mm} - 1 \quad \forall k, m \in H \quad (4.22)$$

$$a_{km} \in \{0, 1\} \quad \forall k, m \in H \quad (4.23)$$

Constraints (4.20) and (4.21) guarantee that if a hub is not located at node k or m (or both), then a_{km} is equal to 0 and if hubs are located at nodes k and m , then Constraints (4.22) ensure that a_{km} is equal to 1.

After linearization of $x_{kk}x_{mm}$, we introduce four new auxiliary decision variables for the remaining nonlinear terms in GHLP-0.

$$u_{ik}^d = (v_{ik}^d)^2 \quad \forall i \in N, k \in H \quad (4.24)$$

$$u_{km}^h = (v_{km}^h)^2 \quad \forall k, m \in H \quad (4.25)$$

$$s_{ik} = \frac{x_{ik}}{v_{ik}^d} \quad \forall i \in N, k \in H \quad (4.26)$$

$$t_{km} = \frac{a_{km}}{v_{km}^h} \quad \forall k, m \in H \quad (4.27)$$

We now reformulate GHLP-0 as a mixed integer SOCP (GHLP-SOCP) by utilizing the auxiliary decision variables.

(GHLP-SOCP)

$$\text{Minimize } z'_1 + z'_2 + z'_3 + z'_4 \quad (4.28)$$

subject to

$$(4.6)-(4.10), (4.15)-(4.18), (4.20)-(4.23)$$

$$z'_1 = z_1 = \sum_{i \in N} \sum_{k \in H} \delta \gamma \lambda d_{ik} (2\omega + O_i + D_i) x_{ik} \quad (4.2')$$

$$z'_2 = \sum_{k \in H} \sum_{m \in H} \alpha_c \delta \gamma \lambda d_{km} (\omega a_{km} + \sum_{i \in N} y_i^{km}) \quad (4.3')$$

$$z'_3 = \sum_{i \in N} \sum_{k \in H} 2\lambda d_{ik} (\beta \gamma u_{ik}^d + K \Upsilon V s_{ik}) \quad (4.4')$$

$$z'_4 = \sum_{k \in H} \sum_{m \in H} \alpha_c \lambda d_{km} (\beta \gamma u_{km}^h + K \Upsilon V t_{km}) \quad (4.5')$$

$$(v_{ik}^d)^2 \leq u_{ik}^d \quad \forall i \in N, k \in H \quad (4.29)$$

$$(v_{km}^h)^2 \leq u_{km}^h \quad \forall k, m \in H \quad (4.30)$$

$$x_{ik} \leq s_{ik} v_{ik}^d \quad \forall i \in N, k \in H : i \neq k \quad (4.31)$$

$$a_{km} \leq t_{km} v_{km}^h \quad \forall k, m \in H \quad (4.32)$$

$$d_{ik} s_{ik} \leq r_k \quad \forall i \in N, k \in H \quad (4.11')$$

$$r_k + r_m + \alpha_t d_{km} t_{km} \leq T \quad \forall k, m \in H \quad (4.12')$$

$$v_{min} x_{ik} \leq v_{ik}^d \leq v_{max} x_{ik} \quad \forall i \in N, k \in H \quad (4.13')$$

$$v_{min} a_{km} \leq v_{km}^h \leq v_{max} a_{km} \quad \forall k, m \in H \quad (4.14')$$

Proposition 4.1. *There exists an optimal solution of GHLP-SOCP with the same optimal objective function value of GHLP-0.*

Proof. We first show that for every feasible solution of GHLP-0, there exists a solution in the feasible space of GHLP-SOCP with the same objective function value. We take a solution of GHLP-0 and assign the same values of decision

variables to their corresponding decision variables $(x, y, r, v^h \text{ and } v^d)$ in GHLP-SOCP. By definition, $z_1 = z'_1$ and for z_2 , we can safely utilize (4.20)-(4.23) without losing from optimality and z'_2 will be equal to z_2 . For z_3 and z_4 , we differentiate based on the possible cases:

Case (i): $x_{ik} = 1$ and $v_{ik}^d > 0$.

For this case, by using Equations (4.24) and (4.26), we directly find values of u_{ik}^d and s_{ik} , and guarantee the same value with z_3 as $(v_{ik}^d)^2 x_{ik}$ will be equal to u_{ik}^d .

Case (ii): $x_{ik} = 0$ and $v_{ik}^d > 0$.

For this case, z_3 will be equal to 0 since $x_{ik} = 0$. There is a feasible solution in GHLP-SOCP with z'_3 equal to zero, as well. For that, we can simply set the values of v_{ik}^d to zero to satisfy the Constraints (4.13'). We then safely set u_{ik}^d and s_{ik} to zero and guarantee that z'_3 is also equal to zero.

Case (iii): $x_{kk}x_{mm} = 1$ and $v_{km}^h > 0$.

We first remark here that if $x_{kk}x_{mm} = 1$ then $a_{km}=1$ by Constraints (4.20)-(4.23). Similar to Case (i), by using Equations (4.25) and (4.27), we find values of u_{km}^h and t_{km} in guaranteeing the same value of z_4 for this case since $(v_{km}^h)^2 x_{kk}x_{mm}$ will be equal to u_{km}^h .

Case (iv): $x_{kk}x_{mm} = 0$ and $v_{km}^h > 0$.

In this case, z_4 will also be equal to 0 since $x_{kk}x_{mm} = 0$. There is a feasible solution in GHLP-SOCP with z'_4 equal to zero. For that, we can simply set the values of v_{km}^h to zero in GHLP-SOCP in order to satisfy the Constraints (4.14'). We then set u_{km}^h and t_{km} to zero and guarantee that z'_4 equals to zero, as well. By combining the four cases, we end up with a feasible solution for GHLP-SOCP with the same objective function value of GHLP-0.

We now prove that the optimal solution GHLP-SOCP is also feasible for

GHLP-0. We first note that, in the optimal solution of GHLP-SOCP, Constraints (4.29)-(4.32) should be binding. (If they are not binding, decreasing the values of u_{ik}^d , u_{km}^h , s_{ik} and t_{km} reduces the optimal solution value without affecting the feasibility of the other constraints.) Then, Constraints (4.29)-(4.32) turn out to be equal to Equations (4.24)-(4.27). Thus, from the optimal solution of GHLP-SOCP, we can generate a feasible solution of GHLP-0 by removing the variables u^d , u^h , s and t . $\square$

We next show that, Constraints (4.29)-(4.32) can be rewritten in the form of Constraint (4.19). Constraints (4.29) and (4.30) are quadratic inequalities and since $u_{ik}^d \geq 0$, $u_{km}^h \geq 0$, $v_{ik}^d \geq 0$ and $v_{km}^h \geq 0$, they can be rewritten as second order cone constraints in the following form:

$$\left\| \begin{bmatrix} 2v_{ik}^d \\ 1 - u_{ik}^d \end{bmatrix} \right\| \leq (1 + u_{ik}^d) \quad \forall i \in N, k \in H \quad (4.29')$$

$$\left\| \begin{bmatrix} 2v_{km}^h \\ 1 - u_{km}^h \end{bmatrix} \right\| \leq (1 + u_{km}^h) \quad \forall k, m \in H \quad (4.30')$$

However, Constraints (4.31) and (4.32) cannot be directly rewritten as second order cone constraints. Thus, we first reformulate Constraints (4.31) and (4.32) as follows:

$$x_{ik}^2 \leq s_{ik}v_{ik}^d \quad \forall i \in N, k \in H : i \neq k \quad (4.33)$$

$$a_{km}^2 \leq t_{km}v_{km}^h \quad \forall k, m \in H \quad (4.34)$$

Constraints (4.33) are hyperbolic inequalities and since $x_{ik} \in \{0, 1\}$, $v_{ik}^d \geq 0$ and $s_{ik} \geq 0$, it can be represented as second order cone constraints in the following form:

$$\left\| \begin{bmatrix} 2x_{ik} \\ v_{ik}^d - s_{ik} \end{bmatrix} \right\| \leq (v_{ik}^d + s_{ik}) \quad \forall i \in N, k \in H : i \neq k \quad (4.33')$$

Similarly, since $a_{km} \in \{0, 1\}$, $v_{km}^h \geq 0$ and $t_{km} \geq 0$, Constraints (4.34) can also be represented as second order cone constraints in the following form:

$$\left\| \begin{bmatrix} 2a_{km} \\ v_{km}^h - t_{km} \end{bmatrix} \right\| \leq (v_{km}^h + t_{km}) \quad \forall k, m \in H \quad (4.34')$$

The reformulated version (GHLP-Base) of the problem is as follows:

(GHLP-Base)

Minimize (4.28)

subject to

(4.2')–(4.5'), (4.6)–(4.10), (4.11')–(4.14'), (4.15)–(4.18), (4.20)–(4.23), (4.29)–(4.30), (4.33)–(4.34).

4.3.1 Perspective cuts

To strengthen the formulation, we utilize the perspective cuts proposed by [186] for the quadratic inequalities. Instead of Constraints (4.29) and (4.30), we add the following perspective cuts to GHLP-Base:

$$(v_{ik}^d)^2 \leq u_{ik}^d x_{ik} \quad \forall i \in N, k \in H \quad (4.35)$$

$$(v_{km}^h)^2 \leq u_{km}^h a_{km} \quad \forall k, m \in H \quad (4.36)$$

Constraints (4.35) and (4.36) are also hyperbolic inequalities and they can be represented as second order cone constraints in the following forms:

$$\left\| \begin{bmatrix} 2v_{ik}^d \\ u_{ik}^d - x_{ik} \end{bmatrix} \right\| \leq (u_{ik}^d + x_{ik}) \quad \forall i \in N, k \in H \quad (4.35')$$

$$\left\| \begin{bmatrix} 2v_{km}^h \\ u_{km}^h - a_{km} \end{bmatrix} \right\| \leq (u_{km}^h + a_{km}) \quad \forall k, m \in H \quad (4.36')$$

4.4 Computational Study

In this section, we present an extensive computational analysis on the GHLP. We first introduce the two datasets that are used in the computational experiments. We then evaluate the performance of the perspective cuts on the GHLP-Base and analyze the solutions of the proposed model by varying several parameters such as maximum service time (T), the number of hubs (p), hub-to-hub discount factor for the travel cost (α_c) and for travel time (α_t), and we evaluate the impact of vehicle speed decision. We also provide a comparison between the solutions of the GHLP and the p -hub median problem to discuss the benefits of incorporating environmental considerations into a hub location problem. All experiments are implemented in a Java platform using Cplex 12.7.1 on a Linux OS environment with Dual Intel Xeon E5-2690 v4 14 Core 2.6 GHz processors with 128 GB of RAM.

4.4.1 Data sets

In the computational experiments, we use the US Civil Aeronautics Board (CAB) and Turkish network (TR) datasets. The CAB dataset [172] is based on airline passenger interactions between 25 US cities in 1970. Figure 4.1 shows the locations of the 25 cities that represent the demand nodes and the potential hubs ($|N| = |H| = 25$). For more information on the CAB dataset, we refer the reader to [187].

The TR dataset introduced by [188] consists of 81 cities in Turkey. The location of these cities are shown in Figure 4.2, where each city is considered as a demand node ($|N| = 81$). There are 22 potential hub nodes ($|H| = 22$), presented with red circles on the map.

For both datasets, the hub-to-hub discount factors for travel cost (α_c) and travel time (α_t) are taken as 0.75 and 0.8, respectively in [189]. The minimum

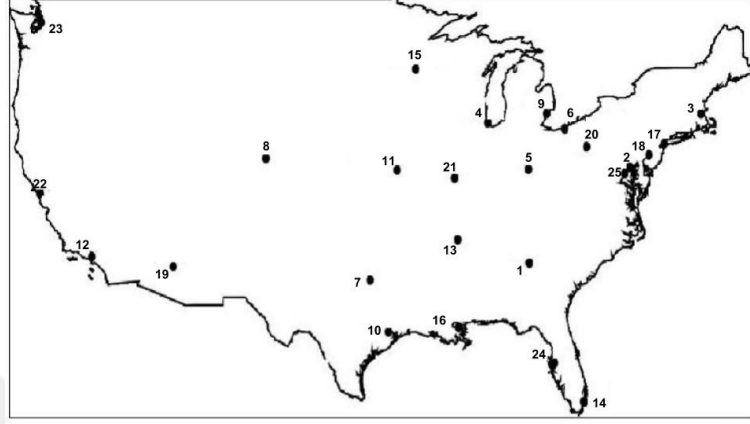


Figure 4.1: Map of the US with 25 Cities

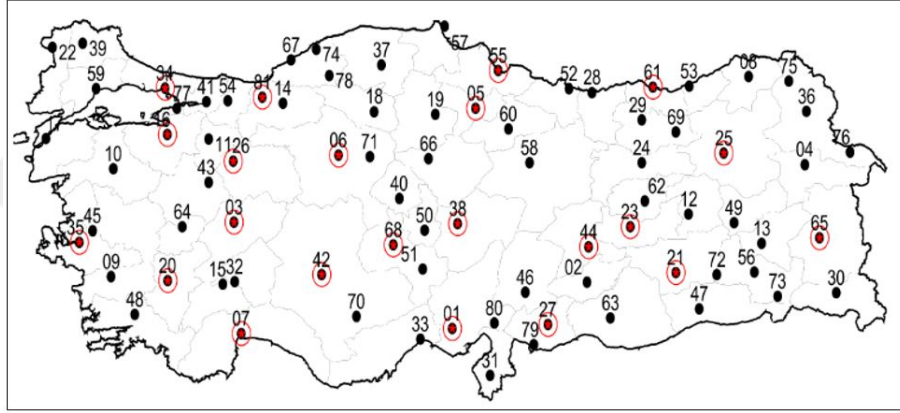


Figure 4.2: Map of Turkey with cities and potential hub locations

(v_{min}) and maximum (v_{max}) speed limits are set to 10 km/h and 90 km/h, respectively.

4.4.2 Performance of perspective cuts

This section presents the results of experiments conducted on the performance of the proposed perspective cuts. In these experiments, we consider the TR dataset with three different T values (24, 22, 20) in hours and four different p values (5, 6, 7, 8), in total 12 instances which are considered as the most difficult cases in our test instances. Table 4.2 depicts the results where the first two columns represent the maximum service time (T) in hours and the number of hubs (p). The next

two columns titled "GHLP-Base" and "With PCs" show the solution times of the formulation without and with perspective cuts in seconds, respectively. The last column titled "Imp (%)" shows the solution time improvement of including perspective cuts in percentages. The last row indicates the average solution time of the 12 instances for both versions of the formulation.

Table 4.2: Performance of the perspective cuts

T (h)	p	GHLP-Base (s)	With PCs (s)	Imp (%)
24	5	3227.58	2236.44	30.71
24	6	3327.03	2429.15	26.99
24	7	6180.05	3365.07	45.55
24	8	11118.79	4771.83	57.08
22	5	3186.44	2676.22	16.01
22	6	5078.18	2416.22	52.42
22	7	7547.38	2959.19	60.79
22	8	11366.13	4478.24	60.60
20	5	9574.38	10230.59	-6.85
20	6	17794.96	14452.02	18.79
20	7	9289.12	8506.75	8.42
20	8	15747.47	8772.71	44.29
Average		8619.79	5607.87	34.57

The results in Table 4.2 show that including the proposed perspective cuts into the model reduces the solution times in all 12 instances except one. For some instances the improvement increases up to 57%. Since, on average, the formulation with perspective cuts reduces the solution time by 34.57%, we use these cuts and include them into the formulation in the rest of the experiments.

4.4.3 Computational analysis

In this section, we present a comprehensive computational analysis on the solutions of the GHLP to evaluate the impacts of several key parameters of the problem. First, we analyze the effects of the maximum service time (T) and the number of hubs (p) on the CAB dataset where T is set as 60, 54 and 48 hours and p is varied between one and eight. The results can be found in Table 4.3 which presents the total emission amounts (in L) and components of it in terms of weight

induced emissions on spoke (z'_1) and hub arcs (z'_2) and speed induced emissions on spoke (z'_3) and hub arcs (z'_4). Table 4.3 also demonstrates the average vehicle speeds on spoke and hub arcs (in km/h) and hub locations, respectively.

Table 4.3: Results on the CAB dataset with different T and p values

T (h)	p	Emission					Av. Speed		Location
		z'_1 (L)	z'_2 (L)	z'_3 (L)	z'_4 (L)	Total (L)	Spoke (km/h)	Hub (km/h)	
60	1	24.01	0.00	6.65	0.00	30.66	59.26	-	11
60	2	15.12	2.36	4.37	0.32	22.17	58.42	85.58	5,8
60	3	11.28	4.45	3.57	0.82	20.12	59.57	66.80	8,21,25
60	4	9.08	5.67	3.03	1.41	19.18	58.55	60.82	1,4,8,18
60	5	8.86	5.66	2.72	1.93	19.17	57.96	58.04	1,2,4,8,13
60	6	7.88	6.38	2.50	2.75	19.51	57.92	56.54	1,4,6,8,13,18
60	7	7.99	6.48	2.40	3.38	20.25	58.20	57.45	1,2,4,6,8,13,21
60	8	7.43	7.23	2.29	4.25	21.20	58.24	56.16	1,4,5,6,8,13,18,21
54	1	24.01	0.00	6.88	0.00	30.88	62.11	-	11
54	2	15.12	2.36	4.52	0.34	22.33	61.50	90.00	5,8
54	3	11.86	4.35	3.42	0.75	20.38	59.60	70.70	8,13,20
54	4	9.08	5.67	3.10	1.47	19.33	60.77	63.98	1,4,8,18
54	5	8.86	5.66	2.79	1.99	19.29	60.04	60.06	1,2,4,8,13
54	6	7.88	6.38	2.56	2.80	19.62	60.19	58.53	1,4,6,8,13,18
54	7	7.99	6.48	2.46	3.43	20.37	60.56	57.60	1,2,4,6,8,13,21
54	8	7.87	6.88	2.39	4.17	21.31	60.63	56.90	1,2,4,5,6,8,13,21
48	1	Infeasible							
48	2	Infeasible							
48	3	11.86	4.35	3.56	0.82	20.59	62.49	77.35	8,13,20
48	4	9.28	5.67	3.18	1.46	19.59	62.69	67.61	4,8,13,18
48	5	8.86	5.66	2.92	2.08	19.51	63.33	63.38	1,2,4,8,13
48	6	7.88	6.38	2.70	2.89	19.84	63.79	61.06	1,4,6,8,13,18
48	7	7.55	6.82	2.55	3.63	20.55	64.09	59.27	1,4,6,8,13,18,21
48	8	7.43	7.23	2.47	4.38	21.52	64.25	58.08	1,4,5,6,8,13,18,21

The results in Table 4.3 suggest that for tighter maximum service time, for the same p value, the total amount of emissions increases along with the average vehicle speed on both spoke and hub arcs (Figure 4.3). We also observe that for a fixed T , the average vehicle speed on spoke arcs does not show a particular trend over the number of hubs (Figure 4.3b) whereas the average vehicle speed on hub arcs reduces as p increases (Figure 4.3c). We note that, if there is no service level requirements, the optimal vehicle speeds are equal to 55km/h as it is explained in

[46]. Although decreasing travel time bound increases the vehicle speed on hub arcs, opening more hubs decreases the average speeds which approach to 55km/h for all time bounds (Figure 4.3c).

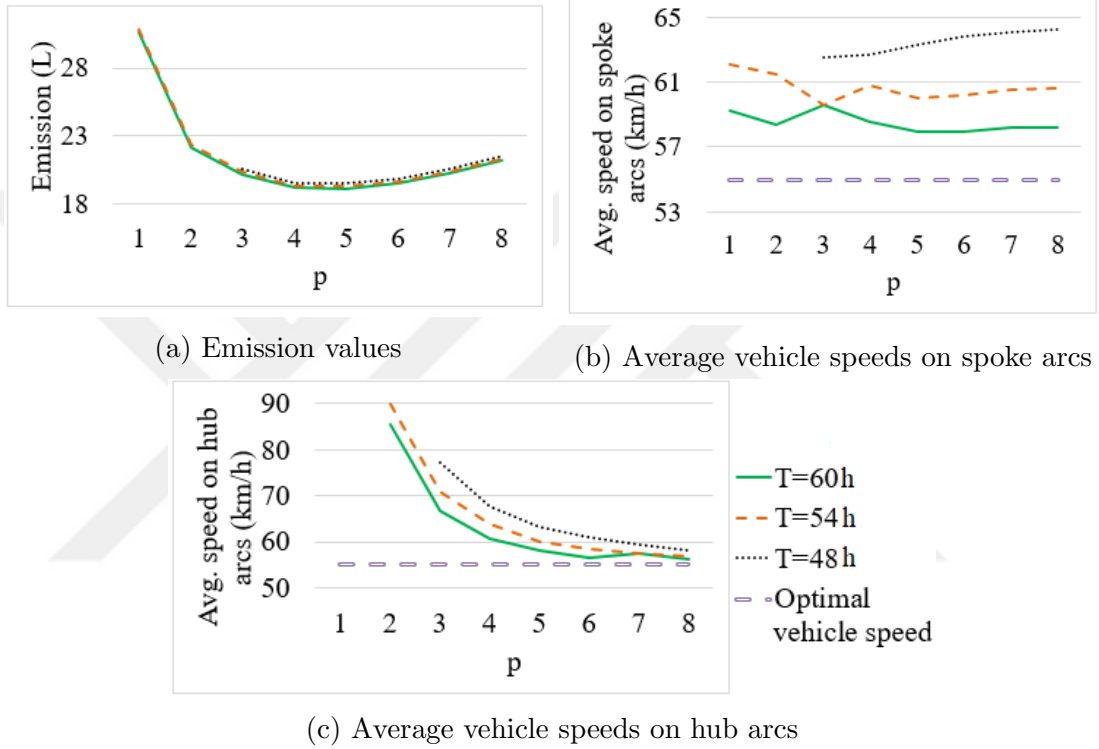
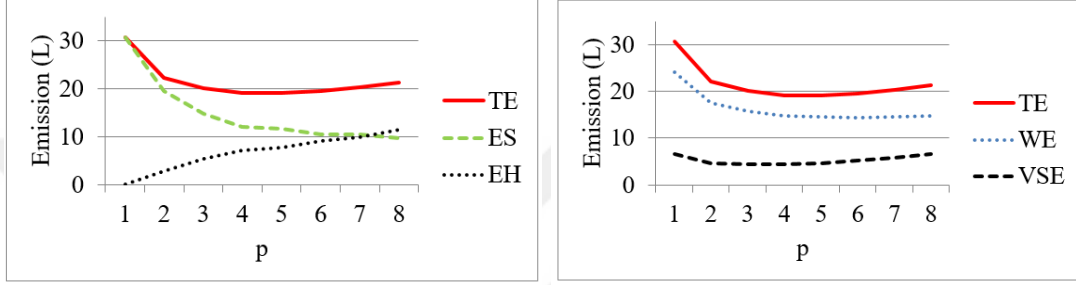


Figure 4.3: Schematic representation of results on the CAB dataset

We also observe that the amount of emissions behave like a convex function on the number of hubs. Initially, increasing p value reduces the emissions amount, but after a certain p , it starts to increase (Figure 4.3a). In our test instances, this certain p value for the CAB dataset is five for each T value as it can be observed in Table 4.3. We further analyze the results to understand the underlying reason behind the convexity of the total emission amounts ($TE = z'_1 + z'_2 + z'_3 + z'_4$) on the number of hubs. The results in Table 4.3 show that in general a higher p value reduces the amount of emissions on spoke arcs ($ES = z'_1 + z'_3$), but it increases the emission amount on hub arcs ($EH = z'_2 + z'_4$). This is consistent as higher p values reduces the number of spoke arcs and increases the number of hub arcs. Up to a certain p value, since the increase in the EH is less than the decrease in ES, total emission reduces. After that certain p value, opening new hubs does not change the assignment of demand nodes to hubs dramatically and leads to a

smaller gain in ES. On the other hand, this behaviour substantially increases the number of hub arcs and thus leads to a higher increase in EH than the decrease in ES. Therefore, the total amount of emissions acts as a convex function as it is depicted in Figure 4.4a when T is set to 60 hours.



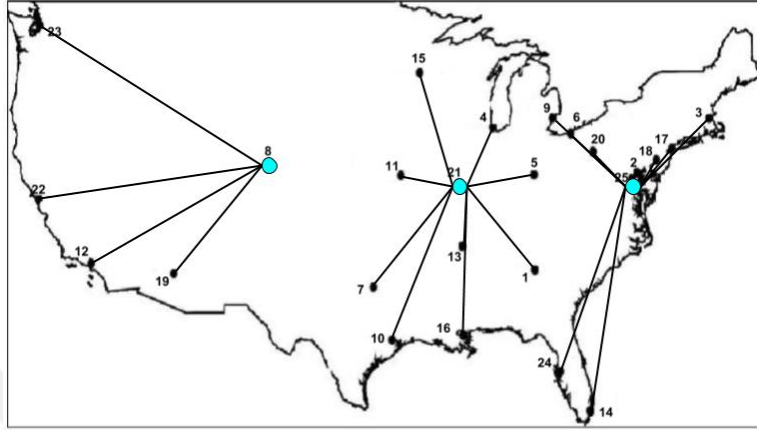
(a) Emissions on hub arcs (EH) and spoke arcs (ES) (b) Weight induced emission (WE) and speed induced emission (VSE)

Figure 4.4: Schematic representation of emission analysis on the CAB dataset with $T = 60$ hours

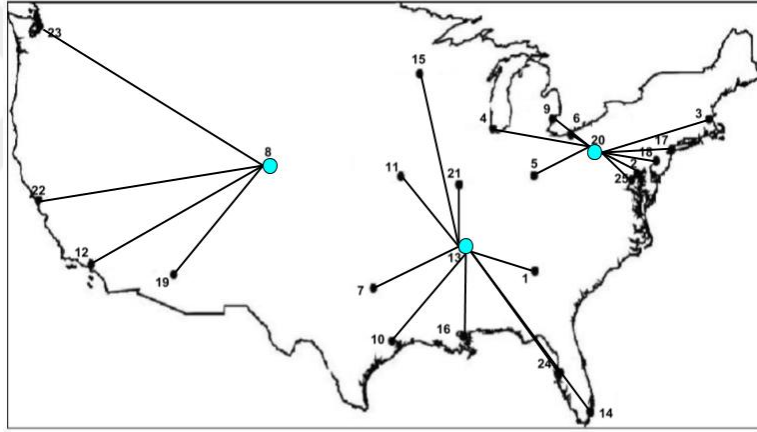
We also analyze the behaviour of the weight induced emission ($WE = z'_1 + z'_2$) and vehicle speed induced emission ($VSE = z'_3 + z'_4$) on the number of hubs in Figure 4.4b, which demonstrates that VSE and WE also behave like convex functions on the number of hubs. While the least WE amount is obtained when $p = 6$, the least VSE amount is obtained when $p = 3$ when the total emission amounts is minimized. Figure 4.4b also shows that the WE amount is higher than the VSE amount suggesting that z'_1 and z'_2 (WE) are more dominant in the objective function compared to the z'_3 and z'_4 (VSE).

We further analyze two instances in more detail to observe the changes on the solutions in terms of the hub locations and demand node assignments. Here, we consider instances with two different T values and the number of hubs is equal to three in both instances (Figure 4.5).

When the maximum service time is set to 60 hours, three hubs are opened in Denver (8), St. Louis (21) and Washington (25). Cities located in the west, center and east are assigned to Denver (8), St. Louis (21) and Washington (25), respectively (Figure 4.5a). For a 48-hour service time, while Denver (8) remains as a hub, other two hubs are located in Memphis (13) and Pittsburgh (20). In



(a) $T = 60$ hours



(b) $T = 48$ hours

Figure 4.5: Results on the CAB dataset with three hubs

this case, some of the cities located in the eastern side of the US (Miami (14) and Tampa (24)) are now assigned to a centrally located hub, Memphis (13) (Figure 4.5b). As it can also be seen on the maps, hubs are selected from the centrally located cities for both cases.

We also conduct experiments on the TR dataset to analyze the effect of the maximum service time and the number of hubs on the solutions. We set T to 24, 22 and 20 hours and vary number of hubs (p) between one to 12 to observe the behaviour of total emission on the number of hubs. We report the results in Table 4.4 and the observations are very similar to the ones obtained from the experiments on the CAB dataset, especially in terms of the impact of the

maximum service time on the solution and convex behaviour of the total emission (Figure 4.6a). We observe that the number of hubs that provides the least amount of emissions is nine for each T value (as opposed to five for the CAB dataset). Thus, for the TR data set, we need to open more hubs to obtain the minimum emission amount. Since there are more demand nodes in the TR dataset (81) than the number of nodes in the CAB dataset (25), opening a new hub in the TR dataset is more likely to change the assignments of demand nodes and reduces the emission on spoke arcs. Therefore, we observe that total emission amount decreases up to a higher p value if there are more demand nodes.

Similar to the results obtained from the experiments on the CAB dataset, the results on Table 4.4 suggest that the average vehicle speeds on spoke arcs do not show a particular pattern (Figure 4.6b), but the average vehicle speed on hub arcs decreases as p increases (Figure 4.6c). For a fixed value of p , reducing time bound increases the total amount of emission and also the average vehicle speed on both spoke and hub arcs, as expected (Figure 4.6).

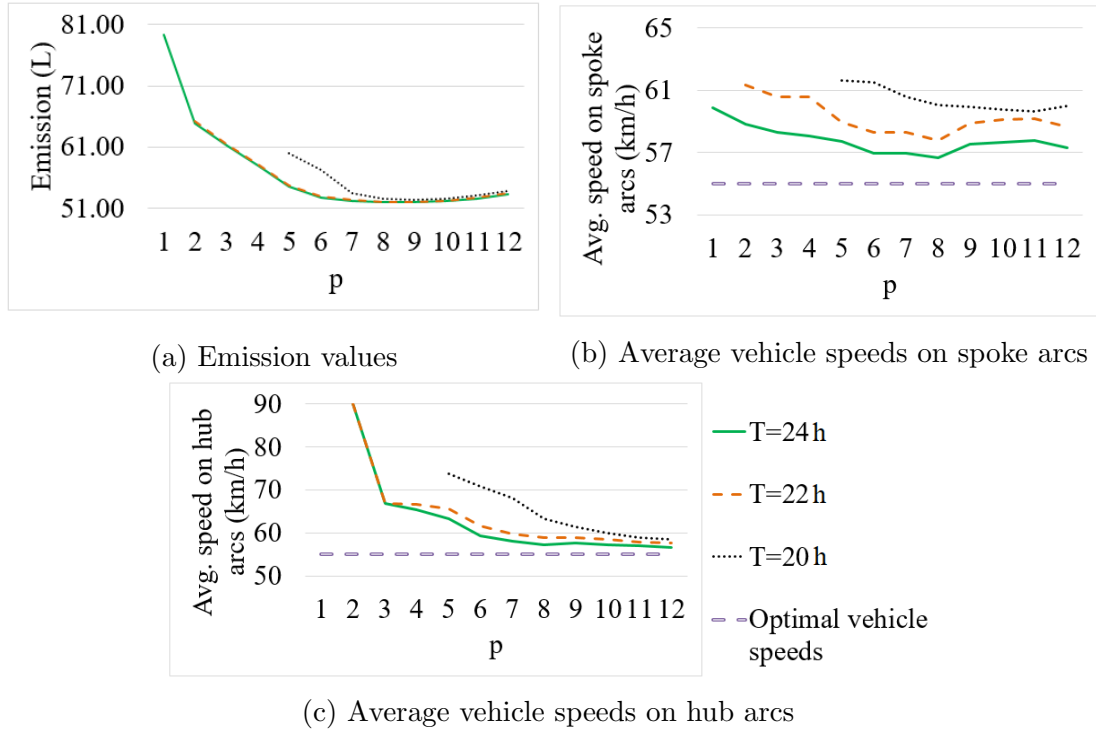
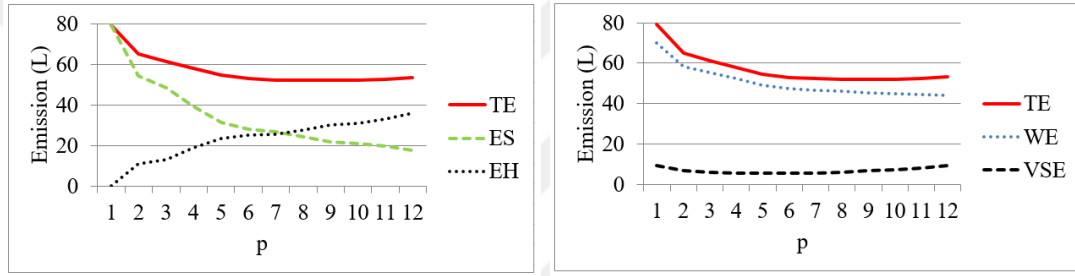


Figure 4.6: Schematic representation of the solutions on the TR dataset

Table 4.4: Results on the TR dataset with different T and p values

T (h)	p	Emission					Av. Speed		Location
		z'_1 (L)	z'_2 (L)	z'_3 (L)	z'_4 (L)	Total (L)	Spoke (km/h)	Hub (km/h)	
24	1	69.87	0.00	9.45	0.00	79.31	59.85	-	38
24	2	47.56	10.67	6.51	0.13	64.87	58.84	90.00	6,44
24	3	42.59	12.59	5.78	0.29	61.26	58.32	66.79	1,6,23
24	4	34.26	18.12	4.97	0.61	57.95	58.04	65.29	1,6,23,26
24	5	26.86	22.13	4.54	1.06	54.59	57.74	63.35	1,3,6,23,34
24	6	23.86	23.45	4.07	1.45	52.82	56.97	59.34	1,3,5,6,23,34
24	7	22.78	23.78	3.87	1.83	52.26	56.93	58.05	1,3,5,6,23,34,68
24	8	21.05	24.92	3.35	2.66	51.98	56.65	57.28	1,3,5,6,23,25,34,68
24	9	18.29	26.81	3.55	3.30	51.95	57.52	57.56	1,3,5,6,16,23,34,35,68
24	10	17.66	27.13	3.42	3.93	52.14	57.68	57.21	1,3,5,6,16,23,34,35,68,81
24	11	16.26	28.21	3.28	4.83	52.57	57.79	56.96	1,3,6,16,23,34,35,38,42,55,81
24	12	14.61	29.62	2.77	6.33	53.33	57.31	56.51	1,3,6,16,23,25,34,35,38,42,55,81
22	1	Infeasible							
22	2	47.29	11.10	6.66	0.13	65.18	61.36	90.00	6,44
22	3	42.15	13.12	5.88	0.29	61.44	60.59	66.79	1,6,23
22	4	34.26	18.12	5.13	0.61	58.12	60.60	66.56	1,6,23,26
22	5	26.41	22.63	4.53	1.10	54.68	58.92	65.70	1,3,6,23,34
22	6	23.84	23.48	4.11	1.49	52.91	58.32	61.61	1,3,5,6,23,34
22	7	22.78	23.78	3.92	1.87	52.35	58.30	59.63	1,3,5,6,23,34,68
22	8	21.05	24.92	3.39	2.71	52.06	57.78	58.84	1,3,5,6,23,25,34,68
22	9	18.29	26.81	3.61	3.36	52.06	58.86	58.93	1,3,5,6,16,23,34,35,68
22	10	17.64	27.16	3.46	4.00	52.26	59.11	58.38	1,3,5,6,16,23,34,35,68,81
22	11	17.05	27.57	3.42	4.67	52.70	59.20	57.81	1,3,5,6,16,23,34,35,42,68,81
22	12	14.61	29.62	2.81	6.41	53.45	58.63	57.62	1,3,6,16,23,25,34,35,38,42,55,81
20	1	Infeasible							
20	2	Infeasible							
20	3	Infeasible							
20	4	Infeasible							
20	5	30.33	23.60	4.69	1.43	60.06	61.61	73.72	21,25,26,34,68
20	6	27.51	23.63	4.31	1.88	57.33	61.51	70.93	6,21,25,26,34,68
20	7	21.52	25.61	3.71	2.61	53.45	60.60	68.06	1,3,6,16,21,34,61
20	8	20.12	25.94	3.37	3.19	52.62	60.02	63.37	1,3,5,6,16,21,25,34
20	9	19.17	26.26	3.22	3.80	52.43	59.92	61.38	1,3,5,6,16,21,25,34,68
20	10	17.68	27.23	3.05	4.61	52.57	59.78	59.92	1,3,6,16,21,25,34,38,42,55
20	11	16.23	28.37	2.87	5.57	53.04	59.62	58.88	1,3,6,16,21,25,27,34,38,42,55
20	12	15.58	28.91	2.72	6.54	53.75	60.01	58.58	1,3,6,16,21,25,27,34,38,42,55,81

Figure 4.7 provides an analysis on the distribution of total emission amount when the time bound is set to 24 hours. As it can be seen from Figure 4.7a, increasing p value reduces the amount of emission on spoke arcs (ES) and increases the amount of emission on hub arcs resulting a convex function of total amount of emissions (TE) similar to the results in the CAB dataset. Figure 4.7b indicates that weight induced emission (WE) amount is higher compared to the vehicle speed induced emission (VSE) for the results of the TR dataset, as well.



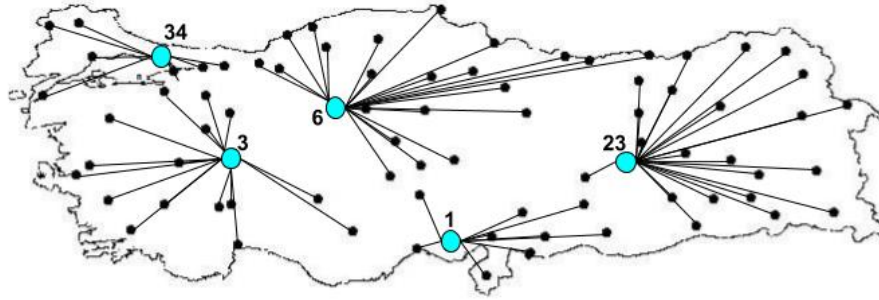
(a) Emissions on hub arcs (EH) and spoke arcs (ES) (b) Weight induced emission (WE) and vehicle speed induced emission (VSE)

Figure 4.7: Schematic representation of emission analysis on the TR dataset with $T = 24$ hours

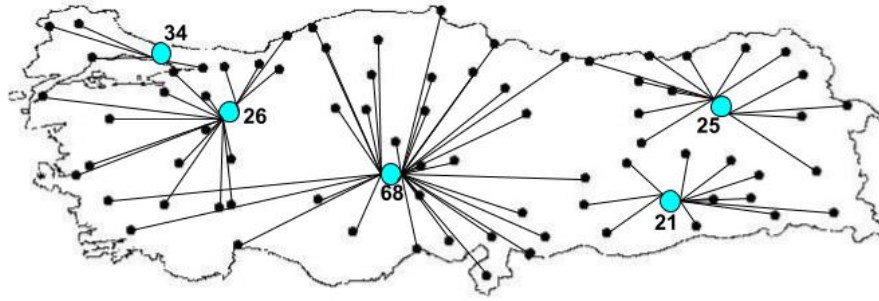
We also provide a further analysis on the solutions of the GHLP with different service time levels on the TR dataset. Figure 4.8 presents the GHLP solutions with five hubs and service times are set to 24 and 20 hours, respectively. For a 24-hour service time, hubs are located in Adana (1), Afyon (3), Ankara (6), Elazig (23) and Istanbul (34) as represented in Figure 4.8a. To complete all deliveries within 20 hours, more dispersed locations are selected as hubs such as Diyarbakir (21), Erzurum (25), Eskisehir (26) and Aksaray (68) while Istanbul is still used as a hub due to its high O_i and D_i values (Figure 4.8b).

4.4.3.1 The impact of α_c

In this section, we analyze the impact of hub-to-hub discount factor for the travel cost (α_c) on the solutions. We first conduct experiments on the CAB dataset with three different α_c values, namely, 0.75, 0.50 and 0.25. We report the detailed results for different service times and number of hubs in Appendix B.1. We



(a) $T = 24$ hours



(b) $T = 20$ hours

Figure 4.8: Results on the TR instance with five hubs

remind the reader that the results with $\alpha_c = 0.75$ are the ones discussed in the previous section. As α_c is a part of objective function, it directly affects the total amount of emissions thus, we do not report those values in Appendix B.1.

The results indicate that decreasing α_c generally changes the hub locations and yields more dispersed hubs. For instance, whereas none of the nodes at the west part of US (i.e. 12, 19, 22, 23) are selected as hubs in the solutions with $\alpha_c = 0.75$, Los Angeles (12) is selected as one of the hubs in most of the instances with $\alpha_c = 0.25$. Moreover, due to the changes in the hub locations, average vehicle speeds on the hub and spoke arcs are also affected. Figure 4.9 visualizes the solutions given in Appendix B.1 and demonstrates that the average vehicle speed on spoke arcs does not show a particular trend over α_c . However, for any T , decreasing α_c generally increases the average vehicle speed on the hub arcs by utilizing discounting cost property between hub locations. Reducing α_c from 0.75 to 0.5 and 0.25 increases the average vehicle speed on hub arcs by 2.15 km/h (3.35%) and 4.98 km/h (7.75%), respectively.

We carry out the same analysis on the TR dataset and present the detailed results in Appendix B.2. The results and deductions about the hub locations obtained here are very similar to the ones for the CAB dataset, and for the TR dataset reducing the discount factor α_c from 0.75 to 0.5 and 0.25 increases the average vehicle speed on the hub arcs by 2.46 km/h (3.67%) and 3.85 km/h (5.75%). The only difference that we observe from Figure 4.10 which visualizes the solutions in Appendix B.2, decreasing α_c generally reduces the average vehicle speed on the spoke arcs.

4.4.3.2 The impact of α_t

In this section, we provide a detailed analysis on the impact of the hub-to-hub discount factor for the travel time (α_t), where we consider three different α_t values; 0.8, 0.6 and 0.4. We remind the reader that the results with $\alpha_t = 0.8$ are the solutions that are already discussed.

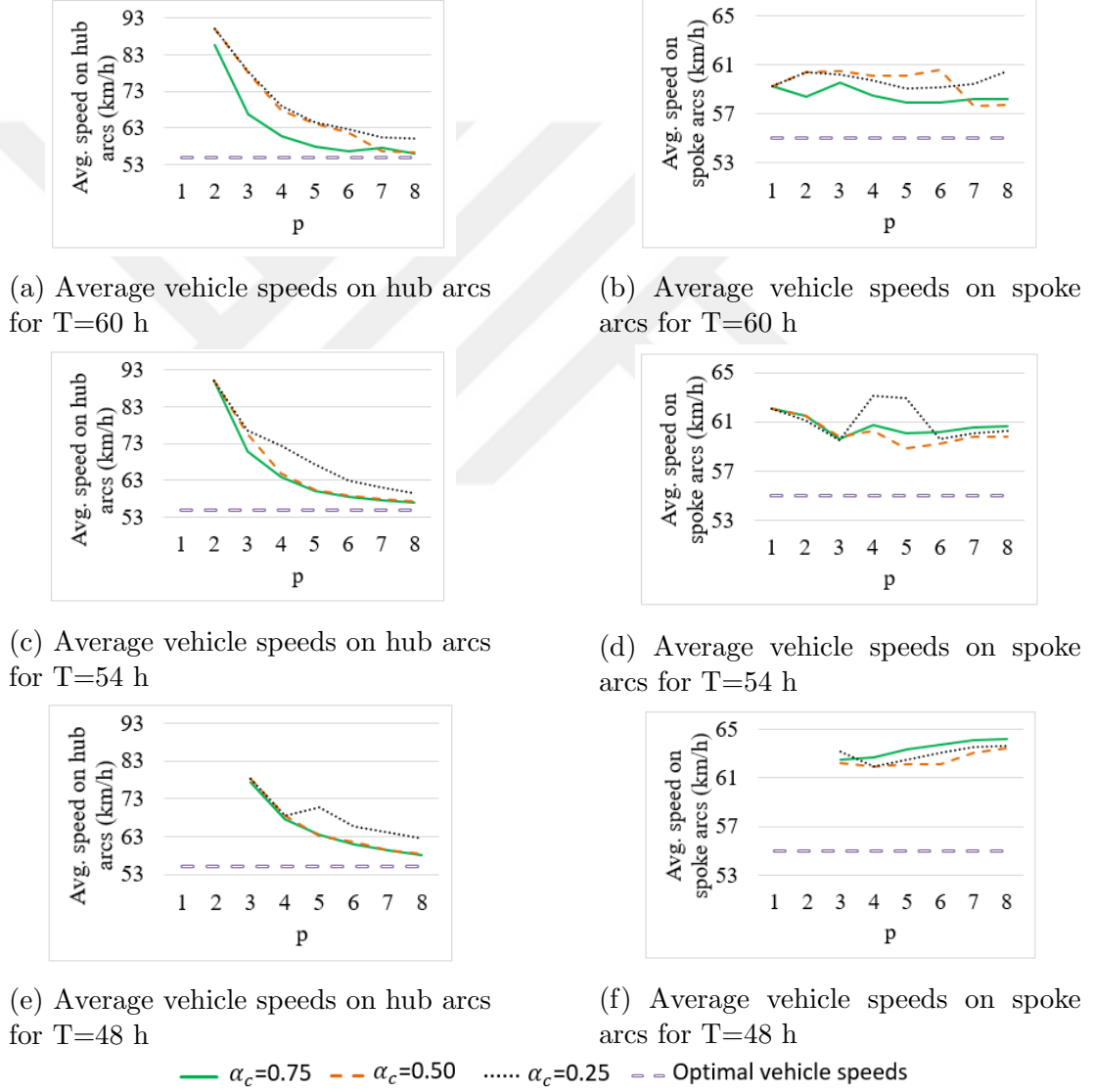


Figure 4.9: Schematic representation of α_c analysis on the CAB dataset

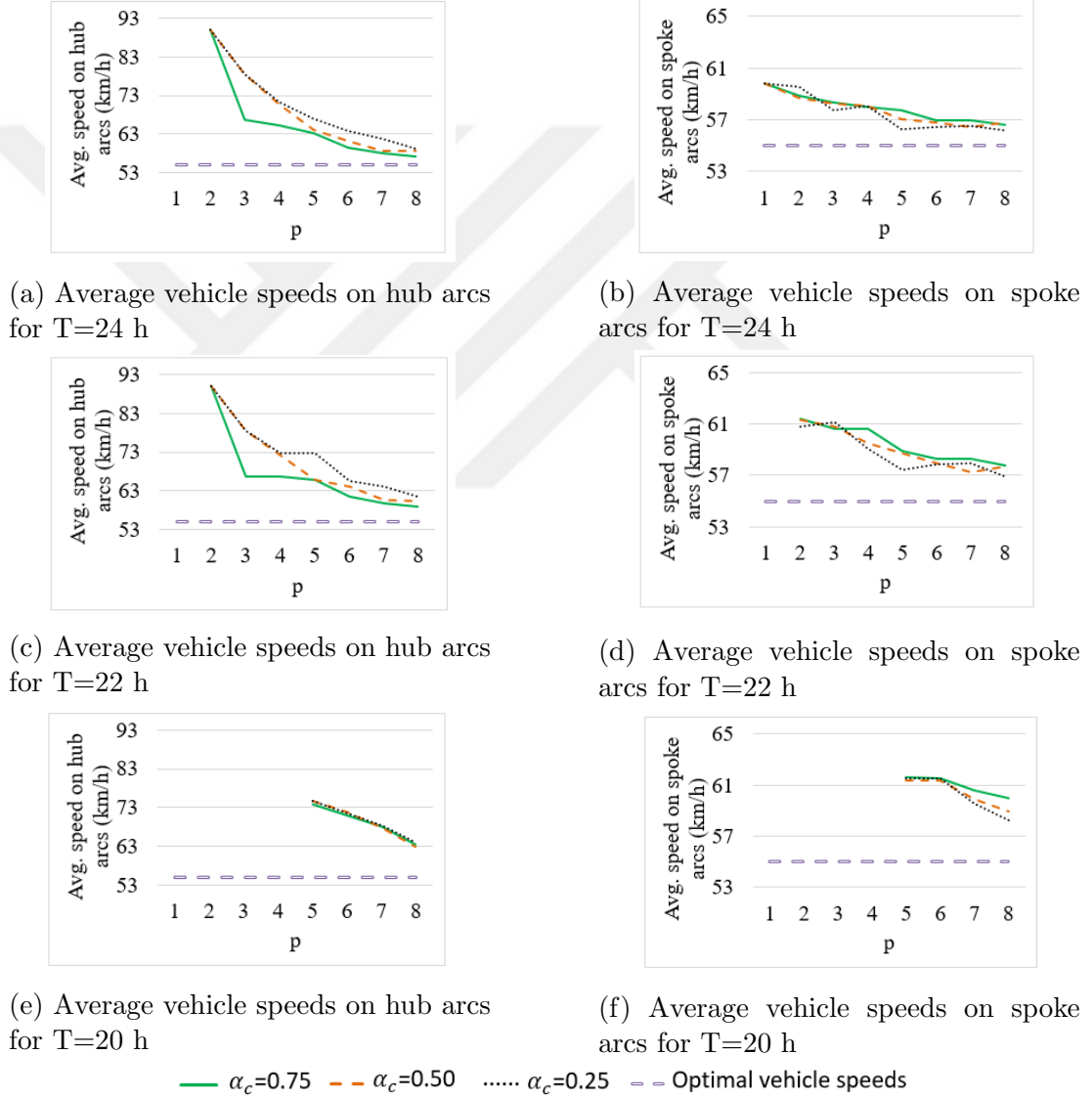


Figure 4.10: Schematic representation of α_c analysis on TR dataset

We first conduct experiments on the CAB dataset and provide the detailed results in Appendix B.3. We first note that although α_t is not a part of the objective function, due to the changes in the hub locations, assignments of demand nodes and vehicle speeds, the total emission amount decreases as α_t reduces. When the discount factor is set to 0.6 and 0.4, the reduction in the emission is 0.12 L (0.58%) and 0.22 L (1.03%), respectively. The results also suggest that reducing α_t decreases the average vehicle speeds on both spoke and hub arcs (Figure 4.11). By decreasing α_t , we relax the service level requirement of each OD pair and thus, vehicle speeds approach to 55 km/h (the optimal vehicle speed if there is no service level requirements). The impact of α_t on the vehicle speed on hub arcs is greater than the one on the spoke arcs. Setting α_t to 0.6 and 0.4 reduces the average vehicle speed on the spoke arcs by 1.53 km/h (2.52%) and 3.02 km/h (4.98%), respectively. The reductions for the average vehicle speed on hub arcs are 2.08 km/h (3.23%) and 5.06 km/h (7.56%). In addition, reducing α_t affects the locations of hubs and in almost half of the instances, at least one of the hub locations is changed when α_t is reduced. Moreover, as α_t affects the feasibility of the problem, we obtain a feasible solution by reducing α_t for one of the infeasible solutions obtained with $\alpha_t = 0.8$.

We also carry out experiments on the TR dataset and present the results in Appendix B.4. The results show that although decreasing α_t does not affect hub locations significantly, it highly affects vehicle speeds on spoke and hub arcs. Decreasing α_t relaxes service time between each OD pair and vehicle speeds approach to 55 km/h (Figure 4.12). Decreasing α_t to 0.6 and 0.4 also results a reduction of 1.59 km/h (2.69%) and 2.56 km/h (4.33%) on the average vehicles speed on spoke arcs, respectively. The same figures for the average vehicle speed on hub arcs are 3.34 km/h (4.99%) and 6.15 km/h (9.18%). Thus, the total emission amounts are also affected and reduced by 0.7 L (1.21%) and 0.77 L (1.33%) when α_t is set to 0.6 and 0.4, respectively. In addition, the results present that α_t has more impact on the feasibility of the problem with the TR dataset than the impact on the CAB dataset as we obtain three more feasible solutions with $\alpha_t=0.6$ and $\alpha_t=0.4$ for the infeasible solutions with $\alpha_t=0.8$.

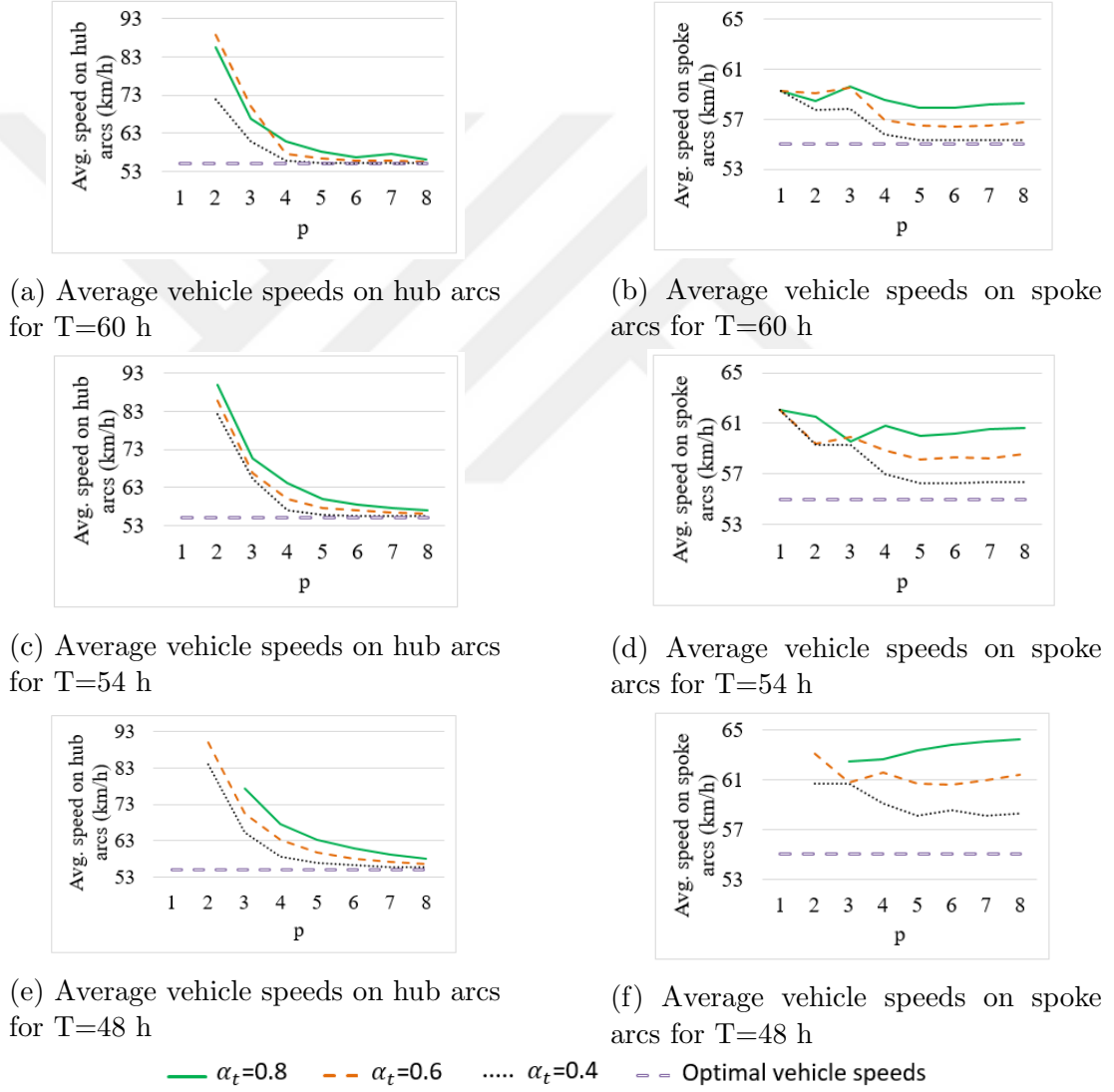
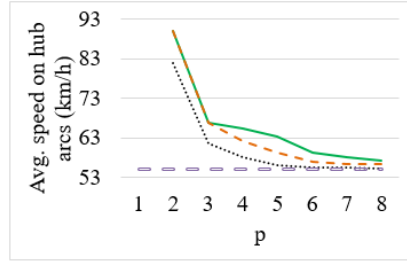
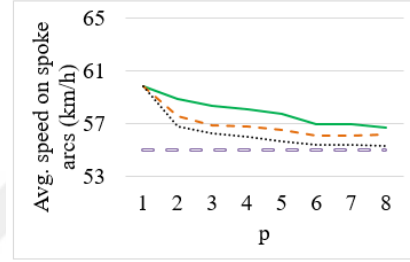


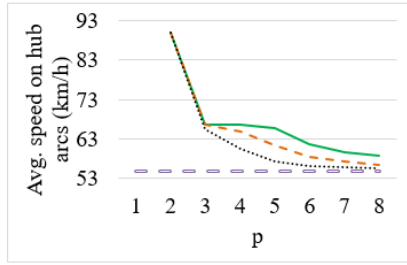
Figure 4.11: Schematic representation of α_t analysis on the CAB dataset



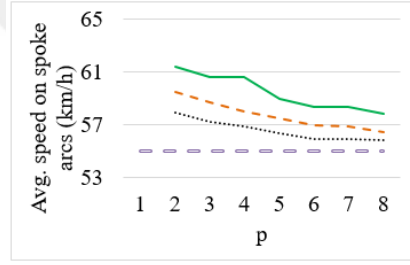
(a) Average vehicle speeds on hub arcs for T=24 h



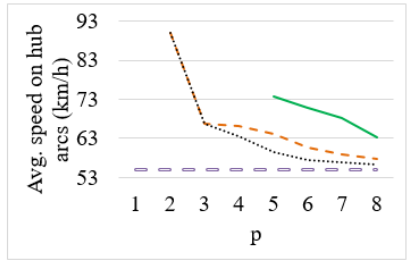
(b) Average vehicle speeds on spoke arcs for T=24 h



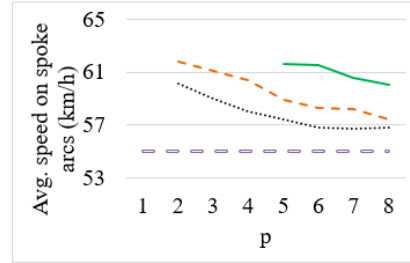
(c) Average vehicle speeds on hub arcs for T=22 h



(d) Average vehicle speeds on spoke arcs for T=22 h



(e) Average vehicle speeds on hub arcs for T=20 h



(f) Average vehicle speeds on spoke arcs for T=20 h

— $\alpha_t=0.8$ - - $\alpha_t=0.6$ $\alpha_t=0.4$ - - - Optimal vehicle speeds

Figure 4.12: Schematic representation of α_t analysis on the TR dataset

4.4.4 The impact of the vehicle speed decision

In this section, we evaluate the impact of considering vehicle speed as a decision by comparing the GHLP with its new version where vehicle speed is set to a fixed value for all spoke and hub arcs. In this analysis, the vehicle speed is fixed to the following values; 55, 60, 65, 70, 75, 80, 85 and 90, and also 62.38 km/h, which is the average optimal vehicle speed obtained by solving the GHLP over all (hub and spoke) arcs and all instances. We conduct computational experiments over the CAB dataset. The results that show the number of instances become infeasible due to fixing vehicle speed and the average deviation from the optimal solutions in terms of the amount of emissions can be found in Table 4.5.

Table 4.5: The impact of the vehicle speed decision on the CAB dataset

Fixed Speed	55	60	62.38	65	70	75	80	85	90
# of Infeasible Solution	10	10	9	8	6	5	3	1	0
Deviation in Emission	16.99	13.66	9.19	7.06	7.4	3.14	3.66	2.85	3.37

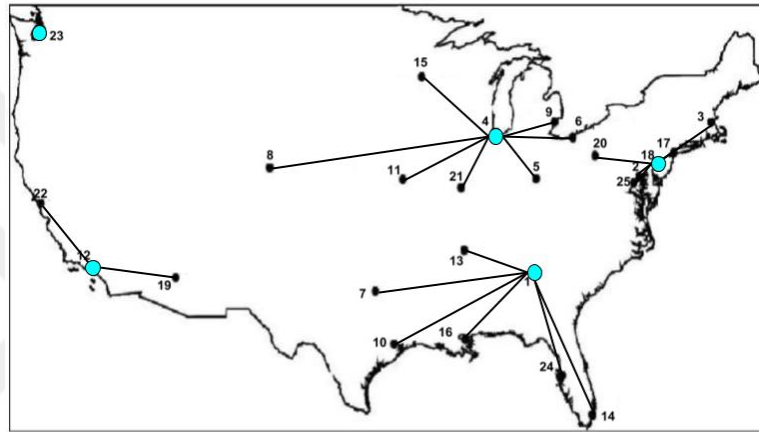
The results on Table 4.5 show that fixing vehicle speed to 55 km/h, which is the optimal speed under no service level requirements, leads to 10 out of 22 instances become infeasible and it also increases the amount of emission by 16.99% compared to the optimal solutions obtained by the GHLP in the remaining 12 instances. Using the average optimal vehicle speed obtained by the GHLP (62.38 km/h) as the fixed vehicle speed results with infeasibility for nine instances and a 9.19% increase in the emission amount. The increase in fixed vehicle speed value reduces the number of instances that become infeasible as it is expected. We also observe that increasing the fixed vehicle speed value decreases the deviation in terms of emission amount up to a certain point, 85 km/h, which is the vehicle speed value that gives the least deviation amount with a 2.85% increase among all possible vehicle speed values. Here we also notice that for different service time values, the fixed speed values that provide the least amount of deviation change, for instance, when T is set as 60, 54 and 48 hours, the fixed speed values with the least deviation amounts are 65, 75 and 90 km/h, respectively. So, we can also see that tighter service levels require higher fixed speed values in order to find solutions with less amount of emissions.

4.4.5 Comparison of GHLP and p-hub median problem

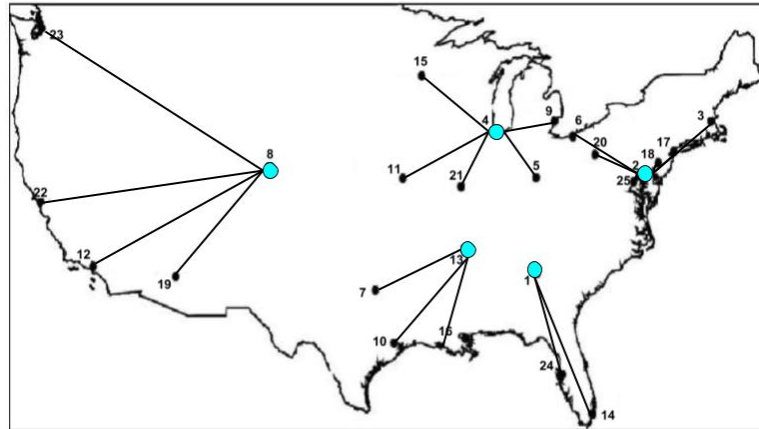
The GHLP can be considered as an extension of the classical p -hub median problem (p -HMP) where the aim is to minimize the total travel cost without any service level requirements. To evaluate considering environmental impact of emissions on the solutions, we compare the results of GHLP and a two-stage p -HMP. In the two-stage p -HMP, we first solve the p -HMP with a service time limit in order to decide the hub locations and demand node assignments. To ensure feasible solutions for the p -HMP, in this stage, we assume that vehicles travel with maximum available speed (v_{max}) on both hub and spoke arcs. After solving the p -HMP, we solve the GHLP-Base in which hub locations and demand node assignments are fixed to decide the vehicle speeds and to minimize the total emission amount. We compare solutions of these two problems on the CAB and TR datasets and analyze the results for different parameters.

Appendix B.5 presents the results of GHLP and two-stage p -HMP for the CAB dataset. The solutions indicate that in 17 out of 22 instances (two instances are infeasible), the two problems yield different results in terms of hub locations and demand node assignments. For those instances, on the average, the GHLP reduces the total amount of emissions by 5.63%. Higher p and lower T values leads a larger reduction on the emission amounts with a maximum reduction of 14.70%.

We further analyze one instance ($T = 48$ hours, $p = 5$) and the solutions of two aforementioned problems are depicted in Figure 4.13. In the solution of the p -HMP, Atlanta (1), Chicago (4), Los Angeles (12), Philadelphia (18) and Seattle (23) are opened as hubs. On the other hand, in the solution of the GHLP, Atlanta (1) and Chicago (4) remain as hubs and the other three hubs are located in Baltimore (2), Denver (8) and Memphis (13). Figure 4.13 demonstrates that hubs in the solutions of the GHLP are much closer to each other compared to the hubs obtained in the solutions of the p -HMP. Moreover, while in the latter problem two hubs are opened in the west coast (Los Angeles (12) and San Francisco (22)), in the former one Denver (8) serves as a hub to cover demand points in the west.



(a) Two stage p -HMP



(b) GHLP

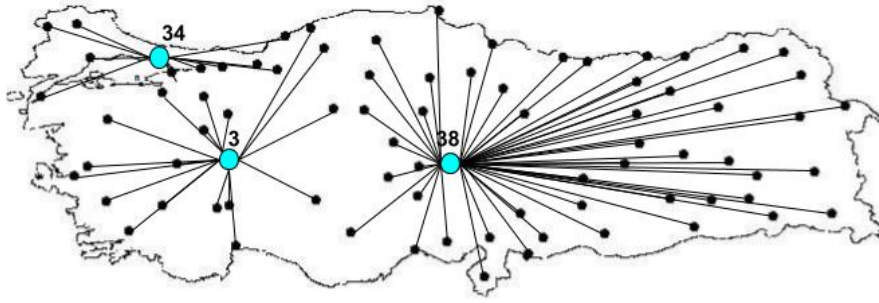
Figure 4.13: Results on the CAB dataset with a 48-hour service time and five hubs

As it can also be seen from Appendix B.5, the p -HMP generally locates the hubs based on the total incoming and outgoing flow amounts of nodes. For instance, three cities (New York (17), Los Angeles (12) and Chicago (4)) which have the highest O_i or D_i values are opened as hubs in most of the instances. On the other hand, the GHLP usually locates the hubs based on their spatial locations. The hub locations in the solutions of the GHLP tend to be more centrally located compared to the ones in the solutions of the p -HMP. The main reason for this tendency is that the GHLP includes objective function components that are based on not only payload, but also vehicle speed.

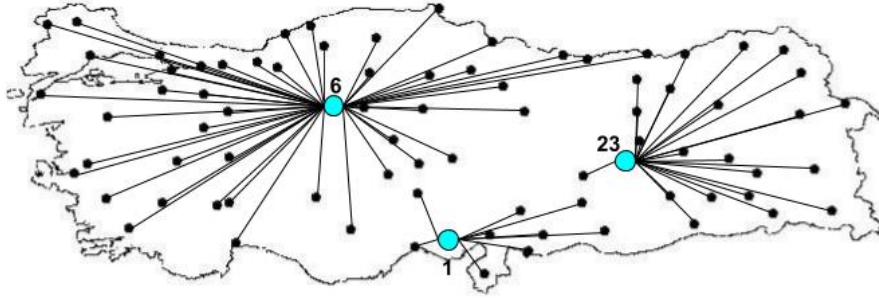
We present the same analysis on the TR dataset and give the results in Appendix B.6. The results show that in seven out 19 instances (five instances are infeasible), these two problems provide different results with respect to hub locations. However, in all but except two instances ($T=24$ hours, $p=1$ and $T=22$ hours, $p=2$), demand node assignments are different from each other, since the total emission amounts are different for the two problems. Therefore, for the TR dataset, on the average, the GHLP reduces the total amount of emission by 0.45%. We can conclude that although the impact of incorporating environmental consideration into the hub location problem with the TR dataset is not as high as the one on the CAB dataset, hub locations and demand node assignments change significantly in the solutions with the TR dataset. Moreover, contrary to the results obtained with the CAB dataset, lower T values provide lesser reductions on the total amount of emissions.

We also present the solutions of these two problems for one particular instance ($T = 24$ hours, $p = 3$) in Figure 4.14. The p -HMP locates three hubs in Afyon (3), Istanbul (34) and Kayseri (38) and most of the demand points (51 out of 81) are assigned to Kayseri (Figure 4.14a). On the other hand, in the GHLP solution, hubs are located in Adana (1), Ankara (6) and Elazig (23), and in this instance, more than half of the demand points (48 out of 81) are assigned to Ankara (6). These two maps also show that in the solution of the p -HMP, no hub is opened in the east side of Turkey, whereas in the solution of the GHLP, no hub is opened in the west side of Turkey. As most of the population is located in the western side, O_i and D_i values are higher in that region. Therefore, while the p -HMP

favors the cities located in the western side as potential hubs, the GHLP selects cities as hubs based on their spatial locations in order to optimize the vehicle speeds along with the flow variables. This pattern can also be observed in other instances in Appendix B.6. For instance, in the instance with $T = 24$ hours and $p = 8$, while the p -HMP opens hubs in Bursa (16) and Izmir (35), which are located in the west, the GHLP selects hubs from eastern region, Erzurum (25) and Aksaray (68).



(a) Two-stage p -HMP



(b) GHLP

Figure 4.14: Results on the TR dataset with a 24-hour service time and three hubs

4.5 Conclusions and Managerial Insights

In this chapter, we propose the Green Hub Location Problem (GHLP) as an extension of the classical hub location problem in which the total amount of emissions is minimized while considering a service time bound. We first develop

a nonlinear programming formulation for the GHLP and then reformulate the problem by using second order cone programming model that is also strengthened by perspective cuts. We present an extensive computational study and conduct sensitivity analyses by changing key parameters of the problem such as the maximum service time, the number of hubs, the hub-to-hub discount factors for the travel cost and travel time, and the vehicle speed decision. We also present a comparison between the solutions of the p -hub median problem and the GHLP to assess the environmental impact of emissions on the results.

The extensive computational analyses discuss results and provide some managerial insights. First, different than the classical hub location problem, in the GHLP, increasing the number of hubs to be opened does not necessarily reduce the objective function value (the total amount of emissions) in the GHLP. Therefore, there is no guarantee that providing service with high number of hubs decreases the amount of pollution (or emissions). However, for larger sized networks, practitioners should open more hubs to guarantee the minimization of emission amount. Second, for tighter service time levels, the service provider should generally increase vehicle speeds on both spoke and hub arcs in order to route flows within the service time level, which also leads to an increase in the emission amount. Therefore, service providers should analyze trade-offs between service levels and environmental impacts. Third, while the hub-to-hub discount factor for the travel cost has a significant impact on the optimal network, the discount factor for the travel time has a less effect on the GHLP solutions in terms of hub locations and demand node assignments. Therefore, setting the discount factor for the travel cost could be more essential than setting the discount factor for the travel time. Fourth, the GHLP does reduce the total amount of emissions compared to p -hub median problem and tends to locate hubs based on their spatial locations. Thus, vehicle speeds and payloads should also be evaluated by the service providers that consider environmental impact of their transportation activities.

Chapter 5

Drone Delivery Problem

In this chapter, we introduce the Drone Delivery Problem (DDP) in which drones are used to make deliveries to a number of customers and the drones themselves are transported by traditional vehicles that act as launch points. The DDP consists of (i) selecting the launch points from a potential set of sites from where drones will take off to serve a number of customers, (ii) assignments of customers to the launch points, and (iii) the speed at which drones are to travel between the customers and the launch points. This chapter presents a nonlinear model for the DDP, which minimizes the total operational cost including an explicit calculation of the energy consumption of the drone as a function of the drone speed, that is limited by both a service time bound and the range of the drone. The model is reformulated by using second order cone programming, and subsequently strengthened by the use of perspective cuts. Both techniques have also been used in Chapter 4, that allows the use off-the-shelf optimization software to solve the problem. Computational results are presented on a realistic data set that quantifies the effect of various parameters on location, assignment and speed decisions.

The structure of this chapter is as follows: Section 5.1 provides an introduction to drone delivery systems. Section 5.2 presents a review of the literature concerning the use of drones within logistics network design problems. Section

5.3 provides descriptions of energy consumption model and range calculation of a drone. Section 5.4 describes a nonlinear mathematical formulation for the problem and presents the second order cone programming reformulation. Results of computational experiments are discussed in Section 5.5. The chapter concludes in Section 5.6 with possible future directions.

The results of this chapter are available online at [190].

5.1 Introduction

Drones are a type of Unmanned Aerial Vehicles (UAV). Initially used within military operations, recent technological developments allowed a wider usage of such vehicles for a variety of purposes, including deliveries from restaurants such as YO! Sushi [191] and Domino's [192], transportation agencies [193], construction companies [194] and airlines [195]. Cargo companies have also started to make deliveries by using drones. In 2014, DHL prepared a report [196] that discussed the potential of drone delivery in detail and successfully completed trials with their so-called parcelcopters in 2016 (see, [197]). Amazon's new delivery system Prime Air, in which drones are used to provide faster service, was first trialled on 7 December 2016 (see, [198]). In a new delivery system introduced by UPS, drones take off from a truck that serves as a launch pad to deliver goods to customers (see, [199]). One of the main benefits of drones is the potential reduction in the negative environmental impacts, such as CO₂ emissions, in comparison to conventional means of transport [200], in addition to that they can also provide economic benefits, particularly as drones can help to ease traffic congestion [201]. It is therefore no surprise that Amazon and UPS are investing in their delivery network to utilize drones in a more efficient way [202].

In such delivery systems, the drone needs to be prepared either at a depot or on a truck, depending on the network configuration of the cargo company. The preparation entails battery installation and package placement, as well as coding the coordinates to which the delivery is to be made. The drone takes off vertically

from a given location, or a ‘pad’, and upon reaching a certain altitude, it cruises horizontally towards the direction of the customer. Upon arrival to the customer, it detects and lands on the drop-off point. After leaving the cargo at the drop-off point, it travels in a reverse manner to return to the initial point of departure, finalizing the delivery. Once it is back at its initial position, the drone is ready to be prepared for a subsequent delivery. Due to safety issues and legislation, drones should be continuously monitored by the drone operator (driver, if it is launched from the truck) ([203]).

Motivated by the developments described above, we propose, in this chapter, a two-echelon delivery system that uses drones in combination of traditional means of transport. Trucks operate at the first echelon acting as dispatch points for drones that travel at the second echelon to make the actual delivery. Drones can either take off from a central depot or are transported by trucks to a parking area from where they are launched. In the latter case, each truck carries one drone to a designated parking area, from which the drone serves one customer and returns to the truck to be prepared for any subsequent delivery, as described above. The distance that a drone traverses is limited to a given range that is a function of battery capacity depending on the drone speed. Once all deliveries are made, the trucks return to the depot with their drones on board. The sequence of events is the same for drones operating from the depot directly, except that there is no transportation to a parking location. The depot and the potential sites are collectively named as launch points. A visual representation of the delivery system just described is depicted in Figure 5.1, with one depot and five parking locations (indicated by ‘P’), where the solid lines represent truck movements, and dashed lines represent drone deliveries between launch points and customers.

The Drone Delivery Problem (DDP) consists of choosing launch points to use from a candidate set of sites, assigning customers to launch points, and determining the speed at which drones travel between customers and launch points, subject to all deliveries made within a given amount of time and the range of a drone. The problem minimizes the total variable cost that comprises the operational cost of trucks and the cost of energy consumption arising from the use of drones. Contrary to the literature on delivery problems with drones, the drone

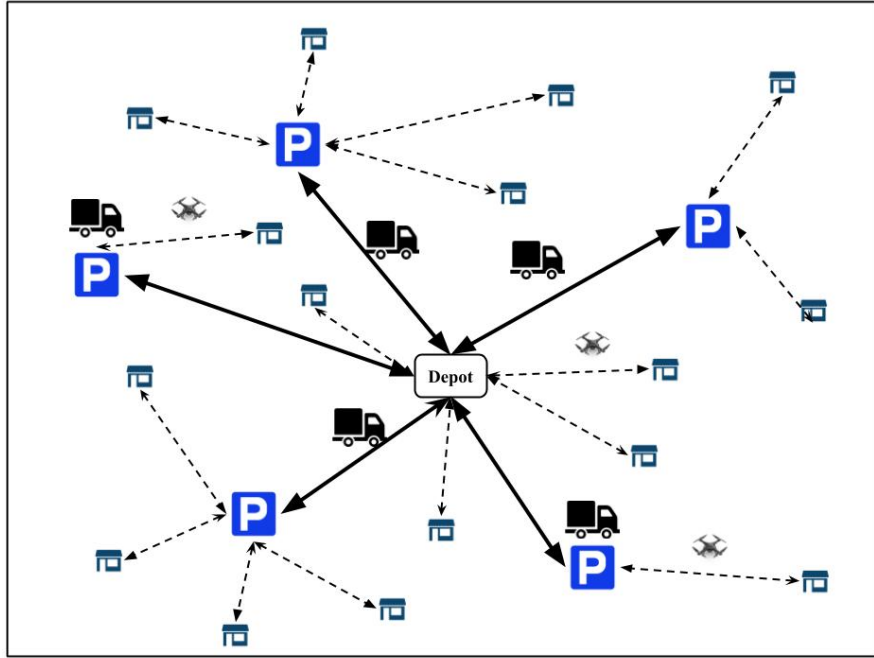


Figure 5.1: An illustration of the proposed drone delivery system

speed in the DDP is considered as a decision variable. The motivation is that the drone speed has a direct impact on the overall time spent and the drone range, as well as the energy consumption of drones.

This chapter makes three main contributions: (i) we introduce and formally define a delivery problem in which drones are used, where the speed of the drone is treated as a decision variable and where the energy consumption and range of the drone is modeled explicitly, (ii) we describe a nonlinear model for the problem and show that it can be reformulated as a second order cone programming formulation and strengthened by perspective cuts, and (iii) we present extensive computational experiments on the DDP on a data set that quantifies the impact of using drones in making deliveries.

5.2 Related Literature on Drone Delivery

In line with the developments in drone deliveries, a body of literature has started to emerge that considers the use of drones within classical transportation problems. First, two drone-assisted cargo delivery problems are introduced in [203]. The first one is the flying sidekick traveling salesman problem (FSTSP). In the FSTSP, while a truck is serving a customer, a drone takes off from the truck, serves another customer, and the drone and the truck meet at the depot or another customer that will subsequently be visited by the truck. The second problem concerns parallel drone scheduling traveling salesman problem (PDSTSP) where trucks and drones operate separately, i.e., while trucks are routed between customers, drones operate from the depot to perform dedicated deliveries. The study of [203] points out that the flight endurance (i.e., range) of a drone is a function of its speed and presents an analysis of the trade-offs between the drone speed and range. They conclude that the speed of a drone has a significant impact on drone delivery operations due to the impact on its range. Higher speeds are preferable even if they imply a lower drone range. In their analysis, they consider nine different speed and range combinations, as opposed to modeling drone range as a function of speed. The underlying setup of the FSTSP has led to other studies that focus on the coordination between trucks and drones. The study by [204] presents the traveling salesman problem with drones (TSP-D), which is very similar to the FSTSP. The authors develop an integer programming formulation and route-first, cluster-second heuristic algorithms based on local search and dynamic programming. For the same problem, in [205], an exact solution approach based on dynamic programming is presented. In [206], a similar problem is studied where drones and trucks perform in tandem. The authors describe the maximum saving that can be obtained from using drones by deriving a number of worst case results. In [207], the results obtained by the study of [206] are extended. The authors also consider the min-max vehicle routing problem, where the longest route is minimized. The study by [208] describes another problem called the horsefly routing problem, for which the authors propose a continuous approximation model and derive upper and lower bounds. In [209], a two-stage

iterative algorithm is presented for the TSP-D and in [210] the TSP-D is extended by minimizing operational cost including transportation cost and penalty cost due to waiting time of trucks. The authors develop two heuristic algorithms to solve this problem. In [211], a vehicle routing problem is studied where the synchronization of multiple drones and trucks is considered. The authors propose an arc-based mixed integer programming model and develop a branch-and-price algorithm. For the PDSTSP, an iterative two-step heuristic is developed in [212].

Vehicle routing problems for drone delivery (VRPDD) are first described in [213], where, in contrast to previous studies, customers are solely served by drones. The authors derive an energy consumption model for drones and analyze the impact of payload and battery weight on energy consumption. The energy consumption used in [213] is only relevant to hovering and does not include that of the actual flight and the speed. The authors present a mathematical formulation and a simulated annealing heuristic to solve this problem. In [214], a multi-objective green UAV routing problem is studied where charging stations are used to extend the limited range of drones. The proposed problem has seven different objective functions, one of which is the minimization of amount of energy required by the drone batteries. However, the energy required is estimated by using a simple function that depends on the drone speed instead of a consumption model. The authors proposed a matheuristic algorithm as a solution method. In [215], a drone scheduling problem for given truck routes is studied, where they consider different variants of the problem based on the number of drones available and whether or not launch and landing points have to be the same. For each variant, they present mixed integer programs. The study by [216] describe a stochastic facility location model for drones, where uncertainty of the maximum flight distance is considered for a post-disaster humanitarian application. The uncertainty aspect of the problem is handled by a chance constraint and a heuristic algorithm using Benders decomposition is proposed to solve the problem. A delivery problem using drones has been introduced by [217], who cast it as a capacitated facility location problem, where facilities act as launching sites, and where the aim is to maximize the demand served subject to battery range constraints. In the model described by [217], speed is not treated as a decision variable, which consequently

Table 5.1: Features of transportation problem with drones

Reference	Objective	Method	Delivery Type		Energy		Drone Speed	Time Bound
			Drones	Drones & Trucks	Factor	Micro		
[203]	Single	Exact & Heuristic		✓				
[204]	Single	Exact & Heuristic		✓				
[205]	Single	Exact		✓				
[206]	Single	-		✓				
[207]	Single	-		✓				
[208]	Single	Heuristic		✓				
[209]	Single	Exact & Heuristic		✓				
[210]	Single	Exact & Heuristic		✓				
[211]	Single	Exact		✓				
[212]	Single	Heuristic		✓				
[213]	Single	Heuristic	✓			✓		✓
[214]	Multi	Heuristic	✓		✓		✓	
[215]	Single	Exact	✓					
[216]	Single	Heuristic	✓					
[217]	Single	Exact & Heuristic	✓		✓			
[218]	Single	Exact & Heuristic	✓					
[219]	Multi	Exact & Heuristic	✓					✓
Our Study	Single	Exact	✓			✓	✓	✓

takes the form of an integer linear programming formulation solvable by an off-the-shelf solver, but the authors also present several heuristics for the problem itself. Other studies include that of [218], which is a location-and-routing problem for drones arising from a military application, and that by [219] which presents a multi-objective unmanned aerial vehicle routing problem with soft time window constraints. In [220], the impact of drone delivery in terms of CO₂ emissions is analyzed where drones are compared with trucks. For a comprehensive survey on optimization approaches for drones, we refer the reader to [221].

Table 5.1 compares and contrasts the studies just reviewed with our study based on the following factors: (i) the number of objective functions used (single or multiple), (ii) the nature of the solution methods (exact or heuristic), (iii, iv) the mode(s) of delivery, (v, vi) whether a factor or a microscopic energy consumption model is used or not, (vii) whether drone speed is considered as a decision or not, and (viii) whether there is a time bound on deliveries or not.

The delivery system used in our problem can be considered as the combination of the systems used in the FSTSP proposed by [203] and the VRPDD studied by [213]. The system proposed here consists of two types of vehicles, namely trucks and drones, as in the FSTSP. However, in our setting, and similar to the VRPDD, only drones take an active role in delivery operations, as opposed to

the FSTSP where both drones and trucks are used. Furthermore, and in contrast to the VRPDD, drones only visit one customer per flight, as is the case in the FSTSP.

5.3 Formulating Drone Energy Consumption and Range

This section describes a model for calculating the energy required during the flight of a drone over a given distance, and the range of a drone in terms of the maximum distance it can traverse under limited battery capacity. We do not explicitly model the energy consumed during takeoff, landing and hovering as this is a constant if there are a fixed number of deliveries to be made (as it is the case in our setup). We consider the use of a commercial quadcopter, with four rotors to lift and propel the drone [222], that is designed to carry packages of up to 0.5kg (see, [223]) which we treat as the assumed weight of an average parcel. We make the assumption that the drone is able to travel at a constant speed between a pair of locations, and whilst windy conditions may impact the actual speed attained, there are ways to adjust the thrust during the journey to maintain stable speed as it is explained in [223].

Following the above assumptions, we only calculate the energy consumption during the flight of the drone. A drone consists of three components; body ($k = 1$), battery ($k = 2$) and package ($k = 3$). As the drone will travel at constant speed, the thrust T (in kg.m/s²) and drag force D (in kg.m/s²) should be equal to each other to ensure a steady flight (see, [224]). The two forces can be calculated as it is described in [225]:

$$T = D = \sum_{k=1}^3 \left(\frac{\frac{1}{2}\rho v^2 \Delta_k A_k}{\eta} + \frac{2m_k^2 g^2}{\pi e_0 \Phi_R \rho A_k v^2 \eta} \right), \quad (5.1)$$

where ρ is the air density (in kg/m³), v is the air speed (in m/s), η is the energy efficiency of the drone, g is the gravitational constant (in m/s²), e_0 is the Oswald

efficiency (wing span efficiency), and Φ_R is the aspect ratio of the wing. For each component k , the parameters Δ_k , A_k and m_k represent the drag coefficient, projected area (in m^2) and mass (in kg), respectively (see, [223]). The first term of equation (5.1) is the *parasitic drag* consisting of multiple components such as form drag, skin friction drag, etc. The second term is the *lift-induced drag* which is the force needed to generate lift for the drone's weight.

The required power P (in $\text{kg.m}^2/\text{s}^3$) to move the drone over a distance of d (in m) at a constant speed v (in m/s) can be calculated as $P = Tv$. Substituting (5.1) for T yields:

$$P = \frac{\frac{1}{2}\rho v^2 \sum_{k=1}^3 \Delta_k A_k d}{\eta t} + \frac{2g^2 d}{\pi e_0 \Phi_R \rho v^2 \eta t} \sum_{k=1}^3 \frac{m_k^2}{A_k}, \quad (5.2)$$

where $t = d/v$ is the travel time (in s). The energy E (in $\text{kg.m}^2/\text{s}^2$) is given by $E = Pt$:

$$E = Pt = \frac{\frac{1}{2}\rho v^2 \sum_{k=1}^3 \Delta_k A_k d}{\eta} + \frac{2g^2 d}{\pi e_0 \Phi_R \rho v^2 \eta} \sum_{k=1}^3 \frac{m_k^2}{A_k}. \quad (5.3)$$

To simplify the above formula, let $\mu_1 = \frac{\rho}{2\eta} \sum_{k=1}^3 \Delta_k A_k$ and $\epsilon_1 = \frac{2g^2}{\pi e_0 \Phi_R \rho \eta} \sum_{k=1}^3 \frac{m_k^2}{A_k}$ be associated with the delivery (with package) and let $\mu_2 = \frac{\rho}{2\eta} \sum_{k=1}^2 \Delta_k A_k$ and $\epsilon_2 = \frac{2g^2}{\pi e_0 \Phi_R \rho \eta} \sum_{k=1}^2 \frac{m_k^2}{A_k}$ be parameters associated with the (empty) return. Then, the total amount of energy E (in $\text{kg.m}^2/\text{s}^2$) for a drone traveling a distance of d units (in m) at a constant speed v (in m/s) can be given as follows:

$$E = (\mu_1 + \mu_2)v^2 d + (\epsilon_1 + \epsilon_2)d/v^2. \quad (5.4)$$

We now present a way in which the range R (in m) of a quadcopter that represents the maximum total distance, which a drone can travel can be calculated. The range also depends on the energy consumption, for that reason we resort to the parameters μ_1 and μ_2 in expressing the range of the drone as follows:

$$R = (m_2 s_{batt} \delta) / (v^2 (\mu_1 + \mu_2) f), \quad (5.5)$$

where m_2 is the mass of the battery (in kg), s_{batt} is the energy capacity of the

battery per mass (in $\text{kg.m}^2/\text{s}^2$), δ is the depth of discharge, and f is the safety factor to reserve energy for unusual conditions. Using $\Theta = m_2 s_{batt} \delta / ((\mu_1 + \mu_2) f)$ to simplify the formulation, the range R (in m) of a drone traveling at a constant speed v (in m/s) can be given as follows:

$$R = \Theta / v^2. \quad (5.6)$$

Typical values of the parameters introduced above are given in Table 5.2 (see, [223]).

Table 5.2: Typical values used for calculating energy consumption and range of a quadrotor drone

Notation	Description	Typical Values
ρ	Air density (kg/m^3)	1.2041
η	Overall energy efficiency	0.7
A_1	Projected area of drone body (m^2)	0.0599
A_2	Projected area of battery (m^2)	0.0037
A_3	Projected area of package (m^2)	0.0135
Δ_1	Drag coefficient of drone body	1.49
Δ_2	Drag coefficient of battery	1
Δ_3	Drag coefficient of package	2.2
m_1	Mass of drone body (kg)	1.07
m_2	Mass of battery (kg)	1
m_3	Mass of package (kg)	0.5
g	Gravitational constant (m/s^3)	9.81
e_0	Wing span efficiency	0.7
Φ_R	Aspect ratio of the wing	1
s_{batt}	Energy capacity (density) of the battery ($\text{kg.m}^2/\text{s}^2$)	540,000
δ	Depth of discharge	0.5
f	Safety factor to reserve energy	1.2

By using the parameter values provided in Table 5.2 and equation (5.4), we show the relation between drone speed and energy consumption in Figure 5.2. As it can be seen from equation (5.6), while drone range limits drone speed as an upper bound, any time related constraint such as time bound gives a lower bound on drone speed. Therefore, regarding these upper and lower limits on drone speed and the relation of drone speed with energy consumption, there could be four possible cases as follows:

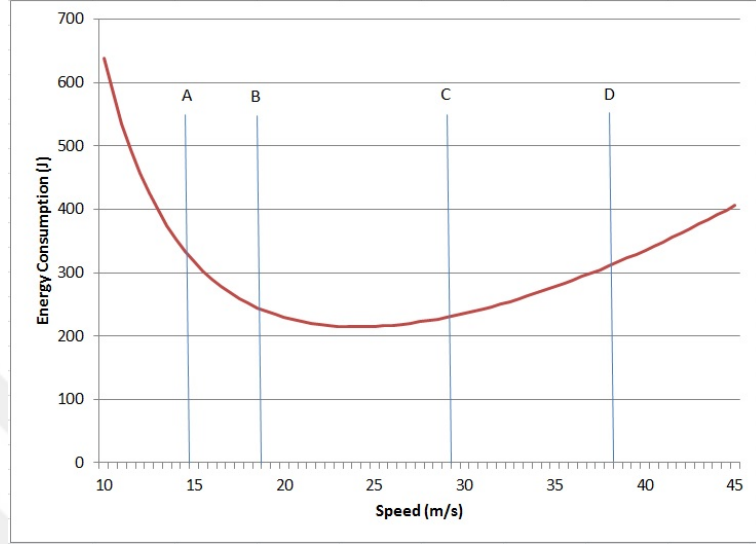


Figure 5.2: Energy consumption as a function of drone speed

Case 1: If lines A and B represent time bound and drone range, respectively, then the drone speed is set by the drone range based on the function represented in Figure 5.2. In this case, while any actions aiming to relax time bound does not affect the drone speed and reduce energy consumption, relaxing the drone range could provide a reduction in energy consumption.

Case 2: If lines B and C represent time bound and drone range, respectively, then the drone speed is the global optimizer of the convex function given in Figure 5.2, which is approximately 24.04 m/s. In this case, relaxing any limitations does not affect drone speed since drones already travel at the optimal speed.

Case 3: If lines C and D represent time bound and drone range, respectively, then the drone speed is set by the time bound based on the function in Figure 5.2. In this case, while relaxing the drone range does not change the solution, relaxing time bound could help to reduce energy consumption.

Case 4: If the upper limit caused by drone range is less than the lower limit provided by time bound, then there is no feasible solution. For instance, in Figure 5.2 if lines B and C represent drone range and time bound, respectively, a feasible solution cannot be found.

As it can be seen from equations (5.4) and (5.6), and also Figure 5.2, speed is a primary determinant of the energy consumption and the range of a drone. For this reason, we consider drone speed as a decision variable in the formulations that will be presented in the next section which will allow us to minimize energy consumption.

5.4 Mathematical Formulations for the DDP

The Drone Delivery Problem (DDP) is defined on a complete directed graph $G = (N, A)$ where $N = \{0, 1, \dots, n\}$ is the set of nodes and includes the depot shown by node 0, and $A = \{(i, j) : i, j \in N, i \neq j\}$ is the set of arcs. We also define a set $P = \{1, \dots, m\}$ of potential parking locations for trucks, and a set $C = \{m + 1, \dots, n\}$ of customers. The set $L = \{0\} \cup P$ of launch points consists of the depot and potential parking areas. All customers should be served within a predetermined time limit U . The preparation time of a drone for a delivery is shown by τ . The flying distance on arc $(i, j) \in A$ is denoted by d_{ij} , which is assumed to be symmetric as would be the case for air travel. The driving distance on arc $(i, j) \in A$ is denoted by c_{ij} . The minimum and maximum speed limits for drones are denoted by v_{min} and v_{max} , respectively. We assume that the (average) speed of the truck is fixed and denote it by v^t . Parameters c_e and c_d represent the unit energy cost and the unit operational cost per distance, respectively, and p is the (fixed) number of launch points used.

In this section, we present a mathematical formulation for the DDP. The decision variables are defined as follows: If a candidate site $j \in L$ is used as a launch point, then a binary variable y_j is equal to 1, and to 0 otherwise. A binary variable x_{ij} equals 1 if a drone takes off from a launch point $j \in L$ to serve customer $i \in C$, and 0 otherwise. The speed that the drone travels between customer $i \in C$ and launch point $j \in L$ is denoted by the continuous nonnegative variable v_{ij} .

A formulation for the DDP is given as follows:

$$\text{(DDP-0) Minimize } c_d \sum_{j \in L} (c_{0j} + c_{j0}) y_j \quad (5.7)$$

$$+ c_e \sum_{i \in C} \sum_{j \in L} \left[(\mu_2 + \mu_1) d_{ij} (v_{ij})^2 x_{ij} + \frac{(\epsilon_2 + \epsilon_1) d_{ij} x_{ij}}{(v_{ij})^2} \right] \quad (5.8)$$

subject to

$$\sum_{j \in L} x_{ij} = 1 \quad \forall i \in C \quad (5.9)$$

$$x_{ij} \leq y_j \quad \forall i \in C, j \in L \quad (5.10)$$

$$\sum_{j \in L} y_j = p \quad (5.11)$$

$$2d_{ij}v_{ij}^2 \leq \Theta \quad \forall i \in C, j \in L \quad (5.12)$$

$$\frac{c_{0j}}{v^t} y_j + \sum_{k \in C} \left(\frac{2d_{kj}}{v_{kj}} + \tau \right) x_{kj} - \frac{d_{ij}}{v_{ij}} x_{ij} - M_j (1 - x_{ij}) \leq U \quad \forall i \in C, j \in L \quad (5.13)$$

$$v_{min} \leq v_{ij} \leq v_{max} \quad \forall i \in C, j \in L \quad (5.14)$$

$$x_{ij} \in \{0, 1\} \quad \forall i \in C, j \in L \quad (5.15)$$

$$y_j \in \{0, 1\} \quad \forall j \in L \quad (5.16)$$

The first term (5.7) of the objective function minimizes the total operational cost associated with trucks and the second term (5.8) minimizes the total amount of energy caused by drones. Constraints (5.9) ensure that each customer will be assigned to a launch point and served by a drone taking off from that launch point. Constraints (5.10) guarantee that a drone will not serve any customer from a launch point if it does not take off from that point. Constraint (5.11) fixes the number of launch points to be used to p . Constraints (5.12) limit the drone to stay within its range during travel. Constraints (5.13) ensure that each customer will be served within the predetermined time limit U , where M_j is a sufficiently large constant that can be set equal to $\max_{i \in C} \{d_{ij}/v_{min}\}$. With Constraints (5.13), it is guaranteed that the last customer will be visited before the time limit, so here the return journey from the last customer to the launch point is excluded. Constraints (5.14) ensure that the drone speed remains between the allowable limits. Constraints (5.15) and (5.16) define the domains of the binary variables.

5.4.1 Second order cone programming

In this section, we show how the formulation for the DDP can be reformulated as a second order cone program (SOCP), which in turn could be solved by using off-the-shelf commercial optimizers. Recall more discussions on the details of the SOCP formulation is presented in Section 4.3.

The formulation of the DDP is nonlinear due to the second term of the objective function (5.8) and Constraints (5.12) and (5.13).

First, we observe that the following formulation (DDP-1) is equivalent to formulation DDP-0:

$$(DDP-1) \text{ Minimize } c_d \sum_{j \in L} (c_{0j} + c_{j0}) y_j \quad (5.7)$$

$$+ c_e \sum_{i \in C} \sum_{j \in L} \left[(\mu_2 + \mu_1) d_{ij} (v_{ij})^2 x_{ij} + \frac{(\epsilon_2 + \epsilon_1) d_{ij} x_{ij}^2}{(v_{ij})^2} \right] \quad (5.17)$$

subject to (5.9)–(5.16).

The only difference between formulations DDP-0 and DDP-1 is the second part of the objective function components (5.8) and (5.17). Here since x_{ij} is a binary variable, if x_{ij} equals to 0, then x_{ij}^2 equals to 0 and if x_{ij} equals to 1, then x_{ij}^2 equals to 1. Therefore, instead of $\frac{x_{ij}}{(v_{ij})^2}$, using $\frac{x_{ij}^2}{(v_{ij})^2}$ does not change what the formulation does. Then, we define two new auxiliary decision variables, namely $w_{ij} = x_{ij}/v_{ij}$ and $z_{ij} = w_{ij}^2$, using which we present the following formulation (DDP-2):

$$(DDP-2) \text{ Minimize } c_d \sum_{j \in L} (c_{0j} + c_{j0}) y_j$$

$$+ c_e \sum_{i \in C} \sum_{j \in L} [(\mu_2 + \mu_1) d_{ij} (v_{ij})^2 x_{ij} + (\epsilon_2 + \epsilon_1) d_{ij} z_{ij}] \quad (5.18)$$

subject to (5.9)–(5.11), (5.15)–(5.16),

$$2d_{ij}v_{ij}^2 \leq \Theta x_{ij} \quad \forall i \in C, j \in L \quad (5.19)$$

$$\frac{c_{0j}}{v^t} y_j + \sum_{k \in C} (2d_{kj}w_{kj} + \tau x_{kj}) - d_{ij}w_{ij} - M_j(1 - x_{ij}) \leq U \quad \forall i \in C, j \in L \quad (5.20)$$

$$v_{min}x_{ij} \leq v_{ij} \leq v_{max}x_{ij} \quad \forall i \in C, j \in L \quad (5.21)$$

$$x_{ij} \leq w_{ij}v_{ij} \quad \forall i \in C, j \in L \quad (5.22)$$

$$w_{ij}^2 \leq z_{ij} \quad \forall i \in C, j \in L \quad (5.23).$$

Now we observe that following formulation (DDP-3) is equivalent to formulation DDP-2:

$$\begin{aligned} \text{(DDP-3) Minimize } & c_d \sum_{j \in L} (c_{0j} + c_{j0})y_j \\ & + c_e \sum_{i \in C} \sum_{j \in L} [(\mu_2 + \mu_1)d_{ij}(v_{ij})^2 + (\epsilon_2 + \epsilon_1)d_{ij}z_{ij}] \end{aligned} \quad (5.24)$$

subject to (5.9)–(5.11), (5.15)–(5.16), (5.19)–(5.23).

The only difference between formulations DDP-2 and DDP-3 is the first part of the objective function components (5.18) and (5.24). We claim that removing x_{ij} variable from the expression (5.18) does not change the solution. This claim is based on the fact that due to Constraints (5.19) and (5.21), if x_{ij} equals to 0, then v_{ij} equals to 0, as well. Then, both of these expressions give the same result, that is 0. If x_{ij} equals to 1, then both of these expressions are the same. Therefore, we can safely remove x_{ij} from first part of the objective function component (5.18).

Here, we define additional auxiliary decision variable, namely $u_{ij} = v_{ij}^2$, using which we reformulate the model as follows:

$$\begin{aligned} \text{(DDP-SOCP) Minimize } & c_d \sum_{j \in L} (c_{0j} + c_{j0})y_j \\ & + c_e \sum_{i \in C} \sum_{j \in L} [(\mu_2 + \mu_1)d_{ij}u_{ij} + (\epsilon_2 + \epsilon_1)d_{ij}z_{ij}] \end{aligned} \quad (5.25)$$

subject to (5.9)–(5.11), (5.15)–(5.16), (5.20)–(5.23)

$$2d_{ij}u_{ij} \leq \Theta x_{ij} \quad \forall i \in C, j \in L \quad (5.26)$$

$$v_{ij}^2 \leq u_{ij} \quad \forall i \in C, j \in L \quad (5.27).$$

Constraints (5.23) and (5.27) are quadratic inequalities, which can be rewritten as second order cone constraints in the form $\left\| \begin{bmatrix} 2w_{ij} \\ 1 - z_{ij} \end{bmatrix} \right\| \leq (1 + z_{ij})$ since $w_{ij} \geq 0$ and $z_{ij} \geq 0$, and in the form $\left\| \begin{bmatrix} 2v_{ij} \\ 1 - u_{ij} \end{bmatrix} \right\| \leq (1 + u_{ij})$ since $u_{ij} \geq 0$ and $v_{ij} \geq 0$, respectively. Constraints (5.22) are also nonlinear constraints, which can be

reformulated as:

$$x_{ij}^2 \leq w_{ij}v_{ij} \quad \forall i \in C, j \in L. \quad (5.28)$$

Constraints (5.28) are hyperbolic inequalities and they can be represented as second order cone constraints in the following form $\left\| \begin{bmatrix} 2x_{ij} \\ v_{ij} - w_{ij} \end{bmatrix} \right\| \leq (v_{ij} + w_{ij})$ since $x_{ij} \geq 0$, $v_{ij} \geq 0$ and $w_{ij} \geq 0$.

Furthermore, Constraints (5.23) and (5.27) can be strengthened by using perspective cuts by [186] in the following forms, respectively,

$$w_{ij}^2 \leq z_{ij}x_{ij} \quad \forall i \in C, j \in L \quad (5.29)$$

$$v_{ij}^2 \leq u_{ij}x_{ij} \quad \forall i \in C, j \in L \quad (5.30).$$

Constraints (5.29) and (5.30) ensure that decision variables w_{ij} and v_{ij} will be zero if there is no drone that launches from launch point $j \in L$ and serves customer $i \in C$. Both (5.29) and (5.30) are hyperbolic inequalities and can be rewritten as second order cone constraints as $\left\| \begin{bmatrix} 2w_{ij} \\ z_{ij} - x_{ij} \end{bmatrix} \right\| \leq (z_{ij} + x_{ij})$ since $w_{ij} \geq 0$, $z_{ij} \geq 0$ and $x_{ij} \geq 0$, and $\left\| \begin{bmatrix} 2v_{ij} \\ u_{ij} - x_{ij} \end{bmatrix} \right\| \leq (u_{ij} + x_{ij})$ since $v_{ij} \geq 0$, $u_{ij} \geq 0$ and $x_{ij} \geq 0$, respectively.

5.5 Computational Study

In this section, we present detailed analyses on the solutions of the DDP. First, we describe the data set. Second, we evaluate the performance of the perspective cuts on the DDP formulation. In the remainder of the section, we numerically analyze the effect of the number p of drones used, changing the bound U on time, the trade-off between ground and air costs, introducing a future battery option, using speed flexibility and, finally, allowing the use of multiple drones. All experiments were carried out on a server using 4 AMD Opteron Interlagos 6282 SE and with 96 GB of RAM using IBM ILOG CPLEX Optimization Studio version 12.6.1.0 as the solver.

5.5.1 Data set

The data used for the computational analysis is drawn from a distribution problem arising in the Kartal district of Istanbul, Turkey, described in [226], that includes one depot (triangle), three schools and four hospitals that collectively correspond to seven potential parking locations (squares), and 37 centers of population each of which is a demand point (circles) (Figure 5.3). Pairwise distances for driving and for flying have been extracted using Google Maps and the visual basic codes in [167], respectively, where the latter takes into account the elliptic structure of the earth.

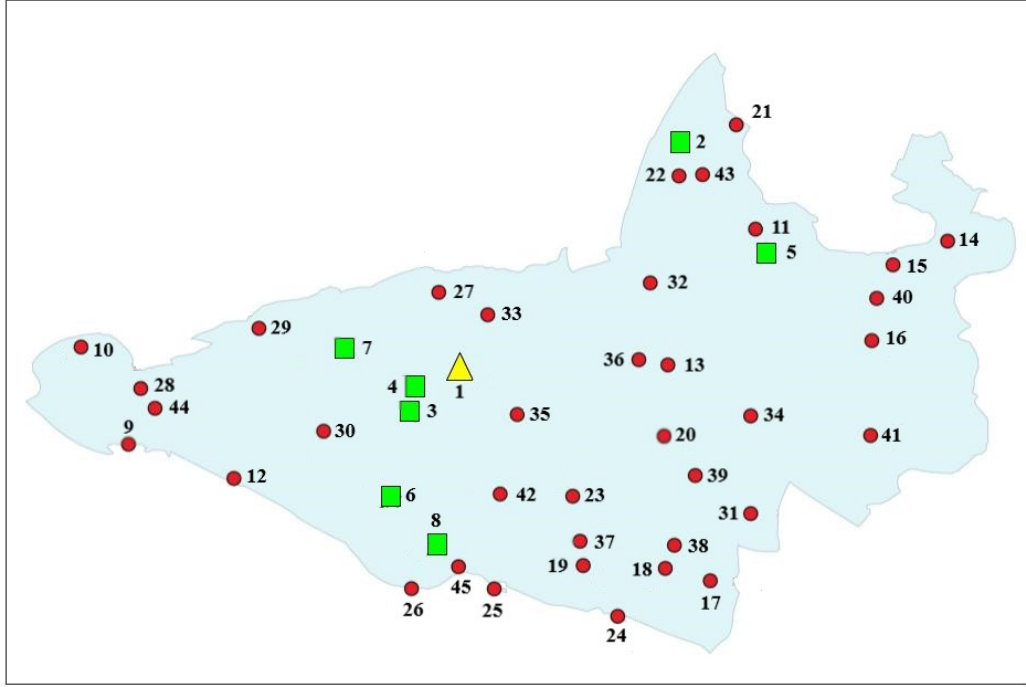


Figure 5.3: The locations of depot, parking areas and customers on Kartal map

Based on the regulations of the General Directory of Highways of Turkey, the average truck speed v^t is set equal to 45 km/h. To ensure same day deliveries, the time bound U is set equal to eight hours. There appear to be no regulations on drone speeds at this time in Turkey, for which reason we set the maximum speed limit v_{max} as 44.7 m/s following the US regulations [227]. Similarly, the minimum speed limit v_{min} is set equal to 1 m/s. As in [203], the preparation time τ of a

drone for a delivery is set equal to two minutes. The average monthly salary of a truck driver in Turkey is approximately 2,500 Turkish Lira (₺) and the workload per month is 120 hours, which, using the average truck speed, translates into 0.463 ₺/km as the driver cost per distance. Fuel cost per distance for a conventional truck in Turkey is approximately 0.6 ₺/km, which results in 1.063 ₺/km as the unit operational cost c_d per distance for a truck. In [213], the unit energy cost is calculated by dividing the cost of the battery by the energy density. The cost of the battery in Turkey is approximately 30 ₺ and the energy density (capacity) of the battery is 540 kilojoule (kJ), resulting in the unit energy cost (c_e) being equal to 0.0556 ₺/kJ. Other parameters are as shown in Table 5.2 by [223].

5.5.2 Performance of perspective cuts

This section analyzes the impact of perspective cuts on the solution time of the DDP. In the experiments, we use three different values for the time bound U as 8, 4 and 2 (hours) and five different values for the number of drones as $p = 2, 3, 4, 5, 6$ resulting in a total of 15 instances. Table 5.3 presents the comparison results of the DDP formulation with and without perspective cuts. A common time limit of two hours has been imposed on the solution time of each instance.

One of the 15 instances is infeasible with the given number of drones and time bound. Of the remaining 14 instances, the formulation without perspective cuts finds optimal solutions for only five instances within the time limit, and yields an average optimality gap of 21.06% for the remaining nine instances. The formulation with perspective cuts optimally solves all instances within a few seconds, which we use in the rest of the experiments.

5.5.3 Analysis on the DDP solutions

This section presents the results of further analyses on the solutions of the DDP using five randomly generated sets of instances with different number of customers

Table 5.3: Performance of perspective cuts

$ C $	$ P $	p	U (hr)	No Pers Cuts		Pers Cuts
				Sol Time (s)	Gap (%)	Sol Time (s)
37	7	2	8	59.54	-	4.85
37	7	2	4	35.86	-	5.49
37	7	2	2	Infeasible		
37	7	3	8	503.29	-	10.07
37	7	3	4	681.82	-	9.15
37	7	3	2	712.19	-	9.44
37	7	4	8	7200.00	7.66	5.40
37	7	4	4	7200.00	15.54	5.82
37	7	4	2	7200.00	15.81	6.59
37	7	5	8	7200.00	22.50	5.09
37	7	5	4	Out of Memory		5.72
37	7	5	2	7200.00	19.11	6.47
37	7	6	8	7200.00	25.90	6.49
37	7	6	4	7200.00	31.66	5.35
37	7	6	2	7200.00	30.30	8.61
Average				4584.05	21.06	6.75

and potential parking areas, using the configurations $(|C|, |P|)$ as (10, 2), (15, 3), (20, 4), (25, 5) and (30, 6). For each configuration, we have generated five instances. The number p of drones is set as one, two and three for all instances. The summary of the results are given in Table 5.4 which presents the average values over five instances for each configuration. Columns titled “Tot. Cost”, “En. Cons”, “Tr. Dist”, “Dr. Dist”, “Av. Spe”, and “Sol. Time” stand for the optimal objective value, the total cost (in €), the total amount of energy consumption (in kJ), the total distance traveled by trucks (in m), the total distance traveled by drones (in m), the average drone speed (in m/s) over each journey, and the solution time (in s), respectively. Detailed results can be found in Appendices C.1 and C.2.

The results presented in Table 5.4 suggest that an increase on the number of drones generally decreases the total cost due to the reduction in the total amount of energy required by drones. This, in turn, is due to the reduction in the total distance traveled by drones and the customers being much closer to launch points,

Table 5.4: Summary of the results with different number of drones

$ C $	$ P $	p	Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)	Sol. Time (s)
10	2	1	570.90	10267.91	0.00	56424.53	15.53	0.55
10	2	2	415.56	7218.35	13380.20	46125.00	17.58	0.65
10	2	3	388.38	6662.56	16876.60	43513.27	18.17	0.65
15	3	1	783.42	14090.35	0.00	80628.02	15.78	0.88
15	3	2	622.50	10962.29	12223.40	68109.54	17.30	1.49
15	3	3	578.73	10122.77	14966.20	64257.42	17.78	1.49
20	4	1	1032.15	18563.77	0.00	105801.00	15.99	1.69
20	4	2	666.93	11715.79	14616.00	79729.41	18.27	3.16
20	4	3	554.40	9558.97	21560.00	69324.87	19.25	2.70
25	5	1	1326.44	23856.90	0.00	136010.95	15.64	2.44
25	5	2	813.30	14255.02	19490.60	98631.42	18.32	3.64
25	5	3	699.01	12106.15	24372.00	88662.26	19.17	4.28
30	6	1	1654.00	29748.28	0.00	166085.01	15.57	3.54
30	6	2	980.23	17283.71	18113.40	119234.02	18.20	5.39
30	6	3	827.17	14430.66	23352.60	106395.61	19.14	5.28

enabling the drones to attain speeds that are closer to the globally optimal speed of 24.04 m/s that minimizes the convex expression (5.4). Decreasing the number of drones moves launch points away from the customers, and in this case drone speed cannot be increased to attain the globally optimized speed due to the range limit. In a few instances, however, when the number of drones available is increased, the total cost also increases. The main reason for this unusual situation is that only a few customers are assigned to the drone associated with the new launch point, but the reduction in the energy requirements does not compensate for the increase in the total distance traveled by trucks, which raises the total cost. For all instances in which $p = 1$, the drone is launched from the depot.

We also analyze the solution of the DDP on the original instance with one, two and three drones, which are depicted in Figure 5.4. When only one drone is available, the depot is used as a launch point and all customers are assigned to the depot (Figure 5.4a). With two drones, one drone is launched from parking area numbered 6 and the other from parking area numbered 5 (Figure 5.4b). With three drones are available, parking areas 5, 7 and 8 are used (Figure 5.4c). These solutions indicate that when several drones are used, the depot is not necessarily

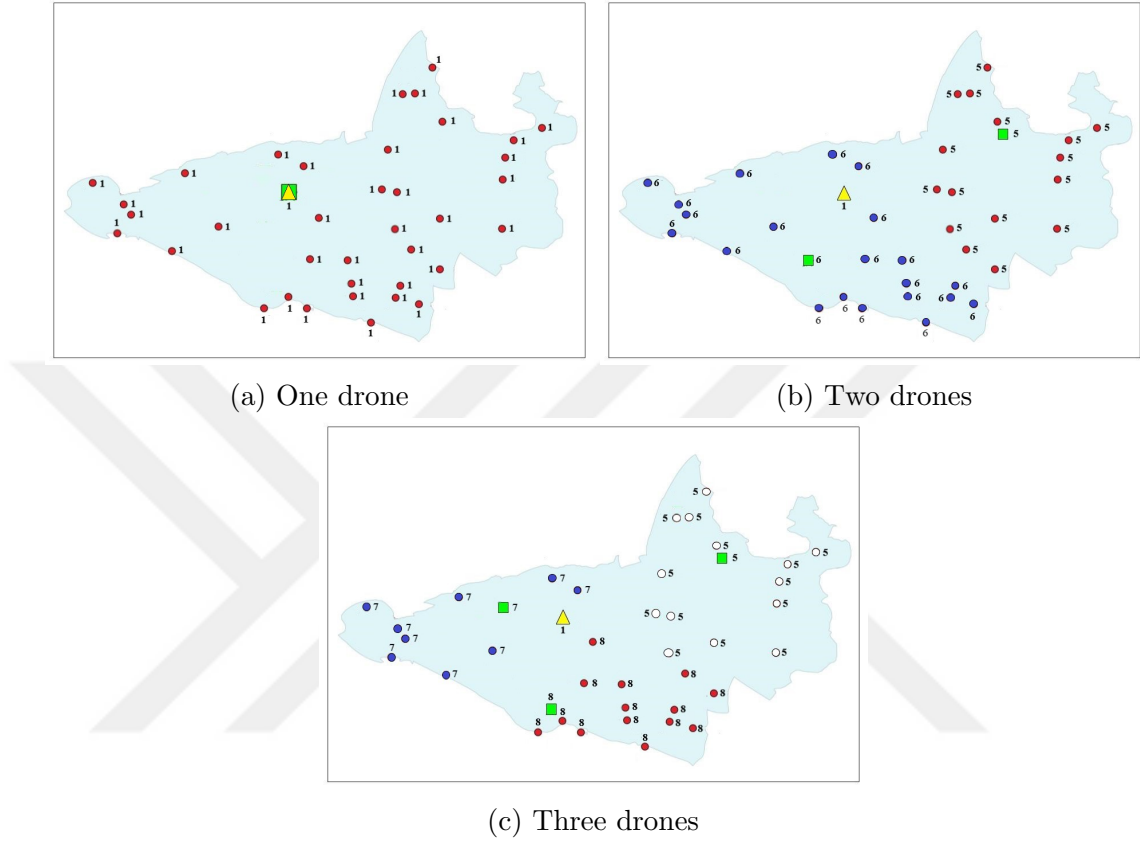


Figure 5.4: Original instance with different number of drones

used as a launch point even though it does not require any trucks.

5.5.4 Impact of the time limit

The aim of this section is to investigate the impact of varying the delivery time bound on the solution of the DDP. In the base case, the delivery time bound (U) is set as eight hours, which we gradually tighten as four, two and one. The results are presented in Table 5.5 where we only report instances for which the base case solution changes. The top four rows of the table compare $U = 4, 8$ hours with $U = 2h$ (we observed no differences in solutions between the cases $U = 4h$ and $U = 8h$ for all 75 instances, except that five instances become infeasible for $U = 4h$). The remaining rows of the table compares $U = 2h$ with $U = 1h$.

Table 5.5: Results with different time bounds

$ C $	$ P $	p	Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)	Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)
$U = 8(\text{or } 4) \text{ hours}$								$U = 2 \text{ hours}$				
25	5	2	932.64	16367	21281	105561.24	17.72	963.89	17196	7340	108966.72	17.55
30	6	2	1036.80	18334	16378	125496.39	17.71	1060.35	18758	16378	126571.30	17.68
30	6	2	982.11	17300	19043	119546.81	18.26	991.12	17462	19043	120150.81	18.23
Average			983.85	17333.77	18900.67	116868.15	17.90	1005.12	17805.17	14253.67	118562.94	17.82
$U = 2 \text{ hours}$								$U = 1 \text{ hour}$				
10	2	2	590.48	10480	7340	55895.20	15.86	593.03	10526	7340	56065.74	15.83
10	2	3	590.93	10420	10881	55598.21	15.92	593.49	10466	10881	55768.76	15.90
15	3	2	650.37	11570	6658	71738.16	16.82	656.64	11683	6658	72064.09	16.80
15	3	3	654.13	11570	10199	71738.16	16.82	660.41	11683	10199	72064.09	16.80
15	3	2	533.54	9283	16378	61629.21	17.99	557.10	9707	16378	62704.12	17.93
15	3	2	470.06	8188	13941	56925.55	18.47	517.31	9038	13941	58162.16	18.13
15	3	3	622.83	10839	18987	68384.33	17.10	631.59	10997	18987	69705.83	16.87
15	3	3	691.81	12226	11333	70336.61	17.40	700.51	12382	11333	71490.60	17.09
25	5	3	738.87	12828	24089	94117.84	18.67	787.45	13799	19043	98104.23	18.34
25	5	3	807.19	14015	26327	95293.98	18.62	837.34	14585	24822	98214.41	18.29
25	5	3	673.17	11663	23266	86768.35	19.11	674.89	11694	23266	86889.72	19.10
25	5	3	661.29	11433	24089	85007.41	19.67	666.80	11532	24089	85555.20	19.61
30	6	3	768.90	13355	24771	100724.59	19.41	805.48	14034	23718	102890.58	19.29
Average			650.27	11374.60	16789.15	74935.20	17.84	667.85	11701.87	16204.23	76129.19	17.69

As it can be seen in Table 5.5, when U is reduced from 8h (or 4h) to 2h, the solutions differ in terms of the location of launch points, customer assignments and drone speeds in only three out of 75 instances, and a further 19 instances become infeasible. Setting $U = 2\text{h}$ increases the total cost and the total energy consumption by 2.16% and 2.72% on average, respectively, reduces the total truck distance by 24.59%, and increases the total drone distance by 1.45%, on average. Surprisingly, the speed of drones is reduced by 0.43% on average, as one would expect a speed-up in order to be able to make deliveries on time. However, as the range constraint limits the drone speed, which corresponds to Case 1 explained in Section 5.3, customer assignments to launch points are changed instead, as evident from the total drone distance travel reported in the table. In some instances, the location of launch points are also changed. The reduction on the drone speed leads an increase in the total energy consumption, as they fly at a speed below, 24.04 m/s, implying an increase in the total cost by 2.16%.

When the time bound is further reduced from $U = 2\text{h}$ to $U = 1\text{h}$, the problem yields different results in 13 out of 75 instances and becomes infeasible in 46 instances. In this case, the total cost and the total energy increase by 2.70% and 2.88%, respectively. While the total distance traveled by trucks reduces by 3.48%, the total distance traveled by drones increases by 1.59% on average. Finally, the average drone speed is reduced by 0.81%. Generally, however, the difference

between $U = 2\text{h}$ and $U = 1\text{h}$ as regards the impact on the total cost is marginal.

5.5.5 Trade-off between ground and air costs

In this section, we analyze the trade-offs between the operational truck costs and the energy cost of the drones. To this end, we consider two variants of the DDP, namely DDP-E, where we only minimize the drone energy consumption cost as shown by expression (5.8) and DDP-O where we minimize the total operational cost shown by expression (5.7). Tables 5.6 and 5.7 present average results for some key metrics using eight and four hours time bounds, respectively, where each figure reported is the percent deviation of the metric from those obtained by the original DDP.

Table 5.6: Trade-off between ground and air costs ($U = 8$ hours)

$ C $	$ P $	p	DDP-E				DDP-O			
			En. Cons. (%)	Tr. Dist. (%)	Dr. Dist. (%)	Av. Spe. (%)	En. Cons. (%)	Tr. Dist. (%)	Dr. Dist. (%)	Av. Spe. (%)
10	2	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	2	2	0.00	0.00	-3.07	0.00	33.03	-54.56	14.19	-6.97
10	2	3	0.00	0.00	-3.17	0.00	0.00	0.00	-3.17	0.00
15	3	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	3	2	0.00	0.00	0.00	0.01	21.85	-63.91	13.30	-6.11
15	3	3	0.00	0.89	0.00	0.00	28.04	-39.78	17.02	-6.77
20	4	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20	4	2	-0.08	17.99	0.39	-0.37	51.35	-70.19	26.83	-9.51
20	4	3	0.00	0.00	0.66	-0.01	70.92	-55.83	38.10	-11.54
25	5	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25	5	2	0.00	0.00	0.00	0.01	57.54	-81.80	31.59	-12.16
25	5	3	-0.01	0.00	0.00	0.00	78.96	-65.94	42.33	-14.43
30	6	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
30	6	2	-0.01	0.00	0.00	0.00	61.39	-80.32	32.96	-11.82
30	6	3	-0.01	0.00	0.00	0.01	89.78	-67.41	46.60	-15.40
Average			-0.01	1.26	-0.35	-0.02	32.86	-38.65	17.32	-6.31

The results suggest that the energy consumption of drones is more significant as compared to the distance traveled by trucks, as the average deviations of the metrics of the DDP-E from those of the DDP are minimal. For the DDP-O, the deviations are very high, namely an average reduction of 41.41% on the total distance traveled by trucks and an average increase of 35.20% on the drone energy consumption when $U = 4$ hours. This shows that energy consumption,

Table 5.7: Trade-off between ground and air costs ($U = 4$ hours)

			DDP-E				DDP-O			
$ C $	$ P $	p	En. Cons. (%)	Tr. Dist. (%)	Dr. Dist. (%)	Av. Spe. (%)	En. Cons. (%)	Tr. Dist. (%)	Dr. Dist. (%)	Av. Spe. (%)
10	2	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	2	2	0.00	0.00	-3.07	0.00	33.03	-54.56	14.19	-6.97
10	2	3	0.00	0.00	-3.17	0.00	0.00	0.00	-3.17	0.00
15	3	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	3	2	0.00	0.00	0.00	0.01	21.85	-63.91	13.30	-6.11
15	3	3	0.00	0.00	0.00	0.00	28.04	-39.78	17.02	-6.77
20	4	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20	4	2	-0.08	17.99	0.39	-0.37	51.35	-70.19	26.83	-9.51
20	4	3	-0.01	0.00	0.63	0.00	70.92	-55.83	38.10	-11.54
25	5	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25	5	2	0.00	0.00	0.00	0.01	57.54	-81.80	31.59	-12.16
25	5	3	-0.01	0.00	0.00	0.01	78.96	-65.94	42.33	-14.43
30	6	1	Infeasible				Infeasible			
30	6	2	-0.01	0.00	0.00	0.00	61.39	-80.32	32.96	-11.82
30	6	3	-0.01	0.00	0.00	0.01	89.78	-67.41	46.60	-15.40
Average			-0.01	1.28	-0.37	-0.02	35.20	-41.41	18.55	-6.76

as opposed to operational cost of trucks, drives the solutions of the DDP. The difference between two cost components is mainly due to the operational dynamics of Turkey, where drone is still considered as a new technology and therefore an expensive alternative for making deliveries.

5.5.6 Future battery option

As mentioned above, the range of a drone is another significant constraint on its speed. To fully analyze the impact of range, we consider the use of a future battery option with an increased energy density $s_{batt} = 900,000 \text{ kg.m}^2/\text{s}^2$ (Joule) (see, [223]), that provides for an extended range. The results obtained with the future battery option are given in Table 5.8 and the detailed results can be found in Appendices C.3 and C.4.

The results reported in Table 5.8 show that the average drone speed increases by 20.44% with the future battery in all 75 instances, suggesting that the range does play a crucial role on energy consumption and total cost, reducing both by 23.76% and 24.11%, respectively. The solutions also change in terms of the launch point locations and customer assignments in four out of 75 instances, resulting in

Table 5.8: Summary of the results with current and future battery options

C	P	p	Current Battery					Future Battery				
			Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)	Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)
10	2	1	570.90	10267.91	0.00	56424.53	15.53	406.46	7310.46	0.00	56424.53	19.19
10	2	2	415.56	7218.35	13380.20	46125.00	17.58	316.60	5453.76	12581.60	44615.03	20.97
10	2	3	388.38	6662.56	16876.60	43513.27	18.17	300.40	5080.24	16876.60	43513.27	21.31
15	3	1	783.42	14090.35	0.00	80628.02	15.78	566.11	10181.90	0.00	80628.02	19.61
15	3	2	622.50	10962.29	12223.40	68109.54	17.30	471.15	8240.20	12223.40	68109.54	20.83
15	3	3	578.73	10122.77	14966.20	64257.42	17.78	443.59	7692.07	14966.20	64257.42	21.18
20	4	1	1032.15	18563.77	0.00	105801.00	15.99	746.61	13428.32	0.00	105801.00	19.78
20	4	2	666.93	11715.79	14616.00	79729.41	18.27	529.01	9235.15	14616.00	79729.41	21.81
20	4	3	554.40	9558.97	21560.00	69324.87	19.25	458.85	7862.42	20414.40	69701.56	22.50
25	5	1	1326.44	23856.90	0.00	136010.95	15.64	958.23	17234.39	0.00	136010.95	19.63
25	5	2	813.30	14255.02	19490.60	98631.42	18.32	650.49	11326.74	19490.60	98631.42	21.93
25	5	3	699.01	12106.15	24372.00	88662.26	19.17	579.99	9990.60	23061.80	88784.50	22.49
30	6	1	1654.00	29748.28	0.00	166085.01	15.57	1186.52	21340.22	0.00	166085.01	19.48
30	6	2	980.23	17283.71	18113.40	119234.02	18.20	781.74	13713.68	18113.40	119234.02	21.92
30	6	3	827.17	14430.66	23352.60	106395.61	19.14	687.15	11912.27	23352.60	106395.61	22.56
Average			794.21	14056.23	11930.07	88595.49	17.45	605.53	10666.83	11713.11	88528.09	21.01

a reduction of 1.82% and 0.08% in total distance traveled by trucks and drones, respectively.

5.5.7 Effect of speed flexibility

One of the assumptions of the DDP is that drones travel at the same speed whilst traveling to and back from a customer. However, given that the parameters $(\mu_2, \mu_1, \epsilon_2, \epsilon_1)$ of the energy model change from the outward to the return journey, the global optimizer speed values derived from equation (5.4) are 23.46 m/s for the former and 24.76 m/s for the latter. In this section, we allow different speed to be used on either leg of the journey, and compare the results to those of the DDP. The results are given in Table 5.9.

Between the two variants, the total distance traveled by trucks and drones do not change in all 75 instances. As it can be seen from the table, allowing speed flexibility increases the average drone speed only by 0.05%, suggesting that such a flexibility has a small impact on the average drone speed, and consequently on energy consumption and the total cost (only a 0.01% reduction). The results indicate that drone speed on a given journey can be equalized, without much impact on cost and energy, which also facilitates the modeling of the problem and eases practical implementation.

Table 5.9: Summary of the results with speed flexibility

$ C $	$ P $	p	Same speed			Different speed		
			Tot. Cost (€)	En. Cons. (kJ)	Av. Spe. (m/s)	Tot. Cost (€)	En. Cons. (kJ)	Av. Spe. (m/s)
10	2	1	570.90	10267.91	15.53	570.84	10266.97	15.54
10	2	2	415.56	7218.35	17.58	415.51	7217.40	17.58
10	2	3	388.38	6662.56	18.17	388.32	6661.50	18.18
15	3	1	783.42	14090.35	15.78	783.35	14089.07	15.79
15	3	2	622.50	10962.29	17.30	622.41	10960.81	17.31
15	3	3	578.73	10122.77	17.78	578.66	10121.46	17.79
20	4	1	1032.15	18563.77	15.99	1032.04	18561.93	16.00
20	4	2	666.93	11715.79	18.27	666.84	11714.12	18.28
20	4	3	554.40	9558.97	19.25	554.28	9556.82	19.26
25	5	1	1326.44	23856.90	15.64	1326.33	23854.93	15.64
25	5	2	813.30	14255.02	18.32	813.17	14252.81	18.33
25	5	3	699.01	12106.15	19.17	698.88	12103.81	19.18
30	6	1	1654.00	29748.28	15.57	1653.84	29745.27	15.58
30	6	2	980.23	17283.71	18.20	980.11	17281.57	18.21
30	6	3	827.17	14430.66	19.14	827.02	14428.05	19.15
Average			794.21	14056.23	17.447	794.11	14054.44	17.455

5.5.8 Allowing the use of multiple drones

In this section, we allow multiple drones to take off from a given launch point. To model this variant, we define a set $D = \{1, \dots, d\}$ of drones and a new decision variable t_{ijd} that equals 1 if drone $d \in D$ takes off from a launch point $j \in L$ to serve customer $i \in C$, and 0 otherwise. We include Constraints (5.27) and update Constraints (5.13) as Constraints (5.28) as below:

$$x_{ij} = \sum_{d \in D} t_{ijd} \quad \forall i \in C, j \in L \quad (5.27)$$

$$\frac{c_{0j}}{v^t} y_j + \sum_{k \in C} \left(\frac{2d_{kj}}{v_{kj}} + \tau \right) t_{kjd} - \frac{d_{ij}}{v_{ij}} t_{ijd} - M_j(1 - t_{ijd}) \leq U \quad \forall i \in C, j \in L, d \in D. \quad (5.28)$$

Constraints (5.27) ensure that if a customer is assigned to a launch point, then only one drone taking off from that launch point serves that customer, and Constraints (5.28) guarantee that each customer will be served within the predetermined time limit U .

In order to analyze the impact of using multiple drones, we conduct some computational experiments. The preliminary results suggest that, although using multiple drones indirectly relaxes the time bound constraint, it does not have any impact on the drone range. Therefore, using multiple drones does not help with attaining the optimal speed and does not therefore reduce the energy consumption. In particular, the range constraint prevents the drones from flying at the optimal speed, which also corresponds to Case 1 described in Section 5.3. The results also suggest that, unless there are batteries with at least three times of capacity of current technology, there will not be significant benefits of employing multiple drones.

5.6 Conclusions

In this chapter, we introduce the Drone Delivery Problem (DDP) where drones are used as the only mode of transportation to make deliveries to a number of customers. The proposed problem includes explicit calculations of drone energy consumption and the drone range, both of which depend on the drone speed, which itself is considered as a decision variable in the DDP. The problem initially modeled as a nonlinear programming formulation, lends itself to a reformulation using second order cone programming, which admits the use of a state-of-the-art optimization package to obtain solutions. We also include the perspective cuts to strengthen the proposed formulation. Extensive computational results have revealed a number of managerial implications, summarized as follows:

- Although the use of the depot as a launch point incurs no operational truck cost, the depot may not always be the best launch point for a drone.
- A reduction in the delivery time bound does not always imply an increase in the drone speed for minimizing total cost, mainly due to the range constraints. Altering customer assignments and launch point locations instead may be a better means to cope with the tighter time bounds.
- The drone speed can be set to the same value for both legs (forward and

return) of a given journey as using two different speed values does not save too much money.

- Deploying more than one drone from a launch point does not always reduce energy consumption due to the range constraints. One should instead consider either launching drones from new launch points or extending the capacity of the drone battery.

All of the drone-based delivery systems mentioned in this chapter neglect one of the most important factors that can directly affect deliveries made by drones, that is the wind. Analyzing the uncertainty of wind and its impact on drone speed could be a future direction for the DDP and in Chapter 6, we will address this problem.

Chapter 6

Stochastic Drone Delivery Problem

This chapter presents an extension of the Drone Delivery Problem described in Chapter 5. The problem is called the Stochastic Drone Delivery Problem where uncertainty of the wind speed and its effect on the drone speed are considered. Similar to Chapter 5, the problem consists of (i) selecting the launch points from where drones will take off, (ii) assignments of customers to the launch points, and (iii) the speed at which drones are to travel between the customers and the launch points. The objective is to minimize a total cost function including operational cost of trucks which acts as a launch points for drones and the expected energy consumption cost which is mainly a function of drone speed. Initially, the model is formulated as a two-stage stochastic nonlinear program and then it is reformulated by using deterministic equivalent problem and second order cone programming approaches. As a solution approach, we propose a scenario decomposition algorithm. Computational results on the performance of the algorithm and the impact of stochastic optimization are discussed.

The remainder of the chapter is structured as follows. Section 6.1 provides an introduction to the problem. Section 6.2 presents a formal definition of the problem, a nonlinear two-stage stochastic formulation and a reformulation of the

model by using the second order cone programming and the deterministic equivalent problem. Section 6.3 describes a scenario decomposition algorithm to solve large-sized instances. Section 6.4 presents results of computational experiments. Conclusions are given in Section 6.5.

6.1 Introduction

It is customarily assumed that drones travel at the speed that is set by the driver at the launch point. However, during its forward journey to the customer and return journey to the truck or the depot, the drone is expected to be affected by wind, especially within that altitude that it cruises. In addition to its impact on drone speed, the speed of wind is not certain and it is not easily predictable. In order to incorporate the effects of wind on drones, the uncertainty aspect of wind speed should be addressed. Therefore, in this study, we propose a new problem called the Stochastic Drone Delivery Problem (SDDP), an extension of the DDP, where the uncertainty of the wind speed and its effect on the drone speed are also included.

The Stochastic Drone Delivery Problem (SDDP) consists of deciding the location of launch points, assignments of customers to launch points, the speed set for a drone before launching and the real speed which drones travel between customers and launch points while completing all deliveries within a predetermined time limit, and without exceeding the range of the drone. The objective is to minimize the total variable costs that comprises the operational cost of trucks and the expected drone energy consumption cost. Since the drone range and the drone energy consumption depend on the drone speed, the wind speed will directly affect both of these terms. To the best of our knowledge, this is the first study that consider the uncertainty of drone speed due to unpredictable weather conditions in a delivery problem with drones.

The contribution of this study is fourfold: (i) we introduce the uncertainty of drone speed to a transportation problem where deliveries are made by drones,

(ii) we first present a nonlinear two-stage stochastic formulation and then, also provide a reformulation of this model by using the second order cone programming and the deterministic equivalent problem, (iii) we apply a scenario decomposition algorithm to solve the instances with higher number of scenarios within reasonable times and (iv) we present an extensive computational analysis to evaluate the performance of the algorithm and to highlight the value of stochasticity.

6.2 Problem Definition and Formulations

Since the delivery system used in the SDDP is the same as the one described in the DDP (Section 5.1), settings and parameters of the problem are also the same (see, Section 5.4 for the mathematical definition of the problem). Additionally, in the SDDP, we assume that the wind speed is random and it can take finite number of different values. Each realization corresponds to a scenario and the set of scenarios is shown by $S = \{1, \dots, |S|\}$. Let ξ be the random variable representing the wind speed. In that case, ξ takes value of ξ_s with probability p_s for each $s \in S$.

In this chapter, we use the same formulations and assumptions for calculating both energy consumption and range of a drone as in the DDP. For a detailed explanation, we refer the reader to Section 5.3.

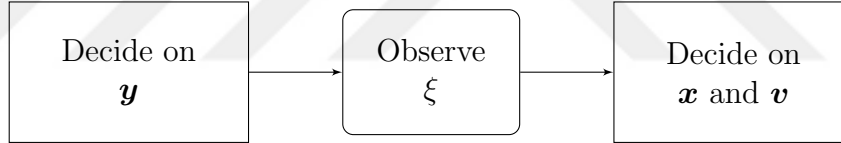
6.2.1 Mathematical formulation for the SDDP

In this section, we first present a nonlinear two-stage stochastic programming formulation of the SDDP that is based on the formulation developed in Section 5.4 for the deterministic version of the problem. The decision variables are defined as follows: A binary variable y_j equals 1 if a drone launches from a launch point $j \in L$, and 0 otherwise. A binary variable x_{ijs} equals 1 if a drone that takes off from a launch point $j \in L$ serves customer $i \in C$ for scenario $s \in S$, and 0 otherwise. The drone speed set by the driver and the real speed (including wind

speed) that the drone travels between customer $i \in C$ and launch point $j \in L$ for scenario $s \in S$ are denoted by the continuous and nonnegative variables v_{ijs}^d and $\bar{v}_{ijs}^d$, respectively.

Decisions in the SDDP can be grouped into two different sets based on their relations with the random wind speed. Decisions on launch points (collectively represented as $\mathbf{y}$) are tactical level decisions which are made before observing the realization of wind speed. On the other hand, allocation of drones to customers and speeds of drones (collectively represented as $\mathbf{x}$ and $\mathbf{v}$, respectively) are operational level decisions. From stochastic programming perspective $\mathbf{y}$ is the first stage decisions and $\mathbf{x}$ and $\mathbf{v}$ are second stage decisions. The order of decisions in the SDDP is depicted in Figure 6.1.

Figure 6.1: Order of decisions in Stochastic Drone Delivery Problem.



The SDDP is a two-stage mixed-integer stochastic programming problem. Since integer variables appear in both stages, the SDDP is a computationally challenging problem. A detailed survey, theoretical properties and practical applications of two stage mixed-integer stochastic programming problems can be found in [228].

We propose the following nonlinear two-stage stochastic programming formulation for the SDDP:

$$\begin{aligned}
 & \text{(SDDP)} \\
 & \text{Minimize } \sum_{j \in L} c_d(c_{0j} + c_{j0})y_j + \mathbb{E}[Q(y, \xi)] \tag{6.1}
 \end{aligned}$$

subject to

$$\sum_{j \in L} y_j = p \tag{6.2}$$

$$y_j \in \{0, 1\} \quad \forall j \in L \tag{6.3}$$

where $[Q(y, \xi)]$ is the optimal value of the second stage problem, that is,

$$Q(y, \xi) = \text{Minimize } c_e \sum_{i \in C} \sum_{j \in L} \sum_{s \in S} \left[(\mu_2 + \mu_1) d_{ij} (v_{ijs}^d)^2 x_{ijs} + \frac{(\epsilon_2 + \epsilon_1) d_{ij} x_{ijs}}{(v_{ijs}^d)^2} \right] \quad (6.4)$$

subject to

$$\sum_{j \in L} x_{ijs} = 1 \quad \forall i \in C, s \in S \quad (6.5)$$

$$x_{ijs} \leq y_j \quad \forall i \in C, j \in L, s \in S \quad (6.6)$$

$$\bar{v}_{ijs}^d = v_{ijs}^d + \xi_s \quad \forall i \in C, j \in L, s \in S \quad (6.7)$$

$$2d_{ij} (v_{ijs}^d)^2 \leq \Theta \quad \forall i \in C, j \in L, s \in S \quad (6.8)$$

$$\frac{c_{0j}}{v^t} y_j + \sum_{k \in C} \left(\frac{2d_{kj}}{\bar{v}_{kjs}^d} + p_t \right) x_{kjs} - \frac{d_{ij}}{\bar{v}_{ijs}^d} x_{ij} - M_j (1 - x_{ijs}) \leq U \quad \forall i \in C, j \in L, s \in S \quad (6.9)$$

$$v_{min} \leq v_{ijs}^d \leq v_{max} \quad \forall i \in C, j \in L, s \in S \quad (6.10)$$

$$\bar{v}_{ijs}^d \geq 0 \quad \forall i \in C, j \in L, s \in S \quad (6.11)$$

$$x_{ijs} \in \{0, 1\} \quad \forall i \in C, j \in L, s \in S \quad (6.12).$$

In the first stage problem, the objective function (6.1) minimizes the sum of total operational cost of trucks in the first stage and the expected cost in the second stage where the cost is given as a function of the first stage variable y and a random variable ξ representing wind speed. Constraint (6.2) sets the number of launch points used equals to p . Constraints (6.3) are binary constraints. In the second stage problem, the objective function (6.4) minimizes the total energy consumption of drones. Constraints (6.5) guarantee that each customer will be served by a drone which takes off from exactly one launch point for each scenario. Constraints (6.6) ensure that no service will be provided by a drone for any customer unless the drone takes off from a launch point for each scenario. Constraints (6.7) set traveling speed of the drone by summing up the drone speed set by the driver and the random variable which represent the drone speed. Constraints (6.8) impose the drone range limitation. Constraints (6.9) ensure that each customer will be served within a predetermined time limit. Constraints (6.10) guarantee that drone speed will be between the minimum and maximum speed limits allowed. Constraints (6.11) and (6.12) are non-negativity and binary constraints, respectively.

6.2.2 Deterministic equivalent problem

Assuming that support of ξ is finite, that is, the speed of wind can take finitely many values with positive probabilities two-stage stochastic formulation can be represented as a large deterministic problem, which is called as the deterministic equivalent problem (DEP). The random variable ξ takes values $\xi_1, \xi_2, \dots, \xi_{|S|}$ with probabilities $p_1, p_2, \dots, p_{|S|}$ for each scenario $s \in S$, respectively. The DEP of two-stage stochastic programming formulation (SDDP-DEP) is given as:

$$\begin{aligned}
 & \text{(SDDP-DEP)} \\
 & \text{Minimize } \sum_{j \in L} c_d(c_{0j} + c_{j0})y_j \\
 & + c_e \sum_{i \in C} \sum_{j \in L} \sum_{s \in S} p_s \left[(\mu_2 + \mu_1) d_{ij} (v_{ijs}^d)^2 x_{ijs} + \frac{(\epsilon_2 + \epsilon_1) d_{ij} x_{ijs}}{(v_{ijs}^d)^2} \right] \\
 & \text{subject to} \\
 & (6.2)-(6.3), (6.5)-(6.12).
 \end{aligned} \tag{6.13}$$

6.2.3 Second order cone programming

In this section, we show how the SDDP-DEP formulation can be reformulated as a second order cone programming (SOCP) formulation. The SDDP-DEP formulation is nonlinear due to the second component of the objective function (6.13), constraints (6.8) and (6.9). Here, we use a similar technique to the one explained in Section 5.4.1 while reformulating the problem. We introduce four new auxiliary decision variables, namely $w_{ijs} = x_{ijs}/v_{ijs}^d$, $\bar{w}_{ijs} = x_{ijs}/\bar{v}_{ijs}^d$, $u_{ijs} = (v_{ijs}^d)^2$ and $z_{ij} = (w_{ij})^2$, using which we reformulate the SDDP-DEP as follows:

$$\begin{aligned}
 & \text{(SDDP-DEP-SOCP)} \\
 & \text{Minimize } \sum_{j \in L} c_d(c_{0j} + c_{j0})y_j \\
 & + c_e \sum_{i \in C} \sum_{j \in L} \sum_{s \in S} p_s [(\mu_2 + \mu_1) d_{ij} u_{ijs} + (\epsilon_2 + \epsilon_1) d_{ij} z_{ijs}] \\
 & \text{subject to} \\
 & (6.2)-(6.3), (6.5)-(6.7), (6.11)-(6.12)
 \end{aligned} \tag{6.14}$$

$$2d_{ij}u_{ijs} \leq \Theta x_{ijs} \quad \forall i \in C, j \in L, s \in S \quad (6.15)$$

$$\frac{c_{0j}}{\bar{v}} y_j + \sum_{k \in C} (2d_{kj}\bar{w}_{kjs} + \tau x_{kjs}) - d_{ij}\bar{w}_{ijs} - M_j(1 - x_{ijs}) \leq U \quad \forall i \in C, j \in L, s \in S \quad (6.16)$$

$$v_{min}x_{ijs} \leq v_{ijs} \leq v_{max}x_{ijs} \quad \forall i \in C, j \in L, s \in S \quad (6.17)$$

$$(v_{ijs})^2 \leq u_{ijs} \quad \forall i \in C, j \in L, s \in S \quad (6.18)$$

$$(w_{ijs})^2 \leq z_{ijs} \quad \forall i \in C, j \in L, s \in S \quad (6.19)$$

$$x_{ijs} \leq w_{ijs}v_{ijs} \quad \forall i \in C, j \in L, s \in S \quad (6.20)$$

$$x_{ijs} \leq \bar{w}_{ijs}\bar{v}_{ijs} \quad \forall i \in C, j \in L, s \in S \quad (6.21).$$

Constraints (6.18) and (6.19) are quadratic inequalities, which can be directly rewritten as second order cone constraints in the form $\left\| \begin{bmatrix} 2v_{ijs}^d \\ 1 - u_{ijs} \end{bmatrix} \right\| \leq (1 + u_{ijs})$ since $u_{ijs} \geq 0$ and $v_{ijs}^d \geq 0$; and $\left\| \begin{bmatrix} 2w_{ijs} \\ 1 - z_{ijs} \end{bmatrix} \right\| \leq (1 + z_{ijs})$ since $w_{ijs} \geq 0$ and $z_{ijs} \geq 0$, respectively. Constraints (6.20) and (6.21) are also nonlinear constraints, which can be reformulated as:

$$x_{ijs}^2 \leq w_{ijs}v_{ijs}^d \quad \forall i \in C, j \in L, s \in S \quad (6.22)$$

$$x_{ijs}^2 \leq \bar{w}_{ijs}\bar{v}_{ijs}^d \quad \forall i \in C, j \in L, s \in S \quad (6.23).$$

Constraints (6.22) and (6.23) are now hyperbolic inequalities which can also be represented as second order cone constraints in the following form $\left\| \begin{bmatrix} 2x_{ijs} \\ v_{ijs}^d - w_{ijs} \end{bmatrix} \right\| \leq (v_{ijs}^d + w_{ijs})$ since $x_{ijs} \geq 0$, $v_{ijs}^d \geq 0$ and $w_{ijs} \geq 0$; and $\left\| \begin{bmatrix} 2x_{ijs} \\ \bar{v}_{ijs}^d - \bar{w}_{ijs} \end{bmatrix} \right\| \leq (\bar{v}_{ijs}^d + \bar{w}_{ijs})$ since $x_{ijs} \geq 0$, $\bar{v}_{ijs}^d \geq 0$ and $\bar{w}_{ijs} \geq 0$, respectively.

To strengthen the SOCP reformulation, we add the following perspective cuts proposed by [186] instead of quadratic constraints (6.18) and (6.19):

$$(v_{ijs}^d)^2 \leq u_{ijs}x_{ijs} \quad \forall i \in C, j \in L, s \in S \quad (6.24)$$

$$(w_{ijs})^2 \leq z_{ijs}x_{ijs} \quad \forall i \in C, j \in L, s \in S \quad (6.25).$$

Now, the formulation SDDP-SOCP-DEP can be solved by a commercial solver.

6.3 Solution Approach

Although including perspective cuts reduce solution time substantially, for some instances with higher number of scenarios, solving the proposed SDDP-DEP-SOCP formulation within reasonable time is not possible. Therefore, we propose an exact solution algorithm to solve the SDDP. The proposed solution approach is based on the scenario decomposition algorithm proposed by [229] for two-stage 0-1 stochastic programs where first stage decisions are binary. In [229], a generic algorithm is presented that can be applied to general problem structures, so we adapted this algorithm into the structure of the SDDP.

The algorithm consists of two phases; in the first one, we first relax non-anticipativity of the first stage variables, which means we drop the requirement of having the same first stage decision for each scenario and then a relaxation of the problem obtained for each scenario is solved by dropping the integrality requirement in the second stage problem (x variables in our case) in order to find a lower bound. Generally, an LP-relaxation provides a loose bound, but it reduces the solution time. In the second phase, an upper bound is generated by using the first stage solutions found in the first phase for each scenario. One significant point of the algorithm is that the first stage variables' solutions (y variables in our case) which are already evaluated are not considered in the following iterations of the algorithm, which helps the algorithm to find tighter lower bounds. Since the first stage decisions are binary, we can add the following constraints into the formulation solved to find a lower bound (first phase) to cut-off the solutions which are already evaluated:

$$\sum_{j \in L: \bar{y}_j = 1} \bar{y}_j + \sum_{j \in L: \bar{y}_j = 0} (1 - \bar{y}_j) \geq 1 \quad \forall \bar{y} \in R \quad (6.26)$$

where R represent the set of the first stage variable solutions which are already evaluated. This inequality is known as “integer” or “no-good” cuts.

Another important property of the algorithm is decomposition. When non-anticipativity of the first stage variables is relaxed in the lower bounding phase,

the resulting problem decomposes into each scenario. Therefore, we solve a deterministic problem for each scenario and obtain a lower bound value by using optimal values of these single scenario problems. Similarly, when we fix the first stage variables in the upper bounding phase we can solve the remaining problem for each scenario. The upper bound value is obtained by taking the expected value of the single scenario problems. The decomposition of the problem in both lower and upper bounding phases of the algorithm significantly reduces the solution time. As it can be seen in the results of the computational experiments in Section 6.4, our algorithm outperforms the SDDP-DEP-SOCP formulation.

Algorithm 6.1 Scenario Decomposition Algorithm

```

initialize:  $UB \leftarrow +\infty, LB \leftarrow -\infty, R = \emptyset, y^* \leftarrow 0$ 
1: while  $UB > LB$  and  $\{0, 1\}^n \setminus R \neq \emptyset$  do
2:   for  $s = 1$  to  $S$  do
3:     solve a relaxation of the second stage formulation including Constraints
       (6.26)
4:     let  $\bar{y}_s$  be the optimal solution and  $lb_s$  be the optimal objective value
5:   end for
6:    $LB \leftarrow \sum_{s=1}^S p_s lb_s, \hat{R} = \bigcup_{s=1}^S \{\bar{y}_s\}, R \leftarrow R \cup \hat{R}$ 
7:   for  $y \in \hat{R}$  do
8:      $u \leftarrow 0$ 
9:     for  $s = 1$  to  $S$  do
10:      solve SDDP-SOCP-DEP formulation given  $y$  variables
11:      let  $f_s(y)$  be the optimal objective value and set  $u \leftarrow u + p_s f_s(y)$ 
12:    end for
13:    if  $UB > u$  then
14:       $UB \leftarrow u$  and  $y^* \leftarrow y$ 
15:    end if
16:  end for
17: end while

```

We provide convergence results for Algorithm 6.1. A similar proof is available in [229], however, for completeness we present the proof for our version in detail.

Lemma 6.1. *At each iteration of Algorithm 6.1, either cardinality of R increases at least by one or the algorithm terminates.*

Proof. We prove Lemma 6.1 by considering two cases:

- If at least one of the scenario problems in the lower bounding phase is infeasible, that is, $lb_s = +\infty$ for at least one $s \in S$ then $LB = +\infty$. In this case algorithm terminates since $UB \leq LB$.
- If all scenario problems in the lower bounding phase is feasible then $\hat{R} \neq \emptyset$ and cardinality of R increase at least by one.

□

Theorem 6.1. *Algorithm 6.1 terminates after a finite number of iterations either finding an optimal solution of SDDP-SOC-DEP or declaration of infeasibility.*

Proof. Lemma 6.1 implies that cardinality of $\{0, 1\}^n \setminus R$ decreases at least by one in each iteration until the algorithm terminates. Thus, the algorithm terminates after at most 2^n iterations.

We now consider two different cases:

- If the problem is infeasible, UB never takes a finite value since $f_s(y) = +\infty$ for each $y \in R$.
- If the problem is feasible, UB takes a finite value and the algorithm terminates either exploring all 2^n first stage feasible solutions or due to $UB \leq LB$. The latter one guarantees that the unexplored first stage solution cannot give a better objective value than UB . Hence y^* is an optimal solution of SDDP-SOC-DEP.

□

Remark 6.1. *The LB is not necessarily a lower bound for SDDP-SOC-DEP. LB is a lower bound for SDDP-SOC-DEP where the first stage decisions (y variables) are restricted to set $\{0, 1\}^n \setminus R$.*

Remark 6.2. *In the worst case, Algorithm 6.1 corresponds to brute force search over the first stage variables. However, as seen in Section 6.4, its performance is very promising in practice.*

6.4 Computational Study

This section presents computational results on the solutions of the SDDP. First, we describe the data set used in the computational experiments. Second, we evaluate the performance of the proposed solution approach compared to solving the formulation. Third, we analyze the expected value of perfect information and the value of stochasticity. Fourth, we provide an analysis on the impact of wind variability on the solutions.

The computational experiments are carried out on a Linux OS environment with Dual Intel Xeon E5-2690 v4 14 Core 2.6GHz processors with 128 GB of RAM. All mathematical models and algorithms are implemented in Java. The IBM ILOG CPLEX Optimization Studio version 12.7.1 is used as the solver. The time limit is set as two hours for any instance.

6.4.1 Data set

In the computational experiments, the Kartal data set, which is described in Section 5.5.1 in detail, is used. The values of some parameters are given in Table 6.1 and the detailed explanation for the derivation of these values can be found in Section 5.5.1. The values of the remaining parameters related to the energy consumption and range formulations can be found in Table 5.2.

Table 6.1: Parameter Values

Notation	Description	Typical Values
v^t	Truck speed (km/h)	45
U	Time bound (h)	1
v_{max}	Maximum drone speed (m/s)	44.7
v_{min}	Minimum drone speed (m/s)	1
p_t	Preparation time of a drone (s)	120
c_d	Unit operational cost per distance for a truck (₺/km)	1.063
c_e	Unit energy consumption cost (₺/kJ)	0.0556

Wind speed, which is a random variable in our problem, is represented by ξ_s for each scenario $s \in S$ and it is generated as follows; first wind speed predictions

are extracted from [230] for the dates between November 12, 2018 and February 8, 2019 and then the data is divided into two categories in terms of wind direction; winds from north and west are categorized as positive wind (the same direction with drone) and winds from south and east as negative wind (opposite direction to drone). Finally, the data is fitted to two different types of distribution: a normal distribution with a mean of 1.98 and a standard deviation of 4.92 and a uniform distribution with a minimum value of -8.33 and a maximum value of 13.33. Since the data used is based on mainly winter season, the variability of wind is very high. To also cover different seasons of the year, a multiplier λ is used as follows; for the normal distribution, the standard deviation is varied by multiplying it with λ and for the uniform distribution, both minimum and maximum values are varied by multiplying them with λ . Based on these parameters, random wind speeds are generated by sampling from the fitted distributions. The number of scenarios ($|S|$) is set as five, 10, 15, 20, 25, and 100.

6.4.2 Performance of the scenario decomposition algorithm

In this section, we compare the scenario decomposition algorithm with the SDDP-SOCP-DEP formulation in terms of solution time. Tables 6.2 and 6.3 provide the comparison to evaluate the performance of the proposed solution algorithm for normal and uniform distributions, respectively. In this comparison, we generate five different instances using different random seed values represented in the first row of the table titled as “Instance No” and two different number of drones (p) namely; five and six, five different number of scenarios ($|S|$) namely; five, 10, 15, 20 and 25 and three different wind variability (λ) namely; 0.25, 0.5 and 1 which are shown in the first three column of the table, respectively. We could not consider some particular instances ($p = 5, \lambda = 1$) since they results with infeasibility of the problem. Since for some instances, the formulation could not find the optimal solution, we also report the optimality gap (in %) for such instances under the column titled as “Gap”. Finally, “NFS” means that no feasible solution is found by the formulation within two-hour time limit.

Table 6.2: Performance of the algorithm (Normal Distribution)

Instance No			1			2			3			4			5		
p	λ	S	Formulation Gap (%)	CPU (s)	Algorithm CPU (s)	Formulation Gap (%)	CPU (s)	Algorithm CPU (s)	Formulation Gap (%)	CPU (s)	Algorithm CPU (s)	Formulation Gap (%)	CPU (s)	Algorithm CPU (s)	Formulation Gap (%)	CPU (s)	Algorithm CPU (s)
6	1	5		293.47	54.56		4045.54	265.74		335.89	205.73		1777.89	299.27		326.45	119.17
6	1	10	0.40	7200.00	525.81	1.50	7200.00	1102.00	0.30	7200.00	590.19	1.29	7200.00	2466.04		1680.80	230.25
6	1	15	0.46	7200.00	725.71	NFS	7200.00	864.27	0.54	7200.00	1178.05	NFS	7200.00	771.87	0.17	7200.00	347.07
6	1	20	0.46	7200.00	845.84	NFS	7200.00	1073.89	0.44	7200.00	1145.88	NFS	7200.00	1172.99	NFS	7200.00	2311.24
6	1	25	0.43	7200.00	977.99	NFS	7200.00	1286.96	0.04	7200.00	1638.67	NFS	7200.00	1380.85	NFS	7200.00	4506.12
5	0.5	5		127.59	113.49		62.81	239.48		901.67	265.07		502.72	446.03		320.86	189.39
5	0.5	10	0.16	7200.00	405.06	0.81	7200.00	559.59	0.56	7200.00	485.40	0.33	7200.00	789.09		4266.35	357.48
5	0.5	15	0.33	7200.00	627.49	1.26	7200.00	797.23	0.44	7200.00	673.39	0.34	7200.00	784.06	0.14	7200.00	567.77
5	0.5	20	0.52	7200.00	752.19	NFS	7200.00	1023.94	0.27	7200.00	767.75	0.39	7200.00	1091.64	0.58	7200.00	823.45
5	0.5	25	0.47	7200.00	1021.63	NFS	7200.00	1270.06	0.41	7200.00	1066.43	0.49	7200.00	1288.63	NFS	7200.00	971.52
6	0.5	5		106.71	92.25		698.35	594.31		2842.35	410.10		1175.53	356.88	0.16	7200.00	284.65
6	0.5	10	0.13	7200.00	465.43		572.58	837.55	0.35	7200.00	701.84	0.43	7200.00	751.56	0.07	7200.00	549.42
6	0.5	15	0.26	7200.00	764.06		975.88	1690.72	0.40	7200.00	942.65	0.33	7200.00	1001.33		673.52	825.88
6	0.5	20	0.33	7200.00	943.39		1693.94	1854.30	0.32	7200.00	1074.14	0.48	7200.00	1438.89	0.34	7200.00	1122.60
6	0.5	25	0.40	7200.00	1272.61	NFS	7200.00	2092.82	0.37	7200.00	1439.05	NFS	7200.00	2087.38	0.43	7200.00	1300.36
5	0.25	5		545.09	221.40		308.10	237.52		890.71	268.72		766.00	243.60		925.34	268.68
5	0.25	10	0.13	7200.00	651.82		413.08	467.71	0.25	7200.00	539.77	0.24	7200.00	541.63	0.17	7200.00	485.46
5	0.25	15	0.27	7200.00	820.21	0.30	7200.00	748.26	0.26	7200.00	645.83	0.28	7200.00	748.60	0.28	7200.00	776.04
5	0.25	20		1187.88	1110.93	0.43	7200.00	1018.75		1411.44	842.71	0.60	7200.00	997.50	0.34	7200.00	1031.74
5	0.25	25	NFS	7200.00	1279.28	0.50	7200.00	1212.45	0.44	7200.00	1050.57	0.33	7200.00	1164.52	NFS	7200.00	1221.13
6	0.25	5		788.61	305.65		646.29	301.70		2327.35	382.96		3592.43	297.19		2604.88	397.34
6	0.25	10	0.23	7200.00	929.25	0.23	7200.00	672.07	0.31	7200.00	791.79	0.27	7200.00	805.89	0.21	7200.00	705.38
6	0.25	15	0.35	7200.00	1364.45	0.44	7200.00	1039.27	0.35	7200.00	1051.85	0.34	7200.00	1120.17	0.35	7200.00	1080.83
6	0.25	20	0.37	7200.00	1504.53	0.38	7200.00	1441.45	0.45	7200.00	1334.82	0.41	7200.00	1622.92	0.53	7200.00	1450.38
6	0.25	25	NFS	7200.00	2080.49	0.41	7200.00	1743.00	0.40	7200.00	1827.58	0.39	7200.00	1712.69	0.40	7200.00	1618.82

The results on Table 6.2 show that solving the formulation provides the optimal solution for 33 out of 125 instances within the time limit. While the formulation finds the optimal solution for 24 out of 25 five-scenario instances, the optimal solution can be found by formulation for only nine out of 100 other instances. This indicates that for higher number of scenarios, it is very difficult to find the optimal solution by solving the formulation. For 76 out of all instances, the optimal solution cannot be found by the formulation within two hours and average optimality gap of those instances is 0.39%. For the remaining 16 instances, the formulation could not find a feasible solution within the time limit. On the other hand, the scenario decomposition algorithm finds the optimal solution for all instances within two hours. While the average solution time for solving formulation is 5,617.50 seconds, it is 916.28 seconds for the algorithm.

The results on Table 6.3 indicate that the formulation can find the optimal solution for 40 out of 125 instances within the time limit. For 58 instances, the optimal solution cannot be found by the formulation within two hours resulting with a 0.47% average optimality gap of those instances. For the remaining 27 instances, the formulation could not find a feasible solution within two hours. On the other hand, the scenario decomposition algorithm finds the optimal solution for all instances within two hours. The average solution times for solving the

Table 6.3: Performance of the algorithm (Uniform Distribution)

Instance No			1			2			3			4			5		
p	λ	$ S $	Formulation Gap (%)	CPU (s)	Algorithm CPU (s)	Formulation Gap (%)	CPU (s)	Algorithm CPU (s)	Formulation Gap (%)	CPU (s)	Algorithm CPU (s)	Formulation Gap (%)	CPU (s)	Algorithm CPU (s)	Formulation Gap (%)	CPU (s)	Algorithm CPU (s)
6	1	5		214.51	148.386		355.89	184.705		141.99	90.20	0.60	7200.00	418.06		950.10	180.72
6	1	10		323.26	323.104	1.02	7200.00	967.599	0.13	7200.00	307.80	0.80	7200.00	585.91	0.23	7200.00	960.94
6	1	15	0.81	7200.00	856.625	NFS	7200.00	1429.76	0.75	7200.00	749.12	0.64	7200.00	740.57		4738.99	1822.89
6	1	20	NFS	7200.00	1054.556	NFS	7200.00	1858.33	NFS	7200.00	1266.51	NFS	7200.00	1135.20	NFS	7200.00	2079.48
6	1	25	NFS	7200.00	1160.597	1.48	7200.00	3009.1	NFS	7200.00	1320.11	NFS	7200.00	1419.64	NFS	7200.00	2186.93
5	0.5	5		610.27	213.677		438.59	181.869		90.67	92.92		130.57	188.27		238.64	136.08
5	0.5	10		7198.26	361.989		1952.75	291.929		764.02	246.69		3898.27	318.31		2857.67	312.36
5	0.5	15	0.97	7200.00	608.473	0.43	7200.00	570.245	2.50	7200.00	426.84	0.26	7200.00	460.62	0.22	7200.00	405.00
5	0.5	20	NFS	7200.00	808.76	0.64	7200.00	774.039	0.13	7200.00	678.45	0.34	7200.00	707.63	0.68	7200.00	652.45
5	0.5	25		2098.13	909.356	NFS	7200.00	950.793	0.52	7200.00	864.17	NFS	7200.00	864.19	NFS	7200.00	722.71
6	0.5	5		98.18	361.218		487.04	148.34		146.02	50.35		1180.26	227.53		26.53	174.24
6	0.5	10	0.12	7200.00	1018.766		282.68	434.862		919.81	247.39		376.46	376.73		3296.28	290.08
6	0.5	15	0.38	7200.00	1056.618	0.26	7200.00	925.188	0.10	7200.00	475.01	0.38	7200.00	470.22	0.26	7200.00	435.19
6	0.5	20	0.10	7200.00	1332.249	0.57	7200.00	1145.68	0.23	7200.00	757.91	0.45	7200.00	763.90	0.62	7200.00	883.06
6	0.5	25	NFS	7200.00	1684.599	NFS	7200.00	1354.85		2010.20	947.88	NFS	7200.00	979.35	0.43	7200.00	1181.81
5	0.25	5		554.38	223.588		97.01	218.432		672.26	219.89		880.99	251.16		931.04	251.67
5	0.25	10	0.19	7200.00	483.001	0.10	7200.00	477.206	0.14	7200.00	449.48	0.25	7200.00	547.23	0.21	7200.00	559.56
5	0.25	15	0.41	7200.00	773.537	0.43	7200.00	774.982	0.23	7200.00	700.283	NFS	7200.00	760.48	0.36	7200.00	842.82
5	0.25	20	0.88	7200.00	1031.556		1737.94	1027.29	0.47	7200.00	886.85	0.41	7200.00	938.52	0.57	7200.00	1138.49
5	0.25	25	NFS	7200.00	1231.926	NFS	7200.00	1291.33	NFS	7200.00	1114.95	0.34	7200.00	1230.12	NFS	7200.00	1391.50
6	0.25	5		2862.43	385.636		2096.40	695.062		1100.46	251.88		1583.74	385.49		3326.31	416.10
6	0.25	10	0.27	7200.00	881.133		707.11	948.277	0.18	7200.00	632.93		490.60	907.34	0.28	7200.00	729.15
6	0.25	15	0.48	7200.00	1534.088	0.43	7200.00	1427.04	0.29	7200.00	1016.37	0.32	7200.00	1259.26	0.41	7200.00	1033.69
6	0.25	20	0.57	7200.00	1897.072	NFS	7200.00	1840.58	0.40	7200.00	1568.07	0.65	7200.00	1611.69	0.79	7200.00	1728.45
6	0.25	25	NFS	7200.00	2205.455	NFS	7200.00	2229.54	0.35	7200.00	2054.70	NFS	7200.00	1944.70	NFS	7200.00	2080.63

formulation and the scenario decomposition algorithm are 5,318.93 and 857.66 seconds, respectively.

Overall, we can conclude that the proposed algorithm solves real-size instances to optimality in reasonable times.

6.4.3 Expected value of perfect information and value of stochasticity

This section presents an analysis on the value of perfect information about the uncertain wind speed and the value of the uncertainty on the solutions. Initially, assuming that the perfect information is available at the beginning, which means that we know the exact value of the wind speed (ξ_s) before making all decisions, the expected profit with perfect information (EPPI) can be calculated by solving the problem for each scenario $s \in S$ given the wind speed. Let z_s be the objective function value of the problem for each scenario s . Then, we can calculate the EPPI as $\sum_{s \in S} p_s z_s$ and the expected value of perfect information (EVPI) in percentages as $(z^{EPPI} - z^{SDDP}) \times 100 / z^{SDDP}$ where z^{SDDP} and z^{EPPI} are the objective function values of the SDDP formulation and the SDDP with perfect

information, respectively.

Secondly, we consider the case in which first the deterministic version of the problem with a priori known wind speed that is the expected value of wind speed over all scenarios ($\sum_{s \in S} p_s \xi_s$) is solved. Then given the first stage decisions obtained by this deterministic problem, the stochastic version of the problem is solved for each scenario s . Let z_s^{Fixed} be the objective function value of this stochastic problem for each scenario s . Then, we can calculate the objective function value of this case as $\sum_{s \in S} p_s z_s^{Fixed}$. The difference between this case (Fixed) and the SDDP gives the value of stochasticity (VS), which is calculated in percentages as $(z^{Fixed} - z^{SDDP}) \times 100 / z^{SDDP}$, where z^{SDDP} and z^{Fixed} are the objective function values of the SDDP formulation and the SDDP with a fixed first stage decisions, respectively.

Tables 6.4 and 6.5 present the average results on both the EVPI and VS for normal and uniform distributions over five different instances. For these analyses, 100 scenarios are considered and thus some instances start to result with infeasibility. Therefore, we report such instances as ‘Infeasible’ in the tables.

The results on Tables 6.4 and 6.5 show that when five or seven drones are available to serve customers solving the stochastic problem almost finds the optimal solution for each possible weather conditions as if we had the perfect weather information. When the number of drones is six, then having the perfect information for the weather reduces the total cost and this reduction in the total cost generally increases with a higher variability in the wind speed. On the other hand, deciding the location of launch points based on a deterministic model provides the same solution as the stochastic model does when five or seven drones are available to operate. With six drones available, fixing the location of launch point based on the deterministic model generally results with solutions which are not the optimal solutions of the stochastic model. For those instances, the value of stochasticity is higher when the wind speed variability is high ($\lambda = 1$) and low ($\lambda = 0.5$) compared to more moderate wind variability values as it can be seen in Table 6.5. The main reason for such small values for value of stochasticity can be explained with the idea of considering only launch point location decisions as

Table 6.4: Expected value of perfect information and value of stochasticity analysis (Normal distribution)

p	λ	SDDP (₺)	EPPI (₺)	EVPI (%)	Fixed (₺)	VS (%)
5	0.5	855.91	855.90	0.00	855.91	0.00
5	0.6	856.43	856.43	0.00	856.43	0.00
5	0.7			Infeasible		
5	0.8			Infeasible		
5	0.9			Infeasible		
5	1			Infeasible		
6	0.5	851.73	851.36	0.04	852.68	0.11
6	0.6	852.05	851.58	0.06	852.76	0.08
6	0.7	852.80	852.13	0.08	853.36	0.07
6	0.8			Infeasible		
6	0.9			Infeasible		
6	1			Infeasible		
7	0.5	853.01	852.98	0.00	853.01	0.00
7	0.6	853.26	853.25	0.00	853.26	0.00
7	0.7	853.82	853.80	0.00	853.82	0.00
7	0.8	854.42	854.41	0.00	854.42	0.00
7	0.9			Infeasible		
7	1			Infeasible		

Table 6.5: Expected value of perfect information and value of stochasticity analysis (Uniform distribution)

p	λ	SDDP (₺)	EPPI (₺)	EVPI (%)	Fixed (₺)	VS (%)
5	0.5	857.68	857.67	0.00	857.68	0.00
5	0.6	858.49	858.49	0.00	858.49	0.00
5	0.7	860.57	860.56	0.00	860.57	0.00
5	0.8	Infeasible				
5	0.9	Infeasible				
5	1	Infeasible				
6	0.5	853.35	852.75	0.07	853.66	0.04
6	0.6	853.86	852.90	0.11	854.16	0.03
6	0.7	854.87	853.65	0.14	854.88	0.00
6	0.8	855.94	854.69	0.15	855.94	0.00
6	0.9	856.89	855.65	0.14	857.38	0.06
6	1	858.25	857.01	0.14	859.02	0.09
7	0.5	854.33	854.32	0.00	854.33	0.00
7	0.6	854.49	854.46	0.00	854.49	0.00
7	0.7	855.22	855.20	0.00	855.22	0.00
7	0.8	856.24	856.23	0.00	856.24	0.00
7	0.9	857.20	857.20	0.00	857.20	0.00
7	1	858.54	858.53	0.00	858.54	0.00

the first stage decisions in the stochastic model.

This section also presents another analysis related to the importance of using the stochastic optimization. Here we consider a solution obtained by the deterministic model in which the wind speed is set equals to the expected value of wind speed over all scenarios and then given all (first and second stage) decisions, the stochastic version of the problem is solved for each scenario. Finally, the number of scenarios that results with infeasible solution is calculated. Computational experiments over 180 instances indicate that instead of stochastic optimization, using a deterministic model leads to an infeasible solution in nearly 90% of scenarios, on average.

6.4.4 The impact of wind variability

In this section, we analyse the impact of variability in wind speed on the solutions of the SDDP by varying λ values from 0.5 to 1 with an increment of 0.1. The number of drones available is five, six and seven. The average results over five different instances with 100 scenarios are depicted in Tables 6.6 and 6.7.

The results on both tables suggest that increasing variability of wind speed results with a higher total cost values mainly due to the increase in the energy consumed by drones. In some instances (Uniform distribution, $p = 6$), wind variability also directly affects the location of launch points. For those instances, increasing λ value leads to use parking areas as launch points which are further away from the depot resulting with a higher operational cost of trucks (Table 6.7). Furthermore, higher variability in wind speed causes an increase in the total distance traveled by drones and generally a reduction in the average drone speed.

Table 6.6: The impact of wind variability (Normal distribution)

p	λ	Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)
5	0.5	855.91	14653.89	38712.00	111951.52	20.21
5	0.6	856.43	14663.26	38712.00	112004.98	20.21
5	0.7			Infeasible		
5	0.8			Infeasible		
5	0.9			Infeasible		
5	1			Infeasible		
6	0.5	851.73	14502.33	42705.00	110869.59	20.24
6	0.6	852.05	14508.21	42705.00	110907.84	20.24
6	0.7	852.80	14521.73	42705.00	110974.40	20.24
6	0.8			Infeasible		
6	0.9			Infeasible		
6	1			Infeasible		
7	0.5	853.01	14398.15	49363.00	110377.03	20.29
7	0.6	853.26	14402.67	49363.00	110387.06	20.28
7	0.7	853.82	14412.67	49363.00	110442.73	20.29
7	0.8	854.42	14423.51	49363.00	110494.53	20.27
7	0.9			Infeasible		
7	1			Infeasible		
Average		853.71	14498.49	44776.78	110934.41	20.25

Table 6.7: The impact of wind variability (Uniform distribution)

p	λ	Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)
5	0.5	857.68	14685.71	38712.00	112112.95	20.20
5	0.6	858.49	14700.34	38712.00	112239.28	20.19
5	0.7	860.57	14737.69	38712.00	112438.78	20.18
5	0.8			Infeasible		
5	0.9			Infeasible		
5	1			Infeasible		
6	0.5	853.35	14531.51	42705.00	111037.41	20.23
6	0.6	853.86	14540.78	42705.00	111118.56	20.22
6	0.7	854.87	14518.17	44837.00	111219.16	20.27
6	0.8	855.94	14527.12	45370.00	111331.70	20.26
6	0.9	856.89	14544.21	45370.00	111388.71	20.26
6	1	858.25	14568.76	45370.00	111511.51	20.26
7	0.5	854.33	14421.81	49363.00	110454.01	20.28
7	0.6	854.49	14424.78	49363.00	110477.69	20.28
7	0.7	855.22	14437.87	49363.00	110575.13	20.27
7	0.8	856.24	14456.27	49363.00	110673.45	20.26
7	0.9	857.20	14473.49	49363.00	110734.78	20.26
7	1	858.54	14497.53	49363.00	110852.31	20.26
Average		854.50	14529.40	43904.25	111176.71	20.25

6.5 Conclusions

In this study, we proposed an extension of the Drone Delivery Problem where the effects of uncertain wind speed on drone speed is considered. The drone speed affects energy consumption of drones which is one of the two objective function components, and also the drone range and the time bound constraints. Therefore, the uncertainty of drone speed should have an impact on the solutions of the SDDP. The problem initially is modeled as a nonlinear two-stage stochastic programming formulation. Then, it is first converted to a nonlinear deterministic equivalent problem formulation to deal with the uncertainty and then to a second order cone deterministic equivalent problem formulation to cope with nonlinear terms. However, solving the reformulation with higher number of scenarios requires too much computational time. Therefore, a scenario decomposition algorithm is proposed to solve this problem. The algorithm decomposes the problem for each scenario by relaxing the non-anticipativity of the first stage decisions. We conduct extensive computational experiments over a real network in Istanbul, Turkey to evaluate the performance of the algorithm and the impact of stochasticity on the solutions of the problem. Overall, the computational results suggest that the scenario decomposition algorithm outperforms the second order cone deterministic equivalent problem formulation in terms of both solution quality and quantity.

Chapter 7

Conclusion

In this dissertation, we focus on network design problems that consider location and routing decisions with the aim of reducing environmental impacts of freight transportation related activities. These impacts are caused by fuel consumption for conventional delivery vehicles such as trucks and energy consumptions for modern delivery vehicles such as drones. The models that estimate fuel or energy consumption generally depend on payload and vehicle speed, which are considered as decisions in the problems that we studied in this dissertation.

In Chapter 2, we present a comprehensive literature review on green network design problems. The existing literature is classified in terms of different levels of decision making; operational, tactical and strategic. For each category, we present definitions, mathematical models and real-life applications. In this chapter, we also provide some future research directions on general green network design problems.

The literature reviewed in Chapter 2 indicates that there are a few studies that consider “green” version of classical network design problems including the location-routing problem and the hub location problem and these studies do not include environmental impacts in full extent. Therefore, in Chapter 3, we present

the Green Location-Routing Problem (GLRP) as an extension of the Location-Routing Problem, that explicitly consider fuel consumption and CO₂ emissions due to transportation related activities. For the GLRP, we present a mixed integer programming formulation and also propose a set of preprocessing rules and valid inequalities. Also, we develop two heuristic algorithms, one of which is an integer-programming based algorithm and the other one is an iterated local search algorithm. Extensive computational experiments are conducted to analyse the GLRP solutions on different setting and to evaluate the performance of the proposed algorithms. Additionally, we present a case study based on a FMCG company in Istanbul, Turkey and provide computational analysis. Finally, the optimal solution characterizations for the special cases of the GLRP are investigated. In Chapter 4, we introduce the Green Hub Location Problem (GHLP), which extends the hub location problem by explicitly accounting fuel consumption and CO₂ emissions caused by transportation related activities. First, a nonlinear programming formulation is presented for the GHLP and then it is reformulated as a second order cone programming formulation. To strengthen the reformulation, perspective cuts are proposed. We conduct extensive computational experiments to present analyses by changing parameters of the problem and compare the GHLP with the p -hub median problem to quantify the impact of emissions on the solutions.

In the GLRP and GHLP described in Chapters 3 and 4, respectively, only environmental impacts caused by vehicles are considered. As it is suggested in Section 2.3, while deciding locations of depots or hubs, environmental impacts due to the processes within such establishments should also be included, which can be considered as a future research direction. Another possible extension of the GLRP could be the use of multiple objectives since measuring environmental impacts in monetary units can be questionable for decision makers. One other possible future research could be a multi-objective vehicle routing problem that can address both environmental and social issues. While environmental impacts can be estimated by fuel consumption models, social impacts can be measured by fairness to drivers in terms of equal payments.

Based on the literature review given in Chapter 2, we also observe that the

number of studies that consider more than one transportation mode in a green network design problem is limited. Therefore, in Chapter 5, we consider a delivery problem called the Drone Delivery Problem (DDP), in which drones are used as the last-mile delivery vehicles and trucks are used to carry these drones and packages up to a certain point and then act as launch points for drones. In the DDP, explicit calculations of drone energy consumption and the drone range are included. We first present a nonlinear programming formulation and then we develop a second order cone programming reformulation, which is strengthened by perspective cuts. Extensive computational experiments are conducted to analyze the DDP solutions under different settings and to derive some managerial implications. In Chapter 6, we extend the DDP presented in Chapter 5 by considering uncertainty of the wind speed and its effect on the drone speed, which has an impact on drone energy consumption, drone range and service time bound. For this extension, first, a nonlinear two-stage stochastic programming formulation is developed and then its reformulation by second order cone programming and deterministic equivalent problem is presented to deal with the nonlinear terms and the uncertainty, respectively. Additionally, a scenario decomposition algorithm is proposed to solve instances with higher number of scenarios. We conduct a comprehensive computational study to evaluate the performance of the scenario decomposition algorithm and the effects of uncertainty on the solutions.

In the DDP and SSDP presented in Chapters 5 and 6, respectively, only energy consumption of drones are explicitly included. However, in both problems, trucks also have a role in deliveries. Estimating fuel consumption of trucks and considering truck speed as a decision could be a future research direction. Another possible extension for both problems can be related to their application. Instead of a freight transportation problem, a humanitarian or healthcare application with the use of drones can be investigated.

Bibliography

- [1] F. Jaehn, “Sustainable operations,” *European Journal of Operational Research*, vol. 253, no. 2, pp. 243–264, 2016.
- [2] T. G. Crainic, N. Ricciardi, and G. Storchi, “Models for evaluating and planning city logistics systems,” *Transportation science*, vol. 43, no. 4, pp. 432–454, 2009.
- [3] A. McKinnon, M. Browne, A. Whiteing, and M. Piecyk, *Green logistics: Improving the environmental sustainability of logistics*. Kogan Page Publishers, New Delhi, India, 2015.
- [4] M. Fleischmann, J. M. Bloemhof-Ruwaard, R. Dekker, E. Van der Laan, J. A. Van Nunen, and L. N. Van Wassenhove, “Quantitative models for reverse logistics: A review,” *European journal of operational research*, vol. 103, no. 1, pp. 1–17, 1997.
- [5] S. K. Srivastava, “Network design for reverse logistics,” *Omega*, vol. 36, no. 4, pp. 535–548, 2008.
- [6] R. Dekker, M. Fleischmann, K. Inderfurth, and L. N. van Wassenhove, *Reverse logistics: quantitative models for closed-loop supply chains*. Springer-Verlag, Berlin Heidelberg, 2013.
- [7] K. Govindan, H. Soleimani, and D. Kannan, “Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future,” *European Journal of Operational Research*, vol. 240, no. 3, pp. 603–626, 2015.

- [8] S. C. Davis, S. W. Diegel, R. G. Boundy, *et al.*, “Transportation energy data book: Edition 33,” tech. rep., Tennessee: Oak Ridge National Laboratory, ORNL-6990, Oak Ridge, 2009. Available from: <https://info.ornl.gov/sites/publications/Files/Pub50854.pdf> [Accessed 28 February 2019].
- [9] S. Pelletier, O. Jabali, and G. Laporte, “50th anniversary invited article—goods distribution with electric vehicles: review and research perspectives,” *Transportation Science*, vol. 50, no. 1, pp. 3–22, 2016.
- [10] L. Bernstein, P. Bosch, O. Canziani, Z. Chen, R. Christ, and K. Riahi, “IPCC, 2007: Climate change 2007: synthesis report,” 2008. Available from: <http://pure.iiasa.ac.at/id/eprint/8667/> [Accessed 28 February 2019].
- [11] E. Demir, T. Bektaş, and G. Laporte, “A review of recent research on green road freight transportation,” *European Journal of Operational Research*, vol. 237, no. 3, pp. 775–793, 2014.
- [12] M. Goedkoop and R. Spriensma, “The eco-indicator 99: A damage oriented method for life-cycle impact assessment: Methodology annex,” tech. rep., PRe Consultants, Amersfoort, Netherlands, 2001. Available from: https://www.pre-sustainability.com/download/EI99_annexe_v3.pdf [Accessed 28 February 2019].
- [13] S. A. I. C. (SAIC) and M. A. Curran, “Life-cycle assessment: principles and practice,” tech. rep., National Risk Management Research Laboratory, Office of Research and Development, US Environmental Protection Agency, Cincinnati, Ohio, 2006. Available from: <https://www.cs.ucsb.edu/~chong/290N-W10/EPAonLCA2006.pdf> [Accessed 28 February 2019].
- [14] EPA, “Greenhouse gas inventory guidance direct emissions from mobile combustion sources,” tech. rep., United States: Environmental Protection Agency, 2016. Available from: https://www.epa.gov/sites/production/files/2016-03/documents/mobileemissions_3_2016.pdf [Accessed 28 February 2019].

- [15] O. Dukkanci, T. Bektaş, and B. Y. Kara, “Green network design problems,” in *Sustainable Transportation and Smart Logistics* (J. Faulin, S. E. Grasman, A. A. Juan, and P. Hirsch, eds.), pp. 169 – 206, Elsevier, 2019.
- [16] S. K. Srivastava, “Green supply-chain management: a state-of-the-art literature review,” *International journal of management reviews*, vol. 9, no. 1, pp. 53–80, 2007.
- [17] A. Sbihi and R. W. Eglese, “Combinatorial optimization and green logistics,” *Annals of Operations Research*, vol. 175, no. 1, pp. 159–175, 2010.
- [18] R. Dekker, J. Bloemhof, and I. Mallidis, “Operations research for green logistics—An overview of aspects, issues, contributions and challenges,” *European Journal of Operational Research*, vol. 219, no. 3, pp. 671–679, 2012.
- [19] E. Hassini, C. Surti, and C. Searcy, “A literature review and a case study of sustainable supply chains with a focus on metrics,” *International Journal of Production Economics*, vol. 140, no. 1, pp. 69–82, 2012.
- [20] C. Lin, K. L. Choy, G. T. Ho, S. Chung, and H. Lam, “Survey of green vehicle routing problem: Past and future trends,” *Expert Systems with Applications*, vol. 41, no. 4, pp. 1118–1138, 2014.
- [21] M. Brandenburg, K. Govindan, J. Sarkis, and S. Seuring, “Quantitative models for sustainable supply chain management: Developments and directions,” *European journal of operational research*, vol. 233, no. 2, pp. 299–312, 2014.
- [22] M. Eskandarpour, P. Dejax, J. Miemczyk, and O. Péton, “Sustainable supply chain network design: An optimization-oriented review,” *Omega*, vol. 54, pp. 11–32, 2015.
- [23] I. Kara, B. Y. Kara, and M. K. Yetis, “Energy minimizing vehicle routing problem,” in *Combinatorial Optimization and Applications, Lecture Notes in Computer Science, vol 4616* (A. Dress, X. Yinfeng, and Z. Binhai, eds.), pp. 62–71, Springer Berlin Heidelberg, 2007.

- [24] T. Bektaş and G. Laporte, “The pollution-routing problem,” *Transportation Research Part B: Methodological*, vol. 45, no. 8, pp. 1232–1250, 2011.
- [25] Y. Xiao, Q. Zhao, I. Kaku, and Y. Xu, “Development of a fuel consumption optimization model for the capacitated vehicle routing problem,” *Computers & Operations Research*, vol. 39, no. 7, pp. 1419–1431, 2012.
- [26] R. Fukasawa, Q. He, and Y. Song, “A branch-cut-and-price algorithm for the energy minimization vehicle routing problem,” *Transportation Science*, vol. 50, no. 1, pp. 23–34, 2015.
- [27] E. E. Zachariadis, C. D. Tarantilis, and C. T. Kiranoudis, “The load-dependent vehicle routing problem and its pick-up and delivery extension,” *Transportation Research Part B: Methodological*, vol. 71, pp. 158–181, 2015.
- [28] L. Pradenas, B. Oportus, and V. Parada, “Mitigation of greenhouse gas emissions in vehicle routing problems with backhauling,” *Expert Systems with Applications*, vol. 40, no. 8, pp. 2985–2991, 2013.
- [29] N. Tajik, R. Tavakkoli-Moghaddam, B. Vahdani, and S. M. Mousavi, “A robust optimization approach for pollution routing problem with pickup and delivery under uncertainty,” *Journal of Manufacturing Systems*, vol. 33, no. 2, pp. 277–286, 2014.
- [30] Y.-J. Kwon, Y.-J. Choi, and D.-H. Lee, “Heterogeneous fixed fleet vehicle routing considering carbon emission,” *Transportation Research Part D: Transport and Environment*, vol. 23, pp. 81–89, 2013.
- [31] H. W. Kopfer, J. Schönberger, and H. Kopfer, “Reducing greenhouse gas emissions of a heterogeneous vehicle fleet,” *Flexible Services and Manufacturing Journal*, vol. 26, no. 1-2, pp. 221–248, 2014.
- [32] Y. Xiao and A. Konak, “The heterogeneous green vehicle routing and scheduling problem with time-varying traffic congestion,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 88, pp. 146–166, 2016.

- [33] Y. Xiao and A. Konak, “A genetic algorithm with exact dynamic programming for the green vehicle routing & scheduling problem,” *Journal of Cleaner Production*, vol. 167, pp. 1450–1463, 2017.
- [34] K. N. Androutsopoulos and K. G. Zografos, “An integrated modelling approach for the bicriterion vehicle routing and scheduling problem with environmental considerations,” *Transportation Research Part C: Emerging Technologies*, vol. 82, pp. 180–209, 2017.
- [35] Y. Huang, L. Zhao, T. Van Woensel, and J.-P. Gross, “Time-dependent vehicle routing problem with path flexibility,” *Transportation Research Part B: Methodological*, vol. 95, pp. 169–195, 2017.
- [36] Y. Suzuki, “A new truck-routing approach for reducing fuel consumption and pollutants emission,” *Transportation Research Part D: Transport and Environment*, vol. 16, no. 1, pp. 73–77, 2011.
- [37] D. Cinar, K. Gakis, and P. M. Pardalos, “Reduction of CO₂ emissions in cumulative multi-trip vehicle routing problems with limited duration,” *Environmental Modeling & Assessment*, vol. 20, no. 4, pp. 273–284, 2015.
- [38] S. Ubeda, F. Arcelus, and J. Faulin, “Green logistics at Eroski: A case study,” *International Journal of Production Economics*, vol. 131, no. 1, pp. 44–51, 2011.
- [39] S. Treitl, P. C. Nolz, and W. Jammerneegg, “Incorporating environmental aspects in an inventory routing problem. a case study from the petrochemical industry,” *Flexible Services and Manufacturing Journal*, vol. 26, no. 1-2, pp. 143–169, 2014.
- [40] H. Li, J. Yuan, T. Lv, and X. Chang, “The two-echelon time-constrained vehicle routing problem in linehaul-delivery systems considering carbon dioxide emissions,” *Transportation Research Part D: Transport and Environment*, vol. 49, pp. 231–245, 2016.
- [41] Y. Suzuki, “A dual-objective metaheuristic approach to solve practical pollution routing problem,” *International Journal of Production Economics*, vol. 176, pp. 143–153, 2016.

- [42] Y. Xiao and A. Konak, “A simulating annealing algorithm to solve the green vehicle routing & scheduling problem with hierarchical objectives and weighted tardiness,” *Applied Soft Computing*, vol. 34, pp. 372–388, 2015.
- [43] G. Scora and M. Barth, “Comprehensive modal emissions model, version 3.01 User’s guide,” tech. rep., Centre for Environmental Research and Technology. University of California, Riverside, United States of America, 2006.
- [44] M. Barth, T. Younglove, and G. Scora, “Development of a heavy-duty diesel modal emissions and fuel consumption model,” tech. rep., California Partners for Advanced Transit and Highways (PATH), Institute of Transportation Studies, University of California at Berkeley, 2005.
- [45] M. Barth and K. Boriboonsomsin, “Real-world carbon dioxide impacts of traffic congestion,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2058, no. 1, pp. 163–171, 2008.
- [46] E. Demir, T. Bektaş, and G. Laporte, “An adaptive large neighborhood search heuristic for the Pollution-Routing Problem,” *European Journal of Operational Research*, vol. 223, no. 2, pp. 346–359, 2012.
- [47] E. Demir, T. Bektaş, and G. Laporte, “The bi-objective pollution-routing problem,” *European Journal of Operational Research*, vol. 232, no. 3, pp. 464–478, 2014.
- [48] R. Kramer, A. Subramanian, T. Vidal, and F. C. Lucídio dos Anjos, “A matheuristic approach for the pollution-routing problem,” *European Journal of Operational Research*, vol. 243, no. 2, pp. 523–539, 2015.
- [49] R. Fukasawa, Q. He, and Y. Song, “A disjunctive convex programming approach to the pollution-routing problem,” *Transportation Research Part B: Methodological*, vol. 94, pp. 61–79, 2016.
- [50] S. Dabia, E. Demir, and T. V. Woensel, “An exact approach for a variant of the pollution-routing problem,” *Transportation Science*, vol. 51, no. 2, pp. 607–628, 2016.

- [51] A. Franceschetti, D. Honhon, T. Van Woensel, T. Bektaş, and G. Laporte, “The time-dependent pollution-routing problem,” *Transportation Research Part B: Methodological*, vol. 56, pp. 265–293, 2013.
- [52] J. F. Ehmke, A. M. Campbell, and B. W. Thomas, “Vehicle routing to minimize time-dependent emissions in urban areas,” *European Journal of Operational Research*, vol. 251, no. 2, pp. 478–494, 2016.
- [53] A. Franceschetti, E. Demir, D. Honhon, T. Van Woensel, G. Laporte, and M. Stobbe, “A metaheuristic for the time-dependent pollution-routing problem,” *European Journal of Operational Research*, vol. 259, no. 3, pp. 972–991, 2017.
- [54] Ç. Koç, T. Bektaş, O. Jabali, and G. Laporte, “The fleet size and mix pollution-routing problem,” *Transportation Research Part B: Methodological*, vol. 70, pp. 239–254, 2014.
- [55] O. C. Saka, S. Gürel, and T. Van Woensel, “Using cost change estimates in a local search heuristic for the pollution routing problem,” *OR spectrum*, vol. 39, no. 2, pp. 557–587, 2017.
- [56] R. S. Kumar, K. Kondapaneni, V. Dixit, A. Goswami, L. S. Thakur, and M. Tiwari, “Multi-objective modeling of production and pollution routing problem with time window: A self-learning particle swarm optimization approach,” *Computers & Industrial Engineering*, vol. 99, pp. 29–40, 2016.
- [57] R. Eshtehadi, M. Fathian, and E. Demir, “Robust solutions to the pollution-routing problem with demand and travel time uncertainty,” *Transportation Research Part D: Transport and Environment*, vol. 51, pp. 351–363, 2017.
- [58] S. Majidi, S.-M. Hosseini-Motlagh, and J. Ignatius, “Adaptive large neighborhood search heuristic for pollution-routing problem with simultaneous pickup and delivery,” *Soft Computing*, vol. 22, no. 9, pp. 2851–2865, 2018.
- [59] M. Soysal, J. M. Bloemhof-Ruwaard, R. Haijema, and J. G. van der Vorst, “Modeling an inventory routing problem for perishable products with environmental considerations and demand uncertainty,” *International Journal of Production Economics*, vol. 164, pp. 118–133, 2015.

- [60] M. Soysal, J. M. Bloemhof-Ruwaard, and T. Bektaş, “The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations,” *International Journal of Production Economics*, vol. 164, pp. 366–378, 2015.
- [61] M. Soysal, J. M. Bloemhof-Ruwaard, R. Haijema, and J. G. van der Vorst, “Modeling a green inventory routing problem for perishable products with horizontal collaboration,” *Computers & Operations Research*, vol. 89, pp. 168–182, 2018.
- [62] M. Alinaghian and M. Naderipour, “A novel comprehensive macroscopic model for time-dependent vehicle routing problem with multi-alternative graph to reduce fuel consumption: A case study,” *Computers & Industrial Engineering*, vol. 99, pp. 210–222, 2016.
- [63] J. F. Ehmke, A. M. Campbell, and B. W. Thomas, “Data-driven approaches for emissions-minimized paths in urban areas,” *Computers & Operations Research*, vol. 67, pp. 34–47, 2016.
- [64] A. Palmer, *The development of an integrated routing and carbon dioxide emissions model for goods vehicles*. PhD thesis, Cranfield University, November 2007.
- [65] Y. Kuo, “Using simulated annealing to minimize fuel consumption for the time-dependent vehicle routing problem,” *Computers & Industrial Engineering*, vol. 59, no. 1, pp. 157–165, 2010.
- [66] M. A. Figliozzi, “Vehicle routing problem for emissions minimization,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2197, no. 1, pp. 1–7, 2010.
- [67] O. Jabali, T. Woensel, and A. de Kok, “Analysis of travel times and CO_2 emissions in time-dependent vehicle routing,” *Production and Operations Management*, vol. 21, no. 6, pp. 1060–1074, 2012.
- [68] S. Mirzapour Al-e hashem and Y. Rekik, “Multi-product multi-period inventory routing problem with a transshipment option: A green approach,” *International Journal of Production Economics*, vol. 157, pp. 80–88, 2014.

- [69] M. Çimen and M. Soysal, “Time-dependent green vehicle routing problem with stochastic vehicle speeds: An approximate dynamic programming algorithm,” *Transportation Research Part D: Transport and Environment*, vol. 54, pp. 82–98, 2017.
- [70] W. Maden, R. Eglese, and D. Black, “Vehicle routing and scheduling with time-varying data: A case study,” *Journal of the Operational Research Society*, vol. 61, no. 3, pp. 515–522, 2010.
- [71] M. A. Figliozzi, “The impacts of congestion on time-definitive urban freight distribution networks CO_2 emission levels: Results from a case study in Portland, Oregon,” *Transportation Research Part C: Emerging Technologies*, vol. 19, no. 5, pp. 766–778, 2011.
- [72] J. Qian and R. Eglese, “Finding least fuel emission paths in a network with time-varying speeds,” *Networks*, vol. 63, no. 1, pp. 96–106, 2014.
- [73] M. Soysal and M. Çimen, “A simulation based restricted dynamic programming approach for the green time dependent vehicle routing problem,” *Computers & Operations Research*, vol. 88, pp. 297–305, 2017.
- [74] A. Aranda Uson, G. Ferreira, I. Zabalza Bribian, and D. Zambrana Vasquez, “Study of the environmental performance of end-of-life tyre recycling through a simplified mathematical approach,” *Thermal science*, vol. 16, no. 3, 2012.
- [75] M. Oberscheider, J. Zazgornik, C. B. Henriksen, M. Gronalt, and P. Hirsch, “Minimizing driving times and greenhouse gas emissions in timber transport with a near-exact solution approach,” *Scandinavian Journal of Forest Research*, vol. 28, no. 5, pp. 493–506, 2013.
- [76] G. P. Cachon, “Retail store density and the cost of greenhouse gas emissions,” *Management Science*, vol. 60, no. 8, pp. 1907–1925, 2014.
- [77] K. Govindan, A. Jafarian, R. Khodaverdi, and K. Devika, “Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food,” *International Journal of Production Economics*, vol. 152, pp. 9–28, 2014.

- [78] Ç. Koç, T. Bektaş, O. Jabali, and G. Laporte, “The impact of depot location, fleet composition and routing on emissions in city logistics,” *Transportation Research Part B: Methodological*, vol. 84, pp. 81–102, 2016.
- [79] E. M. Toro, J. F. Franco, M. G. Echeverri, and F. G. Guimarães, “A multi-objective model for the green capacitated location-routing problem considering environmental impact,” *Computers & Industrial Engineering*, vol. 110, pp. 114–125, 2017.
- [80] M. Zhalechian, R. Tavakkoli-Moghaddam, B. Zahiri, and M. Mohammadi, “Sustainable design of a closed-loop location-routing-inventory supply chain network under mixed uncertainty,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 89, pp. 182–214, 2016.
- [81] F. Tricoire and S. N. Parragh, “Investing in logistics facilities today to reduce routing emissions tomorrow,” *Transportation Research Part B: Methodological*, vol. 103, pp. 56–67, 2017.
- [82] T. Paksoy and E. Özceylan, “Environmentally conscious optimization of supply chain networks,” *Journal of the Operational Research Society*, vol. 65, no. 6, pp. 855–872, 2014.
- [83] M. Soysal, J. Bloemhof-Ruwaard, and J. Van der Vorst, “Modelling food logistics networks with emission considerations: The case of an international beef supply chain,” *International Journal of Production Economics*, vol. 152, pp. 57–70, 2014.
- [84] J. Q. F. Neto, J. M. Bloemhof-Ruwaard, J. A. van Nunen, and E. van Heck, “Designing and evaluating sustainable logistics networks,” *International Journal of Production Economics*, vol. 111, no. 2, pp. 195–208, 2008.
- [85] J. Q. F. Neto, G. Walther, J. Bloemhof, J. Van Nunen, and T. Spengler, “A methodology for assessing eco-efficiency in logistics networks,” *European Journal of Operational Research*, vol. 193, no. 3, pp. 670–682, 2009.
- [86] X. Bing, J. M. Bloemhof-Ruwaard, and J. G. van der Vorst, “Sustainable reverse logistics network design for household plastic waste,” *Flexible Services and Manufacturing Journal*, vol. 26, no. 1-2, pp. 119–142, 2014.

- [87] N. Kim, M. Janic, and B. Van Wee, “Trade-off between carbon dioxide emissions and logistics costs based on multiobjective optimization,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2139, no. 1, pp. 107–116, 2009.
- [88] J. Bauer, T. Bektaş, and T. G. Crainic, “Minimizing greenhouse gas emissions in intermodal freight transport: an application to rail service design,” *Journal of the Operational Research Society*, vol. 61, no. 3, pp. 530–542, 2010.
- [89] S. Pan, E. Ballot, and F. Fontane, “The reduction of greenhouse gas emissions from freight transport by pooling supply chains,” *International Journal of Production Economics*, vol. 143, no. 1, pp. 86–94, 2013.
- [90] Y. Qu, T. Bektaş, and J. Bennell, “Sustainability SI: multimode multicommodity network design model for intermodal freight transportation with transfer and emission costs,” *Networks and Spatial Economics*, vol. 16, no. 1, pp. 303–329, 2016.
- [91] E. Demir, W. Burgholzer, M. Hrušovský, E. Arıkan, W. Jammerneegg, and T. Van Woensel, “A green intermodal service network design problem with travel time uncertainty,” *Transportation Research Part B: Methodological*, vol. 93, pp. 789–807, 2016.
- [92] A. Nagurney, Z. Liu, and T. Woolley, “Sustainable supply chain and transportation networks,” *International Journal of Sustainable Transportation*, vol. 1, no. 1, pp. 29–51, 2007.
- [93] J. M. Cruz and D. Matsypura, “Supply chain networks with corporate social responsibility through integrated environmental decision-making,” *International Journal of Production Research*, vol. 47, no. 3, pp. 621–648, 2009.
- [94] B. Ghaddar and J. Naoum-Sawaya, “Environmentally friendly facility location with market competition,” *Journal of the Operational Research Society*, vol. 63, no. 7, pp. 899–908, 2012.

- [95] T. Xifeng, Z. Ji, and X. Peng, “A multi-objective optimization model for sustainable logistics facility location,” *Transportation Research Part D: Transport and Environment*, vol. 22, pp. 45–48, 2013.
- [96] S. Treitl and W. Jammerneegg, “Facility location decisions with environmental considerations: a case study from the petrochemical industry,” *Journal of Business Economics*, vol. 84, no. 5, pp. 639–664, 2014.
- [97] I. Harris, C. L. Mumford, and M. M. Naim, “A hybrid multi-objective approach to capacitated facility location with flexible store allocation for green logistics modeling,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 66, pp. 1–22, 2014.
- [98] A. A. Khoei, H. Süral, and M. K. Tural, “Time-dependent green Weber problem,” *Computers & Operations Research*, vol. 88, pp. 316–323, 2017.
- [99] M. Mohammadi, S. Torabi, and R. Tavakkoli-Moghaddam, “Sustainable hub location under mixed uncertainty,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 62, pp. 89–115, 2014.
- [100] A. H. Niknamfar and S. T. A. Niaki, “Fair profit contract for a carrier collaboration framework in a green hub network under soft time-windows: Dual lexicographic max–min approach,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 91, pp. 129–151, 2016.
- [101] A. Hugo and E. N. Pistikopoulos, “Environmentally conscious long-range planning and design of supply chain networks,” *Journal of Cleaner Production*, vol. 13, no. 15, pp. 1471–1491, 2005.
- [102] F. Wang, X. Lai, and N. Shi, “A multi-objective optimization for green supply chain network design,” *Decision Support Systems*, vol. 51, no. 2, pp. 262–269, 2011.
- [103] S. Elhedhli and R. Merrick, “Green supply chain network design to reduce carbon emissions,” *Transportation Research Part D: Transport and Environment*, vol. 17, no. 5, pp. 370–379, 2012.

- [104] I. Mallidis, R. Dekker, and D. Vlachos, “The impact of greening on supply chain design and cost: a case for a developing region,” *Journal of Transport Geography*, vol. 22, pp. 118–128, 2012.
- [105] M. Kadziński, T. Tervonen, M. K. Tomczyk, and R. Dekker, “Evaluation of multi-objective optimization approaches for solving green supply chain design problems,” *Omega*, vol. 68, pp. 168–184, 2017.
- [106] M. Varsei and S. Polyakovskiy, “Sustainable supply chain network design: A case of the wine industry in Australia,” *Omega*, vol. 66, pp. 236–247, 2017.
- [107] M. S. Pishvaei and J. Razmi, “Environmental supply chain network design using multi-objective fuzzy mathematical programming,” *Applied Mathematical Modelling*, vol. 36, no. 8, pp. 3433–3446, 2012.
- [108] M. A. Miranda-Ackerman, C. Azzaro-Pantel, and A. A. Aguilar-Lasserre, “A green supply chain network design framework for the processed food industry: Application to the orange juice agrofood cluster,” *Computers & Industrial Engineering*, vol. 109, pp. 369–389, 2017.
- [109] A. Chaabane, A. Ramudhin, and M. Paquet, “Designing supply chains with sustainability considerations,” *Production Planning & Control*, vol. 22, no. 8, pp. 727–741, 2011.
- [110] T. Abdallah, A. Farhat, A. Diabat, and S. Kennedy, “Green supply chains with carbon trading and environmental sourcing: Formulation and life cycle assessment,” *Applied Mathematical Modelling*, vol. 36, no. 9, pp. 4271–4285, 2012.
- [111] A. Chaabane, A. Ramudhin, and M. Paquet, “Design of sustainable supply chains under the emission trading scheme,” *International Journal of Production Economics*, vol. 135, no. 1, pp. 37–49, 2012.
- [112] K. Shaw, M. Irfan, R. Shankar, and S. S. Yadav, “Low carbon chance constrained supply chain network design problem: a benders decomposition based approach,” *Computers & Industrial Engineering*, vol. 98, pp. 483–497, 2016.

- [113] A. Rezaee, F. Dehghanian, B. Fahimnia, and B. Beamon, “Green supply chain network design with stochastic demand and carbon price,” *Annals of Operations Research*, vol. 250, no. 2, pp. 463–485, 2017.
- [114] G. Guillén-Gosálbez and I. E. Grossmann, “Optimal design and planning of sustainable chemical supply chains under uncertainty,” *AIChE Journal*, vol. 55, no. 1, pp. 99–121, 2009.
- [115] A. D. Bojarski, J. M. Laínez, A. Espuña, and L. Puigjaner, “Incorporating environmental impacts and regulations in a holistic supply chains modeling: An LCA approach,” *Computers & Chemical Engineering*, vol. 33, no. 10, pp. 1747–1759, 2009.
- [116] J. Duque, A. P. F. Barbosa-Póvoa, and A. Q. Novais, “Design and planning of sustainable industrial networks: Application to a recovery network of residual products,” *Industrial & Engineering Chemistry Research*, vol. 49, no. 9, pp. 4230–4248, 2010.
- [117] T. Pinto-Varela, A. P. F. Barbosa-Póvoa, and A. Q. Novais, “Bi-objective optimization approach to the design and planning of supply chains: economic versus environmental performances,” *Computers & Chemical Engineering*, vol. 35, no. 8, pp. 1454–1468, 2011.
- [118] F. You, L. Tao, D. J. Graziano, and S. W. Snyder, “Optimal design of sustainable cellulosic biofuel supply chains: multiobjective optimization coupled with life cycle assessment and input–output analysis,” *AIChE Journal*, vol. 58, no. 4, pp. 1157–1180, 2012.
- [119] J. Léonardi and M. Baumgartner, “CO₂ efficiency in road freight transportation: Status quo, measures and potential,” *Transportation Research Part D: Transport and Environment*, vol. 9, no. 6, pp. 451–464, 2004.
- [120] M. Baumgartner, J. Léonardi, and O. Krusch, “Improving computerized routing and scheduling and vehicle telematics: A qualitative survey,” *Transportation Research Part D: Transport and Environment*, vol. 13, no. 6, pp. 377–382, 2008.

- [121] E. Ericsson, H. Larsson, and K. Brundell-Freij, "Optimizing route choice for lowest fuel consumption—potential effects of a new driver support tool," *Transportation Research Part C: Emerging Technologies*, vol. 14, no. 6, pp. 369–383, 2006.
- [122] O. Apaydin and M. T. Gonullu, "Emission control with route optimization in solid waste collection process: A case study," *Sadhana*, vol. 33, no. 2, pp. 71–82, 2008.
- [123] G. Tavares, Z. Zsigraiova, V. Semiao, and M. d. G. Carvalho, "Optimisation of MSW collection routes for minimum fuel consumption using 3D GIS modelling," *Waste Management*, vol. 29, no. 3, pp. 1176–1185, 2009.
- [124] N. M. Jovičić, G. B. Bošković, G. Vujić, G. Jovičić, M. Z. Despotović, D. M. Milovanović, and D. R. Gordić, "Route optimization to increase energy efficiency and reduce fuel consumption of communal vehicles," *Thermal Science*, vol. 14, no. 5, p. 67, 2010.
- [125] Z. Zsigraiova, V. Semiao, and F. Beijoco, "Operation costs and pollutant emissions reduction by definition of new collection scheduling and optimization of MSW collection routes using GIS. the case study of Barreiro, Portugal," *Waste management*, vol. 33, no. 4, pp. 793–806, 2013.
- [126] J. Bandeira, T. G. Almeida, A. J. Khattak, N. M. Roupail, and M. C. Coelho, "Generating emissions information for route selection: Experimental monitoring and routes characterization," *Journal of Intelligent Transportation Systems*, vol. 17, no. 1, pp. 3–17, 2013.
- [127] H.-J. Wu and S. C. Dunn, "Environmentally responsible logistics systems," *International journal of physical distribution & logistics management*, vol. 25, no. 2, pp. 20–38, 1995.
- [128] H. Aronsson and M. Huge Brodin, "The environmental impact of changing logistics structures," *The international journal of logistics management*, vol. 17, no. 3, pp. 394–415, 2006.

- [129] B. Beltran, S. Carrese, E. Cipriani, and M. Petrelli, "Transit network design with allocation of green vehicles: A genetic algorithm approach," *Transportation Research Part C: Emerging Technologies*, vol. 17, no. 5, pp. 475–483, 2009.
- [130] J. G. Van Der Vorst, S.-O. Tromp, and D.-J. v. d. Zee, "Simulation modelling for food supply chain redesign; integrated decision making on product quality, sustainability and logistics," *International Journal of Production Research*, vol. 47, no. 23, pp. 6611–6631, 2009.
- [131] Y. Dou and J. Sarkis, "A joint location and outsourcing sustainability analysis for a strategic offshoring decision," *International Journal of Production Research*, vol. 48, no. 2, pp. 567–592, 2010.
- [132] D. R. Gaur, A. Mudgal, and R. R. Singh, "Routing vehicles to minimize fuel consumption," *Operations Research Letters*, vol. 41, no. 6, pp. 576–580, 2013.
- [133] G. Čirović, D. Pamučar, and D. Božanić, "Green logistic vehicle routing problem: Routing light delivery vehicles in urban areas using a neuro-fuzzy model," *Expert Systems with Applications*, vol. 41, no. 9, pp. 4245–4258, 2014.
- [134] A. D. Jovanović, D. S. Pamučar, and S. Pejčić-Tarle, "Green vehicle routing in urban zones—a neuro-fuzzy approach," *Expert systems with applications*, vol. 41, no. 7, pp. 3189–3203, 2014.
- [135] O. Dukkanci, B. Y. Kara, and T. Bektaş, "The green location-routing problem," *Computers & Operations Research*, vol. 105, pp. 187–202, 2019.
- [136] S. Salhi and G. K. Rand, "The effect of ignoring routes when locating depots," *European Journal of Operational Research*, vol. 39, no. 2, pp. 150–156, 1989.
- [137] C. Prodhon and C. Prins, "A survey of recent research on location-routing problems," *European Journal of Operational Research*, vol. 238, no. 1, pp. 1–17, 2014.

- [138] M. Drexl and M. Schneider, “A survey of variants and extensions of the location-routing problem,” *European Journal of Operational Research*, vol. 241, no. 2, pp. 283–308, 2015.
- [139] Unilever, “Going to market - reducing transport emissions,” 2017. Available from: <https://www.unilever.com/sustainable-living/the-sustainable-living-plan/reducing-environmental-impact/greenhouse-gases/going-to-market-reducing-transport-emissions/> [Accessed 9 March 2017].
- [140] UPS, “Corporate sustainability report,” tech. rep., 2015. Available from: https://sustainability.ups.com/media/ups-pdf-interactive/UPS_2015_CSR.pdf [Accessed 9 March 2017].
- [141] FedEx, “Inbound logistics recognizes FedEx as top green supply chain partner,” 2011. Available from: <http://about.van.fedex.com/newsroom/united-states-english/inbound-logistics-recognizes-fedex-as-top-green-supply-chain-partner/> [Accessed 25 February 2017].
- [142] FedEx, “FedEx 2016 global citizenship report Deliver it forward,” 2016. Available from: http://csr.fedex.com/pdf/FedEx_2016_Global_Citizenship_Report_Single.pdf [Accessed 14 December 2017].
- [143] DHL, “DHL bundles competences at a new logistics center in Milan,” 2012. Available from: http://www.dhl.com/en/press/releases/releases_2012/logistics/040312.html [Accessed 23 February 2017].
- [144] DHL, “DHL express expands at Milano Malpensa: new hub in the cargo city,” 2016. February 17, 2016. Available from: http://www.seamilano.eu/sites/sea14.message-asp.com/files/downloads/20160217_cs_dhl_sea_def_en.pdf [Accessed 12 December 2017].
- [145] M. Ward, “Road train technology trials get rolling,” *BBC*, 2011. January 18, 2011. Available from: <http://www.bbc.com/news/technology-12215915> [Accessed 27 December 2017].

- [146] Volvo, “SARTRE road train premiere on public roads,” 2012. May 28, 2012. Available from: <https://www.media.volvocars.com/global/en-gb/media/pressreleases/43899> [Accessed 27 December 2017].
- [147] K. Wysocky, “Mercedes’ self-driving truck,” *BBC*, 2014. November 13, 2014. Available from: <http://www.bbc.com/autos/story/20140926-mercedes-self-driving-truck> [Accessed 27 December 2017].
- [148] J. Linshi, “Meet the country’s first self-driving semi truck,” *Time*, 2015. May 6, 2015. Available from: <http://time.com/3848456/self-driving-freightliner-truck/> [Accessed 27 December 2017].
- [149] C. Dougherty, “Self-driving trucks may be closer than they appear,” *The New York Times*, 2017. November 13, 2017. Available from: <https://www.nytimes.com/2017/11/13/business/self-driving-trucks.html> [Accessed 20 December 2017].
- [150] DHL, “Self-driving vehicles in logistics,” 2014. Available from: http://www.dhl.com/content/dam/downloads/g0/about_us/logistics_insights/dhl_self_driving_vehicles.pdf [Accessed 13 December 2017].
- [151] A. Marshall, “The Us Postal Service is building a self-driving mail truck,” *Wired*, 2017. October 9, 2017. Available from: <https://www.wired.com/story/postal-service-office-self-driving-mail-trucks/> [Accessed 15 December 2017].
- [152] E. Woyke, “FedEx bets on automation as it prepares to fend off Uber and Amazon,” *MIT Technology Review*, 2017. February 3, 2017. Available from: <https://www.technologyreview.com/s/602896/fedex-bets-on-automation-as-it-prepares-to-fend-off-uber-and-amazon/> [Accessed 27 December 2017].
- [153] L. Stevens and T. Higgins, “Amazon forms team to focus on driverless technology,” *The Wall Street Journal*, 2017. April 24, 2017. Available from: <https://www.wsj.com/articles/amazon-team-focuses-on->

exploiting-driverless-technology-1493035203 [Accessed 27 December 2017].

- [154] C. E. Miller, A. W. Tucker, and R. A. Zemlin, “Integer programming formulation of traveling salesman problems,” *Journal of the Association for Computing Machinery (JACM)*, vol. 7, no. 4, pp. 326–329, 1960.
- [155] G. Dantzig, R. Fulkerson, and S. Johnson, “Solution of a large-scale traveling-salesman problem,” *Journal of the Operations Research Society of America*, vol. 2, no. 4, pp. 393–410, 1954.
- [156] N. R. Achuthan, L. Caccetta, and S. P. Hill, “An improved branch-and-cut algorithm for the capacitated vehicle routing problem,” *Transportation Science*, vol. 37, no. 2, pp. 153–169, 2003.
- [157] I. Karaoglan, F. Altiparmak, I. Kara, and B. Dengiz, “The location-routing problem with simultaneous pickup and delivery: Formulations and a heuristic approach,” *Omega*, vol. 40, no. 4, pp. 465–477, 2012.
- [158] R. R. Singh and D. R. Gaur, “Cumulative VRP: A simplified model of green vehicle routing,” in *Sustainable Logistics and Transportation: Optimization Models and Algorithms* (D. Cinar, K. Gakis, and P. M. Pardalos, eds.), pp. 39–55, Springer Cham, 2017.
- [159] I. Norstad, K. Fagerholt, and G. Laporte, “Tramp ship routing and scheduling with speed optimization,” *Transportation Research Part C: Emerging Technologies*, vol. 19, no. 5, pp. 853–865, 2011.
- [160] L. M. Hvattum, I. Norstad, K. Fagerholt, and G. Laporte, “Analysis of an exact algorithm for the vessel speed optimization problem,” *Networks*, vol. 62, no. 2, pp. 132–135, 2013.
- [161] R. Kramer, N. Maculan, A. Subramanian, and T. Vidal, “A speed and departure time optimization algorithm for the pollution-routing problem,” *European Journal of Operational Research*, vol. 247, no. 3, pp. 782–787, 2015.

- [162] H. R. Lourenço, O. C. Martin, and T. Stützle, “Iterated local search,” in *Handbook of metaheuristics* (F. W. Glover and G. A. Kochenberger, eds.), pp. 320–353, Springer, 2003.
- [163] H. Derbel, B. Jarboui, S. Hanafi, and H. Chabchoub, “Genetic algorithm with iterated local search for solving a location-routing problem,” *Expert Systems with Applications*, vol. 39, no. 3, pp. 2865–2871, 2012.
- [164] V.-P. Nguyen, C. Prins, and C. Prodhon, “A multi-start iterated local search with tabu list and path relinking for the two-echelon location-routing problem,” *Engineering Applications of Artificial Intelligence*, vol. 25, no. 1, pp. 56–71, 2012.
- [165] G. Clarke and J. W. Wright, “Scheduling of vehicles from a central depot to a number of delivery points,” *Operations Research*, vol. 12, no. 4, pp. 568–581, 1964.
- [166] G. A. Croes, “A method for solving traveling-salesman problems,” *Operations Research*, vol. 6, no. 6, pp. 791–812, 1958.
- [167] Analystcave, “Excel VBA calculate distance between two addresses or coordinates,” 2014. Available from: <http://analystcave.com/excel-calculate-distances-between-addresses/> [Accessed 20 April 2017].
- [168] O. Dukkanci, M. Peker, and B. Y. Kara, “Green hub location problem,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 125, pp. 116–139, 2019.
- [169] S. A. Alumur, B. Y. Kara, and O. E. Karasan, “Multimodal hub location and hub network design,” *Omega*, vol. 40, no. 6, pp. 927–939, 2012.
- [170] M. E. O’Kelly, “Activity levels at hub facilities in interacting networks,” *Geographical Analysis*, vol. 18, no. 4, pp. 343–356, 1986.
- [171] M. E. O’Kelly, “The location of interacting hub facilities,” *Transportation Science*, vol. 20, no. 2, pp. 92–106, 1986.

- [172] M. E. O’Kelly, “A quadratic integer program for the location of interacting hub facilities,” *European Journal of Operational Research*, vol. 32, no. 3, pp. 393–404, 1987.
- [173] J. F. Campbell, “Integer programming formulations of discrete hub location problems,” *European Journal of Operational Research*, vol. 72, no. 2, pp. 387–405, 1994.
- [174] S. Alumur and B. Y. Kara, “Network hub location problems: The state of the art,” *European journal of operational research*, vol. 190, no. 1, pp. 1–21, 2008.
- [175] R. Z. Farahani, M. Hekmatfar, A. B. Arabani, and E. Nikbakhsh, “Hub location problems: A review of models, classification, solution techniques, and applications,” *Computers & Industrial Engineering*, vol. 64, no. 4, pp. 1096–1109, 2013.
- [176] S. A. Alumur, H. Yaman, and B. Y. Kara, “Hierarchical multimodal hub location problem with time-definite deliveries,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 48, no. 6, pp. 1107–1120, 2012.
- [177] C.-C. Lin and S.-H. Chen, “The hierarchical network design problem for time-definite express common carriers,” *Transportation Research Part B: Methodological*, vol. 38, no. 3, pp. 271–283, 2004.
- [178] J. F. Campbell, “Hub location for time definite transportation,” *Computers & Operations Research*, vol. 36, no. 12, pp. 3107–3116, 2009.
- [179] H. Yaman, “The hierarchical hub median problem with single assignment,” *Transportation Research Part B: Methodological*, vol. 43, no. 6, pp. 643–658, 2009.
- [180] R. Ishfaq and C. R. Sox, “Hub location–allocation in intermodal logistic networks,” *European Journal of Operational Research*, vol. 210, no. 2, pp. 213–230, 2011.

- [181] O. Dukkanci and B. Y. Kara, "Routing and scheduling decisions in the hierarchical hub location problem," *Computers & Operations Research*, vol. 85, pp. 45–57, 2017.
- [182] H. W. Hamacher and T. Meyer, *Hub cover and hub center problems*. Department of Mathematics, University of Kaiserslautern, Gottlieb-Daimler-Strasse, 67663 Kaiserslautern, Germany, 2006. Technical Report. <https://kluedo.ub.uni-kl.de/frontdoor/deliver/index/docId/1748/file/Nr.98.pdf>.
- [183] A. T. Ernst, H. Jiang, M. Krishnamoorthy, and D. Baatar, "Reformulations and computational results for the uncapacitated single allocation hub covering problem," in *Data and Decision Sciences in Action. Lecture Notes in Management and Industrial Engineering* (R. Sarker, H. A. Abbass, S. Dunstall, P. Kilby, R. Davis, and L. Young, eds.), pp. 133–148, Springer Cham, 2018.
- [184] M. S. Lobo, L. Vandenberghe, S. Boyd, and H. Lebret, "Applications of second-order cone programming," *Linear Algebra and its Applications*, vol. 284, no. 1-3, pp. 193–228, 1998.
- [185] F. Alizadeh and D. Goldfarb, "Second-order cone programming," *Mathematical Programming*, vol. 95, no. 1, pp. 3–51, 2003.
- [186] O. Günlük and J. Linderoth, "Perspective reformulation and applications," in *Mixed Integer Nonlinear Programming* (J. Lee and S. Leyffer, eds.), pp. 61–89, New York: Springer, 2012.
- [187] J. E. Beasley, "Or-library: Hub location." <http://people.brunel.ac.uk/~mastjjb/jeb/orlib/phubinfo.html>, 2012. Accessed: 2018-08-17.
- [188] P. Z. Tan and B. Y. Kara, "A hub covering model for cargo delivery systems," *Networks: An International Journal*, vol. 49, no. 1, pp. 28–39, 2007.
- [189] S. A. Alumur, B. Y. Kara, and O. E. Karasan, "The design of single allocation incomplete hub networks," *Transportation Research Part B: Methodological*, vol. 43, no. 10, pp. 936–951, 2009.

- [190] O. Dukkanci, B. Y. Kara, and T. Bektaş, “The drone delivery problem,” 2019. January 10, 2019. Available at SSRN: <https://ssrn.com/abstract=3314556> [Accessed 15 January 2019].
- [191] M. Willett, “A London sushi chain delivers dinner by drone.” Business Insider, 2013. June 11, 2013. Available from: <http://www.businessinsider.com/yo-sushi-debuts-flying-trays-2013-6> [Accessed 21 July 2018].
- [192] D. Reid, “Domino’s delivers world’s first ever pizza by drone.” CNBC, 2016. November 16, 2016. Available from: <https://www.cnbc.com/2016/11/16/dominos-has-delivered-the-worlds-first-ever-pizza-by-drone-to-a-new-zealand-couple.html> [Accessed 21 July 2018].
- [193] S. Overly, “A drone carrying humans prepares to take flight in Dubai.” The Washington Post, 2017. February 15, 2017. Available from: https://www.washingtonpost.com/news/innovations/wp/2017/02/15/a-drone-carrying-human-passengers-prepares-to-take-flight-in-dubai/?noredirect=on&utm_term=.d3922a0d66d3 [Accessed 21 July 2018].
- [194] Balfour Beatty, “Flying into the future of bridge inspections,” 2017. May 12, 2017. Available from: <https://www.balfourbeatty.com/news/flying-into-the-future-of-bridge-inspections/> [Accessed 21 July 2018].
- [195] M. Manalo, “This budget airline is doing something really smart with drones — and big airlines should pay attention.” Business Insider, 2015. June 13, 2015. Available from: <http://www.businessinsider.com/easyjet-uk-uses-drones-airplane-inspection-2015-6> [Accessed 21 July 2018].
- [196] DHL, “Unmanned aerial vehicles in logistics,” 2014. Available from: http://www.dhl.com/content/dam/downloads/g0/about_us/logistics_insights/dhl_trend_report_uav.pdf [Accessed 13 July 2018].

- [197] DHL, “Successful trial integration of DHL parcelcopter into logistics chain,” 2016. September 5, 2016. Available from: http://www.dhl.com/en/press/releases/releases_2016/all/parcel_ecommerce/successful_trial_integration_dhl_parcelcopter_logistics_chain.html [Accessed 21 July 2018].
- [198] Amazon, “Amazon Prime Air,” 2016. Available from: <https://www.amazon.com/Amazon-Prime-Air/b?ie=UTF8&node=8037720011> [Accessed 15 June 2018].
- [199] UPS, “UPS tests residential delivery via drone launched from atop package car,” 2017. February 21, 2017. Available from: <https://pressroom.ups.com/pressroom/ContentDetailsViewer.page?ConceptType=PressReleases&id=1487687844847-162> [Accessed 20 June 2018].
- [200] E. Mack, “How delivery drones can help save the world.” Forbes, 2018. February 13, 2018. Available from: <https://www.forbes.com/sites/ericmack/2018/02/13/delivery-drones-amazon-energy-efficient-reduce-climate-change-pollution/#1ca420506a87> [Accessed 30 June 2018].
- [201] B. Farmer, “Drones to tackle traffic and deliver medical supplies in UK cities.” The Telegraph, 2017. November 27, 2017. Available from: <https://www.telegraph.co.uk/news/2017/11/27/drones-tackle-traffic-deliver-medical-supplies-uk-cities/> [Accessed 18 July 2018].
- [202] J. Desjardins, “Amazon and UPS are betting big on drone delivery.” Business Insider, 2018. March 11, 2018. Available from: <http://www.businessinsider.com/amazon-and-ups-are-betting-big-on-drone-delivery-2018-3> [Accessed 30 June 2018].
- [203] C. C. Murray and A. G. Chu, “The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery,” *Transportation Research Part C: Emerging Technologies*, vol. 54, pp. 86–109, 2015.

- [204] N. Agatz, P. Bouman, and M. Schmidt, “Optimization approaches for the traveling salesman problem with drone,” *Transportation Science*, vol. 52, no. 4, pp. 965–981, 2018.
- [205] P. Bouman, N. Agatz, and M. Schmidt, “Dynamic programming approaches for the traveling salesman problem with drone,” *Networks*, vol. 72, no. 4, pp. 528–542, 2018.
- [206] X. Wang, S. Poikonen, and B. Golden, “The vehicle routing problem with drones: Several worst-case results,” *Optimization Letters*, vol. 11, no. 4, pp. 679–697, 2017.
- [207] S. Poikonen, X. Wang, and B. Golden, “The vehicle routing problem with drones: Extended models and connections,” *Networks*, vol. 70, no. 1, pp. 34–43, 2017.
- [208] J. G. Carlsson and S. Song, “Coordinated logistics with a truck and a drone,” *Management Science*, vol. 64, no. 9, pp. 4052–4069, 2017.
- [209] E. E. Yurek and H. C. Ozmutlu, “A decomposition-based iterative optimization algorithm for traveling salesman problem with drone,” *Transportation Research Part C: Emerging Technologies*, vol. 91, pp. 249–262, 2018.
- [210] Q. M. Ha, Y. Deville, Q. D. Pham, and M. H. Hà, “On the min-cost traveling salesman problem with drone,” *Transportation Research Part C: Emerging Technologies*, vol. 86, pp. 597–621, 2018.
- [211] Z. Wang and J.-B. Sheu, “Vehicle routing problem with drones,” *Transportation Research Part B: Methodological*, vol. 122, pp. 350–364, 2019.
- [212] R. G. Mbiadou Saleu, L. Deroussi, D. Feillet, N. Grangeon, and A. Quilliot, “An iterative two-step heuristic for the parallel drone scheduling traveling salesman problem,” *Networks*, vol. 72, no. 4, pp. 459–474, 2018.
- [213] K. Dorling, J. Heinrichs, G. G. Messier, and S. Magierowski, “Vehicle routing problems for drone delivery,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 1, pp. 70–85, 2017.

- [214] B. N. Coelho, V. N. Coelho, I. M. Coelho, L. S. Ochi, D. Zuidema, M. S. Lima, A. R. da Costa, *et al.*, “A multi-objective green UAV routing problem,” *Computers & Operations Research*, vol. 88, pp. 306–315, 2017.
- [215] N. Boysen, D. Briskorn, S. Fedtke, and S. Schwerdfeger, “Drone delivery from trucks: Drone scheduling for given truck routes,” *Networks*, vol. 72, no. 4, pp. 506–527, 2018.
- [216] D. Kim, K. Lee, and I. Moon, “Stochastic facility location model for drones considering uncertain flight distance,” *Annals of Operations Research*, pp. 1–20, 2018.
- [217] D. Chauhan, A. Unnikrishnan, and M. Figliozzi, “Maximum coverage capacitated facility location problem with range constrained drones,” *Transportation Research Part C: Emerging Technologies*, vol. 99, pp. 1–18, 2019.
- [218] E. Yakıcı, “Solving location and routing problem for UAVs,” *Computers & Industrial Engineering*, vol. 102, pp. 294–301, 2016.
- [219] F. Guerriero, R. Surace, V. Loscri, and E. Natalizio, “A multi-objective approach for unmanned aerial vehicle routing problem with soft time windows constraints,” *Applied Mathematical Modelling*, vol. 38, no. 3, pp. 839–852, 2014.
- [220] A. Goodchild and J. Toy, “Delivery by drone: An evaluation of unmanned aerial vehicle technology in reducing CO₂ emissions in the delivery service industry,” *Transportation Research Part D: Transport and Environment*, vol. 61, pp. 58–67, 2018.
- [221] A. Otto, N. Agatz, J. Campbell, B. Golden, and E. Pesch, “Optimization approaches for civil applications of unmanned aerial vehicles UAVs or aerial drones: A survey,” *Networks*, vol. 72, no. 4, pp. 411–458, 2018.
- [222] R. Allain, “How do drones fly? physics, of course!.” *Wired*, 2017. May 19, 2017. Available from: <https://www.wired.com/2017/05/the-physics-of-drones/> [Accessed 23 July 2018].

- [223] J. K. Stolaroff, C. Samaras, E. R. O'Neill, A. Lubers, A. S. Mitchell, and D. Ceperley, "Energy use and life cycle greenhouse gas emissions of drones for commercial package delivery," *Nature Communications*, vol. 9, no. 1, p. 409, 2018.
- [224] M. A. Figliozzi, "Lifecycle modeling and assessment of unmanned aerial vehicles (drones) CO₂e emissions," *Transportation Research Part D: Transport and Environment*, vol. 57, pp. 251–261, 2017.
- [225] Y. Zeng and R. Zhang, "Energy-efficient UAV communication with trajectory optimization," *IEEE Transactions on Wireless Communications*, vol. 16, no. 6, pp. 3747–3760, 2017.
- [226] F. Kilci, B. Bozkaya, B. Y. Kara, and B. E. Oruc, "Kartal district of Istanbul," 2018. January 11, 2018. Available from: <http://dx.doi.org/10.17632/xhz8m74pp7.1#folder-fa3e580b-3b75-4960-88ec-f8daa9e5b5a6> [Accessed 26 June 2018].
- [227] AAF, "Fact sheet – small unmanned aircraft regulations (part 107)," 2016. June 21, 2016. Available from: https://www.faa.gov/news/fact_sheets/news_story.cfm?newsId=20516 [Accessed 11 July 2018].
- [228] A. Shapiro, D. Dentcheva, and A. Ruszczyński, *Lectures on stochastic programming: modeling and theory*. SIAM, 2009.
- [229] S. Ahmed, "A scenario decomposition algorithm for 0–1 stochastic programs," *Operations Research Letters*, vol. 41, no. 6, pp. 565–569, 2013.
- [230] AccuWeather, 2018. Available from: <https://www.accuweather.com/en/tr/kartal/318228/weather-forecast/318228> [Accessed 12 November 2018].

Appendix A

Green Location-Routing Problem

A.1 Speed Optimization Algorithm (SOA)

The decision variables to be optimized in the algorithm are as follows: the vehicle speed between node $i \in N$ and $i + 1 \in N$ is denoted by v_i . $\underline{e}_i$ and $\bar{e}_i$ represent the arrival and departure time from node $i \in N$.

```

initialize:  $s \leftarrow 0, e \leftarrow n, violation \leftarrow 0, p \leftarrow 0, k \leftarrow 1, \underline{e}_0 = \bar{e}_0 = l_0 = u_0 = 0, D = \sum_{i=s}^{e-1} d_i, S = \sum_{i=s}^e s_i$ 
1: for  $i = s + 1$  to  $e$  do
2:    $v_{i-1} \leftarrow D / (u_e + t_e - \max\{l_s, \underline{e}_s\} - S)$ 
3:   if  $k \neq 1$  then
4:     if  $\bar{e}_{i-1} + d_{i-1}/v_{i-1} < l_i$  and  $\bar{e}_i \geq l_i + s_i$  then
5:        $v_{i-1} \leftarrow d_{i-1} / (l_i - \bar{e}_{i-1})$ 
6:     else if  $\bar{e}_{i-1} + d_{i-1}/v_{i-1} < u_i$  and  $\bar{e}_i \geq u_i + s_i$  then
7:        $v_{i-1} \leftarrow d_{i-1} / (u_i - \bar{e}_{i-1})$ 
8:     end if
9:   end if
10:   $v_{i-1}^* \leftarrow \text{OptimalSpeed}$ 
11:  if  $v_{i-1} < v^l$  then
12:     $v_{i-1} \leftarrow v^l$ 
13:  else if  $v_{i-1} > v^u$  then
14:     $v_{i-1} \leftarrow v^u$ 
15:  end if
16:  if  $v_{i-1}^* > v_{i-1}$  then
17:     $v_{i-1} \leftarrow v_{i-1}^*$ 
18:  end if
19:  if  $k = 1$  then
20:     $\underline{e}_i = \bar{e}_{i-1} + d_{i-1}/v_{i-1}$ 
21:     $\bar{e}_i = \underline{e}_i + s_i$ 
22:  else if  $k \neq 1$  then
23:    if  $i \neq e$  then
24:       $\underline{e}_i = \bar{e}_{i-1} + d_{i-1}/v_{i-1}$ 
25:       $\bar{e}_i = \underline{e}_i + s_i$ 
26:    end if
27:  end if
28:   $g_i \leftarrow \max\{0, \underline{e}_i - u_i, l_i + s_i - \bar{e}_i\}$ 
29:  if  $g_i > violation$  then
30:     $violation \leftarrow g_i$ 
31:     $p \leftarrow i$ 
32:  end if
33: end for
34:  $k \leftarrow k + 1$ 
35: if  $violation > 0$  and  $\underline{e}_p > u_p$  then
36:    $\bar{e}_p \leftarrow u_p + s_p$ 
37:   Speed Optimization Algorithm( $s, p$ )
38:   Speed Optimization Algorithm( $p, e$ )
39: end if
40: if  $violation > 0$  and  $\bar{e}_p < l_p + s_p$  then
41:    $\bar{e}_p \leftarrow l_p + s_p$ 
42:   Speed Optimization Algorithm( $s, p$ )
43:   Speed Optimization Algorithm( $p, e$ )
44: end if

```

A.2 Parameter Values for CMEM

Notation	Description	Typical Values
e	Emission and fuel consumption cost (£/L)	1.4
w	Curb weight (kg)	6350
k	Engine friction factor (kJ/rev/L)	0.2
Υ	Engine speed (rev/s)	33
V	Engine displacement (L)	5
a	Acceleration (m/s ²)	0
g	Gravitational constant (m/s ²)	9.81
θ	Road Angle	0
C_r	Coefficient of rolling resistance	0.01
C_d	Coefficient of aerodynamic drag	0.7
ρ	Air density (kg/m ³)	1.2041
S	Frontal Surface Area (m ²)	3.912
n_{tf}	Vehicle drive train efficiency	0.4
η	Efficiency parameter for diesel engines	0.9
ξ	Fuel to air mass ratio	1
κ	Heating value of a typical diesel fuel (kJ/g)	44
ψ	Conversion factor of fuel (g/s) to (L/s)	737
P_{acc}	Engine power demand	0

A.3 Performance of the valid inequalities

	20,1,3,1		20,1,3,2		20,1,3,3		20,2,3,1		20,2,3,2		20,2,3,3		20,3,3,1		20,3,3,2		20,3,3,3		20,4,3,1		20,4,3,2		20,4,3,3		
Comb.	CPU	N.CPU	CPU	N.CPU	CPU	N.CPU	CPU	N.CPU	CPU	N.CPU	CPU	N.CPU	CPU	N.CPU	CPU	N.CPU	CPU	N.CPU	CPU	N.CPU	CPU	N.CPU	CPU	N.CPU	Av. N. CPU
Base	3483.90	1.00	6233.13	1.00	900.50	1.00	158.88	1.00	219.44	1.00	617.66	1.00	529.51	1.00	653.21	1.00	639.41	1.00	190.46	1.00	953.75	1.00	6581.21	1.00	1.00
1-1	7200.00	2.07	2275.56	0.57	1948.22	2.16	148.63	0.94	148.05	0.67	714.99	1.16	410.59	0.78	1038.59	1.59	745.07	1.17	788.38	4.14	4637.97	4.86	4473.36	0.68	1.71
1-2	1324.21	0.38	6274.56	1.01	890.35	0.99	103.69	0.65	292.39	1.33	310.64	0.50	476.95	0.90	892.33	1.37	823.77	1.29	182.92	0.96	5149.58	5.40	3739.19	0.57	1.28
2	5037.88	1.45	2048.76	0.33	1448.65	1.61	113.06	0.71	204.39	0.93	589.01	0.95	438.25	0.83	4874.25	7.46	3755.76	5.87	460.43	2.42	5309.04	5.57	7200.00	1.09	2.44
3	5556.02	1.59	1058.99	0.17	675.16	0.75	75.42	0.47	96.34	0.44	364.03	0.59	145.68	0.28	598.22	0.92	534.12	0.84	146.91	0.77	3437.06	3.60	4432.87	0.67	0.92
4	2452.66	0.70	6921.07	1.11	1812.97	2.01	288.08	1.81	490.54	2.24	1416.93	2.29	672.08	1.27	1532.30	2.35	1614.65	2.53	231.59	1.22	7200.00	7.55	5719.12	0.87	2.16
1-1-2	649.98	0.19	1346.65	0.22	1365.05	1.52	114.70	0.72	188.30	0.86	255.94	0.41	308.34	0.58	2884.72	4.42	914.06	1.43	1277.57	6.71	2892.55	3.03	3074.87	0.47	1.71
1-1-3	4313.98	1.24	1062.72	0.17	1203.24	1.34	73.55	0.46	215.01	0.98	196.90	0.32	420.47	0.79	795.37	1.22	812.68	1.27	118.39	0.62	780.73	0.82	1057.67	0.16	0.78
1-1-4	7200.00	2.07	2248.76	0.36	2310.59	2.57	218.22	1.37	253.28	1.15	576.12	0.93	683.57	1.29	1938.31	2.97	2117.82	3.31	244.14	1.28	5905.83	6.19	6176.75	0.94	2.04
1-2-2	1277.91	0.37	3091.40	0.50	831.54	0.92	101.11	0.64	160.09	0.73	421.55	0.68	355.25	0.67	5503.84	8.43	914.34	1.43	116.16	0.61	3889.35	4.08	4179.90	0.64	1.64
1-2-3	2864.73	0.82	746.82	0.12	904.23	1.00	67.51	0.42	114.01	0.52	147.81	0.24	100.60	0.19	657.89	1.01	642.50	1.00	151.82	0.80	849.33	0.89	2138.37	0.32	0.61
1-2-4	2624.10	0.75	7200.00	1.16	1403.27	1.56	157.05	0.99	286.42	1.35	434.63	0.70	712.14	1.34	1855.65	2.84	1705.02	2.67	225.44	1.18	6318.59	6.62	4877.18	0.74	1.83
2-3	3037.83	0.87	1268.50	0.20	807.22	0.90	98.65	0.62	98.24	0.45	192.62	0.31	335.38	0.63	934.32	1.43	5519.40	8.63	122.92	0.65	4688.20	4.92	3940.58	0.60	1.68
2-4	5675.14	1.63	1866.87	0.30	2290.42	2.54	216.32	1.36	269.70	1.23	926.11	1.50	641.49	1.21	2256.36	3.45	7200.00	11.26	233.27	1.22	7200.00	7.55	7200.00	1.09	2.86
3-4	4245.84	1.22	2245.85	0.36	1598.37	1.77	143.60	0.90	193.31	0.88	283.05	0.46	1033.87	1.95	1942.19	2.97	1585.92	2.48	228.02	1.20	5711.39	5.99	6453.51	0.98	1.76
1-1-2-3	3648.49	1.05	1138.23	0.18	692.01	0.77	65.14	0.41	78.21	0.36	220.88	0.36	154.47	0.29	769.89	1.18	760.86	1.19	115.09	0.60	686.94	0.72	1979.28	0.30	0.62
1-1-2-4	1571.87	0.45	3041.08	0.49	2401.91	2.67	221.09	1.39	235.59	1.07	485.53	0.79	563.95	1.07	1992.42	3.05	5046.06	7.89	615.66	3.23	1217.68	1.28	4149.09	0.63	2.00
1-1-3-4	2504.64	0.72	1868.04	0.30	1403.78	1.56	107.07	0.67	149.81	0.68	154.19	0.25	290.32	0.55	1297.45	1.99	1160.73	1.82	261.01	1.37	1875.35	1.97	1861.18	0.28	1.01
1-2-2-3	680.57	0.20	1262.73	0.20	906.13	1.01	61.90	0.39	80.55	0.37	80.55	0.13	92.59	0.17	3998.63	6.12	552.02	0.86	107.41	0.56	3869.96	4.06	3314.18	0.50	1.21
1-2-2-4	2594.95	0.74	6093.46	0.98	1558.58	1.73	218.15	1.37	294.14	1.34	379.93	0.62	405.38	0.77	7200.00	11.02	2249.01	3.52	152.83	0.80	5168.52	5.42	5362.01	0.81	2.43
1-2-3-4	1034.52	0.30	1718.78	0.28	1120.11	1.24	107.14	0.67	97.33	0.44	206.15	0.33	210.25	0.40	1833.63	2.81	1436.42	2.25	148.31	0.78	1098.12	1.15	3532.37	0.54	0.93
2-3-4	1647.79	0.47	1634.40	0.26	1939.98	2.15	132.87	0.84	140.27	0.64	422.97	0.68	213.83	0.40	1909.03	2.92	1682.95	2.63	163.84	0.86	5013.03	5.26	7200.00	1.09	1.52
1-1-2-3-4	4163.60	1.20	1311.91	0.21	2832.83	3.15	121.69	0.77	104.47	0.48	221.60	0.36	510.64	0.96	2582.24	3.95	1440.17	1.78	190.32	1.05	894.07	0.94	1030.88	0.16	1.25
1-2-2-3-4	4798.35	1.38	1604.25	0.26	1390.62	1.54	133.27	0.84	149.26	0.68	246.74	0.40	156.11	0.29	5112.90	7.83	5492.51	8.59	136.18	0.72	2802.33	2.94	2720.23	0.41	2.16

A.4 GLRP results for 10, 15 and 20-node instances

$ N $	I	m	p	Fuel Consumption					# of Vehicles	Average Speed (km/h)	Distance (km)	CPU (s)
				Total Cost (£)	Depot Cost (£)	Weight (L)	Speed (L)	Total (L)				
10	1	2	1	197.58	114.14	23.00	36.60	59.60	2	55.00	367550	4.59
10	1	2	2	303.55	232.10	19.42	31.62	51.03	2	55.00	317520	2.15
10	1	2	3	433.75	366.09	18.13	30.20	48.33	2	55.00	303250	7.02
10	2	2	1	265.07	146.78	31.32	53.18	84.50	2	59.09	528590	7.87
10	2	2	2	419.10	308.31	29.73	49.40	79.13	2	55.00	496161	11.83
10	2	2	3	578.19	471.84	29.10	46.86	75.96	2	55.00	470610	11.80
10	3	2	1	267.16	158.64	30.30	47.21	77.51	2	55.00	474160	10.61
10	3	2	2	410.68	318.20	25.64	40.42	66.05	2	55.00	405910	8.57
10	3	2	3	574.54	484.79	24.53	39.57	64.10	2	55.00	397400	3.70
10	4	2	1	244.29	141.64	27.67	45.65	73.32	2	55.00	458440	3.27
10	4	2	2	393.37	293.84	27.98	43.11	71.10	2	60.00	425974	9.82
10	4	2	3	547.25	448.82	27.69	42.61	70.30	2	60.56	420904	7.85
15	1	2	1	310.23	158.81	42.04	66.12	108.16	2	64.06	615352	1333.66
15	1	2	2	462.84	313.80	41.26	65.19	106.46	2	64.67	606032	70.87
15	1	2	3	616.77	478.11	38.89	60.15	99.04	2	57.50	599362	39.63
15	2	2	1	241.04	128.25	30.85	49.71	80.57	2	60.00	487951	28.19
15	2	2	2	366.93	260.82	29.18	46.61	75.79	2	56.67	466791	16.36
15	2	2	3	497.23	396.15	27.38	44.82	72.20	2	56.79	448811	29.37
15	3	2	1	360.18	194.25	46.40	72.13	118.53	2	61.88	712440	1450.34
15	3	2	2	544.97	384.44	44.82	69.85	114.67	2	61.33	690470	1517.44
15	3	2	3	746.14	625.25	33.58	52.77	86.35	2	55.00	529950	1238.87
15	4	2	1	267.04	128.16	37.09	62.11	99.20	2	63.75	581850	427.52
15	4	2	2	366.35	249.03	31.79	52.00	83.80	2	59.33	511640	17.40
15	4	2	3	489.17	374.26	31.00	51.08	82.08	2	59.64	502380	19.58
20	1	3	1	346.34	168.82	49.94	76.87	126.81	3	57.95	763601	2864.73
20	1	3	2	506.47	353.12	43.06	66.47	109.53	3	57.62	661061	746.82
20	1	3	3	673.49	522.26	42.38	65.65	108.03	3	58.00	652861	904.23
20	2	3	1	306.33	145.12	44.47	70.68	115.15	3	55.23	709652	67.51
20	2	3	2	446.75	291.04	42.74	68.48	111.22	3	55.24	687622	114.01
20	2	3	3	600.98	450.16	41.20	66.53	107.73	3	55.25	667991	147.81
20	3	3	1	206.05	101.97	29.18	45.17	74.34	3	58.41	449111	100.60
20	3	3	2	309.15	210.79	27.43	42.82	70.25	3	57.14	428331	657.89
20	3	3	3	412.67	316.58	26.95	41.69	68.64	3	57.75	416151	642.5
20	4	3	1	296.31	131.54	46.29	71.40	117.70	3	55.00	717110	151.82
20	4	3	2	417.54	269.71	41.19	64.41	105.59	3	55.00	646830	849.33
20	4	3	3	553.35	409.63	39.94	62.71	102.66	3	55.00	629820	2138.37

A.5 The impact of the location decision

$ N $	I	m	p	GLRP								GLRP with a known depot location							
				Fuel Consumption								Fuel Consumption							
				Total Cost (£)	Depot Cost (£)	Weight (L)	Speed (L)	Total (L)	Avg. Speed (km/h)	Distance (km)		Total Cost (£)	Depot Cost (£)	Weight (L)	Speed (L)	Total (L)	Avg. Speed (km/h)	Distance (km)	
11	1	2	1	208.31	117.28	25.62	39.40	65.02	55.00	395.70		237.96	143.38	26.56	41.00	67.56	58.75	409.33	
11	2	2	1	269.73	148.15	33.92	52.93	86.84	56.25	530.61		284.79	165.81	32.49	52.49	84.99	55.42	527.11	
11	3	2	1	254.96	141.09	32.04	49.29	81.33	57.08	493.05		254.96	141.09	32.04	49.29	81.33	57.08	493.05	
11	4	2	1	236.49	132.15	28.67	45.86	74.52	57.50	458.44		247.10	139.19	29.27	47.80	77.08	55.00	480.09	
11				242.37	134.67	30.06	46.87	76.93	56.46	469.45		256.20	147.37	30.09	47.65	77.74	56.56	477.40	
16	1	2	1	319.02	158.81	42.24	72.19	114.43	65.29	656.12		348.12	180.40	47.52	72.28	119.80	60.88	709.14	
16	2	2	1	238.02	121.03	31.91	51.65	83.56	57.35	516.88		238.02	121.03	31.91	51.65	83.56	57.35	516.88	
16	3	3	1	343.04	186.30	42.93	69.03	111.96	55.83	692.55		348.92	187.48	44.10	71.22	115.32	55.83	714.65	
16	4	3	1	262.31	126.14	37.53	59.73	97.26	55.00	599.85		375.62	205.85	46.94	74.32	121.27	55.00	746.44	
16				290.60	148.07	38.65	63.15	101.80	58.37	616.35		327.67	173.69	42.62	67.37	109.99	57.27	671.78	
21	1	3	1	344.47	164.71	50.22	78.18	128.40	55.43	784.46		347.07	167.16	50.56	77.95	128.51	55.00	782.85	
21	2	3	1	308.18	143.58	46.16	71.41	117.57	56.30	715.47		384.67	194.25	53.43	82.59	136.01	55.00	829.41	
21	3	3	1	205.33	98.81	29.88	46.21	76.09	58.26	459.55		208.71	102.78	29.56	46.10	75.66	58.26	458.50	
21	4	3	1	308.73	132.51	50.11	75.76	125.87	55.65	759.63		350.32	166.01	51.76	79.89	131.65	55.00	802.38	
21				291.68	134.90	44.09	67.89	111.98	56.41	679.78		322.69	157.55	46.32	71.63	117.96	55.82	718.28	
Average				274.88	139.21	37.60	59.30	96.91	57.08	588.53		302.19	159.53	39.68	62.22	101.89	56.55	622.49	

Appendix B

Green Hub Location Problem

B.1 α_c analysis on the CAB dataset

α_c		0.75			0.5			0.25		
T (h)	p	Av. Speed		Location	Av. Speed		Location	Av. Speed		Location
		Spoke (km/h)	Hub (km/h)		Spoke (km/h)	Hub (km/h)		Spoke (km/h)	Hub (km/h)	
60	1	59.26	-	11	59.26	-	11	59.26	-	11
60	2	58.42	85.58	5,8	60.45	90.00	8,20	60.46	90.00	8,20
60	3	59.57	66.80	8,21,25	60.55	78.03	12,18,21	60.21	78.36	12,18,21
60	4	58.55	60.82	1,4,8,18	60.17	67.63	4,12,16,18	59.78	68.90	4,12,16,17
60	5	57.96	58.04	1,2,4,8,13	60.13	64.18	1,4,7,12,18	59.05	64.55	4,7,12,17,24
60	6	57.92	56.54	1,4,6,8,13,18	60.61	61.71	1,4,6,7,12,18	59.21	62.58	4,6,7,12,17,24
60	7	58.20	57.45	1,2,4,6,8,13,21	57.61	56.71	1,4,6,7,8,18,21	59.44	60.52	4,6,7,12,17,21,24
60	8	58.24	56.16	1,4,5,6,8,13,18,21	57.75	56.33	1,4,5,6,8,13,18,21	60.46	60.18	4,6,7,8,12,17,21,24
54	1	62.11	-	11	62.11	-	11	62.11	-	11
54	2	61.50	90.00	5,8	61.50	90.00	5,8	61.07	90.00	5,8
54	3	59.60	70.70	8,13,20	59.80	75.44	8,18,21	59.47	76.64	8,18,21
54	4	60.77	63.98	1,4,8,18	60.29	64.76	1,4,8,18	63.09	72.57	14,18,21,22
54	5	60.04	60.06	1,2,4,8,13	58.87	60.29	4,8,13,18,24	62.93	67.53	4,7,14,18,22
54	6	60.19	58.53	1,4,6,8,13,18	59.19	58.99	4,6,8,13,18,24	59.61	62.99	4,7,8,12,17,24
54	7	60.56	57.60	1,2,4,6,8,13,21	59.78	58.04	1,4,6,8,13,18,21	60.11	61.14	4,6,7,8,12,17,24
54	8	60.63	56.90	1,2,4,5,6,8,13,21	59.80	57.18	1,4,5,6,8,13,18,21	60.29	59.55	4,6,7,8,12,17,21,24
48	1	Infeasible			Infeasible			Infeasible		
48	2	Infeasible			Infeasible			Infeasible		
48	3	62.49	77.35	8,13,20	62.20	78.39	8,13,20	63.17	78.40	2,8,13
48	4	62.69	67.61	4,8,13,18	61.94	68.44	4,8,16,18	61.99	68.43	4,8,16,17
48	5	63.33	63.38	1,2,4,8,13	62.10	63.30	4,8,13,18,24	62.47	70.67	4,8,12,16,18
48	6	63.79	61.06	1,4,6,8,13,18	62.09	61.68	4,6,8,13,18,24	63.12	65.80	4,7,8,12,18,24
48	7	64.09	59.27	1,4,6,8,13,18,21	63.07	59.31	1,4,6,7,8,18,21	63.59	64.21	4,6,7,8,12,17,24
48	8	64.25	58.08	1,4,5,6,8,13,18,21	63.45	58.49	1,4,5,6,8,13,18,21	63.62	62.48	4,6,7,8,12,17,21,24
Average		60.64	64.29		60.58	66.45		61.11	69.27	

B.2 α_c analysis on the TR dataset

α_c		0.75			0.5			0.25		
T (h)	p	Av. Speed		Location	Av. Speed		Location	Av. Speed		Location
		Spoke (km/h)	Hub (km/h)		Spoke (km/h)	Hub (km/h)		Spoke (km/h)	Hub (km/h)	
24	1	59.85	-	38	59.85	-	38	59.85	-	38
24	2	58.84	90.00	6,44	58.68	90.00	6,44	59.53	90.00	26,44
24	3	58.32	66.79	1,6,23	58.27	78.39	6,34,44	57.71	78.40	6,23,34
24	4	58.04	65.29	1,6,23,26	58.11	70.58	3,5,27,34	58.08	71.25	3,21,34,38
24	5	57.74	63.35	1,3,6,23,34	57.07	63.98	1,3,6,23,34	56.27	66.87	6,20,25,27,34
24	6	56.97	59.34	1,3,5,6,23,34	56.80	61.11	1,3,6,21,34,61	56.42	63.82	1,6,20,21,34,68
24	7	56.93	58.05	1,3,5,6,23,34,68	56.44	58.59	1,3,5,6,21,25,34	56.54	61.76	1,3,6,21,34,35,61
24	8	56.65	57.28	1,3,5,6,23,25,34,68	56.77	58.52	1,3,5,6,21,25,34,35	56.20	59.09	1,3,6,21,25,34,35,55
22	1	Infeasible			Infeasible			Infeasible		
22	2	61.36	90.00	6,44	61.35	90.00	6,44	60.83	90.00	6,23
22	3	60.59	66.79	1,6,23	60.80	78.39	6,34,44	61.16	78.40	6,16,23
22	4	60.60	66.56	1,6,23,26	59.50	72.21	3,6,34,44	59.09	72.59	6,20,23,34
22	5	58.92	65.70	1,3,6,23,34	58.74	65.82	1,3,6,23,34	57.46	72.67	6,20,25,27,34
22	6	58.32	61.61	1,3,5,6,23,34	57.97	64.06	1,3,6,21,34,61	57.84	65.44	1,6,20,21,34,68
22	7	58.30	59.63	1,3,5,6,23,34,68	57.21	60.50	1,3,5,6,21,25,34	57.92	64.14	1,3,6,21,34,35,61
22	8	57.78	58.84	1,3,5,6,23,25,34,68	57.67	60.31	1,3,5,6,21,25,34,35	56.91	61.37	1,3,6,21,25,34,35,55
20	1	Infeasible			Infeasible			Infeasible		
20	2	Infeasible			Infeasible			Infeasible		
20	3	Infeasible			Infeasible			Infeasible		
20	4	Infeasible			Infeasible			Infeasible		
20	5	61.61	73.72	21,25,26,34,68	61.40	74.76	21,25,26,34,68	61.57	74.76	21,25,26,34,68
20	6	61.51	70.93	6,21,25,26,34,68	61.38	71.76	20,21,26,34,61,68	61.51	71.52	16,20,21,34,61,68
20	7	60.60	68.06	1,3,6,16,21,34,61	59.89	67.65	1,3,6,16,21,34,61	59.52	68.42	1,6,16,20,21,34,68
20	8	60.02	63.37	1,3,5,6,16,21,25,34	58.99	62.95	1,3,5,6,16,21,25,34	58.24	64.16	1,6,16,20,21,25,34,55
Average		59.10	66.96		58.78	69.42		58.56	70.81	

B.3 α_t analysis on the CAB dataset

α_t		0.8				0.6				0.4			
T	p	Av. Speed		Location	Emission (L)	Av. Speed		Location	Emission (L)	Av. Speed		Location	Emission (L)
(h)		Spoke (km/h)	Hub (km/h)			Spoke (km/h)	Hub (km/h)			Spoke (km/h)	Hub (km/h)		
60	1	30.66	59.26	-	11	30.66	59.26	-	11	30.66	59.25	-	11
60	2	22.17	58.42	85.58	5,8	22.07	59.06	88.87	5,12	21.90	57.76	71.77	5,12
60	3	20.12	59.57	66.80	8,21,25	19.98	59.57	69.97	12,21,25	19.75	57.81	60.78	12,21,25
60	4	19.18	58.55	60.82	1,4,8,18	19.11	56.98	57.63	1,2,4,8	19.07	55.78	55.75	1,4,8,18
60	5	19.17	57.96	58.04	1,2,4,8,13	19.11	56.49	56.26	1,2,4,8,13	19.09	55.32	55.26	1,2,4,8,13
60	6	19.51	57.92	56.54	1,4,6,8,13,18	19.45	56.40	55.82	1,4,6,8,13,18	19.44	55.33	55.24	1,4,6,8,13,18
60	7	20.25	58.20	57.45	1,2,4,6,8,13,21	20.17	56.47	55.64	1,4,6,8,13,18,21	20.17	55.33	55.22	1,2,4,6,8,13,21
60	8	21.20	58.24	56.16	1,4,5,6,8,13,18,21	21.14	56.72	55.57	1,2,4,5,6,8,13,21	21.22	55.34	55.22	1,2,4,5,8,9,13,21
54	1	30.88	62.11	-	11	30.88	62.11	-	11	30.88	62.11	-	11
54	2	22.33	61.50	90.00	5,8	22.21	59.41	85.83	5,8	22.03	59.26	82.25	5,12
54	3	20.38	59.60	70.70	8,13,20	20.14	59.92	66.77	8,21,25	19.89	59.31	65.16	12,21,25
54	4	19.33	60.77	63.98	1,4,8,18	19.19	58.89	59.97	1,4,8,18	19.11	57.01	56.89	1,4,8,18
54	5	19.29	60.04	60.06	1,2,4,8,13	19.17	58.12	57.57	1,2,4,8,13	19.11	56.27	55.79	1,2,4,8,13
54	6	19.62	60.19	58.53	1,4,6,8,13,18	19.52	58.36	56.87	1,4,6,8,18,21	19.46	56.23	55.56	1,4,6,8,13,18
54	7	20.37	60.56	57.60	1,2,4,6,8,13,21	20.22	58.19	56.24	1,4,6,8,13,18,21	20.19	56.39	55.48	1,2,4,6,8,13,21
54	8	21.31	60.63	56.90	1,2,4,5,6,8,13,21	21.19	58.58	56.03	1,2,4,5,6,8,13,21	21.14	56.35	55.39	1,4,5,6,8,13,18,21
48	1	Infeasible				Infeasible				Infeasible			
48	2	Infeasible				22.43	63.12	90.00	5,8	22.27	60.71	84.03	5,8
48	3	20.59	62.49	77.35	8,13,20	20.43	60.75	70.42	8,13,20	20.19	60.66	65.37	8,21,25
48	4	19.59	62.69	67.61	4,8,13,18	19.35	61.63	63.19	1,4,8,18	19.19	59.11	58.63	1,4,8,18
48	5	19.51	63.33	63.38	1,2,4,8,13	19.30	60.72	59.66	1,2,4,8,13	19.16	58.15	56.90	1,2,4,8,13
48	6	19.84	63.79	61.06	1,4,6,8,13,18	19.65	60.64	58.07	1,4,6,8,13,18	19.53	58.54	56.44	1,4,6,8,18,21
48	7	20.55	64.09	59.27	1,4,6,8,13,18,21	20.34	60.94	57.24	1,4,6,8,13,18,21	20.21	58.12	55.91	1,4,6,8,13,18,21
48	8	21.52	64.25	58.08	1,4,5,6,8,13,18,21	21.40	61.38	56.75	1,2,4,5,8,9,13,21	21.19	58.30	55.74	1,4,5,6,8,13,18,21
Average		21.24	60.64	64.29		21.12	59.12	62.22		21.03	57.63	59.24	

B.4 α_t analysis on the TR dataset

α_t		0.8				0.6				0.4			
T	p	Av. Speed			Location	Av. Speed			Location	Av. Speed			Location
(h)		Emission (L)	Spoke (km/h)	Hub (km/h)		Emission (L)	Spoke (km/h)	Hub (km/h)		Emission (L)	Spoke (km/h)	Hub (km/h)	
24	1	79.31	59.85	-	38	79.31	59.85	-	38	79.31	59.85	-	38
24	2	64.87	58.84	90.00	6,44	64.78	57.56	90.00	6,44	64.73	56.77	81.78	6,44
24	3	61.26	58.32	66.79	1,6,23	61.18	56.83	66.79	1,6,23	61.14	56.25	61.44	1,6,23
24	4	57.95	58.04	65.29	1,6,23,26	57.87	56.81	62.17	1,6,23,26	57.81	56.01	57.95	1,6,23,26
24	5	54.59	57.74	63.35	1,3,6,23,34	54.47	56.54	59.10	1,3,6,23,34	54.43	55.66	56.14	1,3,6,23,34
24	6	52.82	56.97	59.34	1,3,5,6,23,34	52.75	56.10	56.98	1,3,5,6,23,34	52.72	55.39	55.46	1,3,5,6,23,34
24	7	52.26	56.93	58.05	1,3,5,6,23,34,68	52.19	56.10	56.46	1,3,5,6,23,34,68	52.16	55.39	55.38	1,3,5,6,23,34,68
24	8	51.98	56.65	57.28	1,3,5,6,23,25,34,68	51.91	56.19	56.23	1,3,5,6,16,23,34,68	51.88	55.31	55.28	1,3,5,6,16,23,34,68
22	1	Infeasible				Infeasible				Infeasible			
22	2	65.18	61.36	90.00	6,44	64.92	59.46	90.00	6,44	64.81	57.93	90.00	6,44
22	3	61.44	60.59	66.79	1,6,23	61.28	58.67	66.79	1,6,23	61.19	57.19	65.52	1,6,23
22	4	58.12	60.60	66.56	1,6,23,26	57.97	57.94	65.01	1,6,23,26	57.86	56.85	60.41	1,6,23,26
22	5	54.68	58.92	65.70	1,3,6,23,34	54.54	57.50	61.48	1,3,6,23,34	54.46	56.32	57.48	1,3,6,23,34
22	6	52.91	58.32	61.61	1,3,5,6,23,34	52.80	56.91	58.43	1,3,5,6,23,34	52.74	55.88	56.16	1,3,5,6,23,34
22	7	52.35	58.30	59.63	1,3,5,6,23,34,68	52.24	56.88	57.43	1,3,5,6,23,34,68	52.17	55.88	55.88	1,3,5,6,23,34,68
22	8	52.06	57.78	58.84	1,3,5,6,23,25,34,68	51.96	56.37	56.52	1,3,5,6,23,25,34,68	51.89	55.81	55.64	1,3,5,6,16,23,34,68
20	1	Infeasible				Infeasible				Infeasible			
20	2	Infeasible				65.57	61.78	90.00	6,23	64.97	60.14	90.00	6,44
20	3	Infeasible				61.48	61.10	66.79	1,6,23	61.31	59.03	66.79	1,6,23
20	4	Infeasible				58.11	60.44	66.26	1,6,23,26	57.94	58.07	63.53	1,6,23,26
20	5	60.06	61.61	73.72	21,25,26,34,68	54.68	58.95	64.23	1,3,6,23,34	54.52	57.42	59.58	1,3,6,23,34
20	6	57.33	61.51	70.93	6,21,25,26,34,68	52.89	58.30	60.73	1,3,5,6,23,34	52.77	56.79	57.37	1,3,5,6,23,34
20	7	53.45	60.60	68.06	1,3,6,16,21,34,61	52.33	58.21	58.98	1,3,5,6,23,34,68	52.21	56.76	56.72	1,3,5,6,23,34,68
20	8	52.62	60.02	63.37	1,3,5,6,16,21,25,34	52.02	57.46	57.74	1,3,5,6,23,25,34,68	51.93	56.81	56.36	1,3,5,6,16,23,34,68
Average		57.65	59.10	66.96		56.95	57.51	63.62		56.88	56.54	60.81	

B.5 GHLP and two-stage p -HMP comparison on the CAB dataset

T (h)	p	two-stage p -HMP		GHLP		Improvement (%)
		Emission (L)	Location	Emission (L)	Location	
60	1	30.66	11	30.66	11	0.00
60	2	22.61	8,20	22.17	5,8	1.99
60	3	20.42	2,4,8	20.12	8,21,25	1.52
60	4	19.88	1,4,12,18	19.18	1,4,8,18	3.62
60	5	19.80	1,4,7,12,18	19.17	1,2,4,8,13	3.28
60	6	20.73	1,4,6,7,12,17	19.51	1,4,6,8,13,18	6.26
60	7	22.16	1,4,6,7,8,12,17	20.25	1,2,4,6,8,13,21	9.39
60	8	24.08	1,4,6,7,8,12,17,25	21.20	1,4,5,6,8,13,18,21	13.56
54	1	30.88	11	30.88	11	0.00
54	2	22.33	5,8	22.33	5,8	0.00
54	3	20.52	5,8,18	20.38	8,13,20	0.66
54	4	19.32	1,4,8,18	19.33	1,4,8,18	0.00
54	5	20.50	1,4,8,12,18	19.29	1,2,4,8,13	6.27
54	6	20.97	1,4,7,8,12,18	19.62	1,4,6,8,13,18	6.84
54	7	22.34	1,4,6,7,8,12,17	20.37	1,2,4,6,8,13,21	9.69
54	8	24.28	1,4,6,7,8,12,17,25	21.31	1,2,4,5,6,8,13,21	13.93
48	1	Infeasible		Infeasible		-
48	2	Infeasible		Infeasible		-
48	3	20.59	8,13,20	20.59	8,13,20	0.00
48	4	19.91	1,4,8,18	19.59	4,8,13,18	1.63
48	5	22.01	1,4,12,18,23	19.51	1,2,4,8,13	12.83
48	6	21.29	1,4,7,8,12,18	19.84	1,4,6,8,13,18	7.31
48	7	22.70	1,4,6,7,8,12,17	20.55	1,4,6,8,13,18,21	10.45
48	8	24.68	1,4,6,7,8,12,17,25	21.52	1,4,5,6,8,13,18,21	14.70
Average		22.39		21.24		5.63

B.6 GHLP and two-stage p -HMP comparison on the TR dataset

T (h)	p	two-stage p -HMP		GHLP		Improvement (%)
		Emission (L)	Location	Emission (L)	Location	
24	1	79.31	38	79.31	38	0.00
24	2	65.88	6,38	64.87	6,44	1.56
24	3	62.29	3,34,38	61.26	1,6,23	1.68
24	4	58.90	3,6,34,38	57.95	1,6,23,26	1.63
24	5	54.70	1,3,6,23,34	54.59	1,3,6,23,34	0.21
24	6	52.87	1,3,5,6,23,34	52.82	1,3,5,6,23,34	0.09
24	7	52.51	1,3,5,6,16,23,34	52.26	1,3,5,6,23,34,68	0.48
24	8	52.33	1,3,5,6,16,23,34,35	51.98	1,3,5,6,23,25,34,68	0.66
22	1	Infeasible		Infeasible		-
22	2	65.18	6,44	65.18	6,44	0.00
22	3	61.47	1,6,23	61.44	1,6,23	0.05
22	4	58.17	1,6,23,26	58.12	1,6,23,26	0.08
22	5	54.78	1,3,6,23,34	54.68	1,3,6,23,34	0.18
22	6	52.97	1,3,5,6,23,34	52.91	1,3,5,6,23,34	0.10
22	7	52.62	1,3,5,6,16,23,34	52.35	1,3,5,6,23,34,68	0.52
22	8	52.45	1,3,5,6,16,23,34,35	52.06	1,3,5,6,23,25,34,68	0.75
20	1	Infeasible		Infeasible		-
20	2	Infeasible		Infeasible		-
20	3	Infeasible		Infeasible		-
20	4	Infeasible		Infeasible		-
20	5	60.10	21,25,26,34,68	60.06	21,25,26,34,68	0.07
20	6	57.40	6,21,25,26,34,68	57.33	6,21,25,26,34,68	0.11
20	7	53.51	1,3,6,16,21,34,61	53.45	1,3,6,16,21,34,61	0.12
20	8	52.75	1,3,5,6,16,21,25,34	52.62	1,3,5,6,16,21,25,34	0.25
Average		57.91		57.65		0.45

Appendix C

The Drone Delivery Problem

C.1 Results for instances with 10, 15 and 20 customers

$ C $	$ P $	p	Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)	Sol. Time (s)
10	2	1	480.62	8644.19	0	50733.02	16.47	0.68
10	2	2	330.98	5559.12	20599	37861.34	18.47	0.91
10	2	3	253.57	4166.86	20599	30729.23	20.20	0.51
10	2	1	571.45	10277.83	0	56814.96	15.46	0.51
10	2	2	344.61	5884.93	16378	47454.61	18.37	0.48
10	2	3	329.91	5620.57	16378	45924.91	18.89	0.52
10	2	1	584.98	10521.25	0	57422.87	15.24	0.49
10	2	2	350.45	5998.57	15926	41242.02	18.04	0.53
10	2	3	324.91	5539.27	15926	38827.77	18.52	0.99
10	2	1	651.14	11711.23	0	60826.46	15.01	0.53
10	2	2	590.48	10479.86	7340	55895.20	15.86	0.50
10	2	3	590.93	10420.28	10881	55598.21	15.92	0.53
10	2	1	566.29	10185.06	0	56325.34	15.48	0.55
10	2	2	461.29	8169.25	6658	48171.84	17.15	0.81
10	2	3	442.56	7565.81	20599	46486.21	17.31	0.68
15	3	1	753.02	13543.56	0	80689.83	15.47	0.81
15	3	2	650.37	11570.01	6658	71738.16	16.82	1.47
15	3	3	654.13	11569.94	10199	71738.16	16.82	1.49
15	3	1	794.24	14284.85	0	82480.47	15.41	0.85
15	3	2	533.54	9282.89	16378	61629.21	17.99	1.85
15	3	3	499.44	8669.65	16378	58536.96	18.42	1.56
15	3	1	639.16	11495.67	0	70167.92	17.00	0.89
15	3	2	470.06	8187.85	13941	56925.55	18.47	0.89
15	3	3	425.47	7309.47	17934	52291.03	19.15	1.90
15	3	1	916.21	16478.58	0	89291.26	14.85	0.91
15	3	2	723.60	12680.14	17482	76532.67	15.99	1.57
15	3	3	622.83	10838.89	18987	68384.33	17.10	0.86
15	3	1	814.49	14649.12	0	80510.62	16.16	0.94
15	3	2	734.91	13090.57	6658	73722.10	17.22	1.66
15	3	3	691.81	12225.89	11333	70336.61	17.40	1.65
20	4	1	986.73	17746.87	0	102328.81	16.37	1.86
20	4	2	782.63	13809.57	13941	87410.21	17.57	3.84
20	4	3	652.52	11232.70	26327	75370.77	18.42	3.87
20	4	1	1141.89	20537.57	0	112637.68	15.42	1.62
20	4	2	595.71	10401.16	16378	73629.03	18.81	2.36
20	4	3	569.86	9936.19	16378	71391.17	19.00	2.17
20	4	1	983.86	17695.38	0	104909.90	15.81	1.62
20	4	2	705.89	12382.68	16378	85299.70	17.49	3.06
20	4	3	511.91	8733.36	24771	66212.61	19.56	1.93
20	4	1	1186.66	21342.82	0	114310.47	15.43	1.53
20	4	2	552.46	9572.18	19043	71892.68	19.15	3.22
20	4	3	498.75	8606.31	19043	66065.64	19.87	3.15
20	4	1	861.59	15496.20	0	94818.14	16.93	1.84
20	4	2	697.99	12413.36	7340	80415.42	18.34	3.34
20	4	3	538.94	9286.32	21281	67584.16	19.42	2.36

C.2 Results for instances with 25 and 30 customers

$ C $	$ P $	p	Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)	Sol. Time (s)
25	5	1	1455.79	26183.23	0	145024.97	15.02	2.76
25	5	2	840.45	14751.93	19043	102848.28	17.88	2.55
25	5	3	738.87	12828.50	24089	94117.84	18.67	4.70
25	5	1	1246.43	22417.84	0	132882.81	15.65	2.67
25	5	2	932.64	16367.22	21281	105561.24	17.72	4.39
25	5	3	807.19	14014.50	26327	95293.98	18.62	4.05
25	5	1	1197.36	21535.19	0	128445.18	16.04	2.43
25	5	2	737.08	12892.78	19043	92305.19	18.95	4.70
25	5	3	614.52	10592.02	24089	82123.71	19.80	4.06
25	5	1	1447.67	26037.24	0	142916.63	15.26	2.07
25	5	2	790.35	13850.80	19043	97506.37	18.37	3.33
25	5	3	673.17	11662.56	23266	86768.35	19.11	3.43
25	5	1	1284.97	23111.00	0	130785.16	16.21	2.26
25	5	2	765.97	13412.36	19043	94936.02	18.69	3.24
25	5	3	661.29	11433.20	24089	85007.41	19.67	5.15
30	6	1	1690.90	30411.96	0	168317.68	15.48	3.43
30	6	2	991.41	17517.93	16378	120154.05	18.12	6.91
30	6	3	849.12	14811.36	24089	108023.18	19.13	3.51
30	6	1	1660.76	29869.84	0	165482.58	15.71	3.29
30	6	2	976.34	17196.05	19043	120200.66	18.10	6.84
30	6	3	863.73	15170.70	19043	109369.95	18.97	7.23
30	6	1	1640.75	29509.81	0	163824.09	15.81	3.18
30	6	2	1036.80	18334.34	16378	125496.39	17.71	6.47
30	6	3	798.30	13884.31	24771	104765.82	19.20	3.21
30	6	1	1498.31	26947.99	0	158189.49	15.81	4.33
30	6	2	982.11	17299.77	19043	119546.81	18.26	3.36
30	6	3	855.79	14931.44	24089	109094.52	18.98	6.27
30	6	1	1779.30	32001.78	0	174611.22	15.07	3.46
30	6	2	914.48	16070.44	19725	110772.18	18.83	3.39
30	6	3	768.90	13355.47	24771	100724.59	19.41	6.16

C.3 Results with current and future battery over instances with 10, 15 and 20 customers

$ C $	$ P $	p	Current Battery					Future Battery				
			Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)	Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)
10	2	1	480.62	8644.19	0	50733.02	16.47	350.50	6303.88	0	50733.02	19.86
10	2	2	330.98	5559.12	20599	37861.34	18.47	264.15	4357.03	20599	37861.34	21.67
10	2	3	253.57	4166.86	20599	30729.23	20.20	213.15	3439.80	20599	30729.23	22.58
10	2	1	571.45	10277.83	0	56814.96	15.46	407.87	7335.85	0	56814.96	19.25
10	2	2	344.61	5884.93	16378	47454.61	18.37	275.49	4718.03	12385	39904.77	21.80
10	2	3	329.91	5620.57	16378	45924.91	18.89	266.67	4483.11	16378	45924.91	22.00
10	2	1	584.98	10521.25	0	57422.87	15.24	414.77	7459.90	0	57422.87	18.97
10	2	2	350.45	5998.57	15926	41242.02	18.04	280.41	4738.80	15926	41242.02	21.56
10	2	3	324.91	5539.27	15926	38827.77	18.52	262.74	4421.02	15926	38827.77	21.83
10	2	1	651.14	11711.23	0	60826.46	15.01	455.69	8195.87	0	60826.46	18.68
10	2	2	590.48	10479.86	7340	55895.20	15.86	422.19	7452.94	7340	55895.20	19.57
10	2	3	590.93	10420.28	10881	55598.21	15.92	423.97	7417.32	10881	55598.21	19.66
10	2	1	566.29	10185.06	0	56325.34	15.48	403.48	7256.82	0	56325.34	19.18
10	2	2	461.29	8169.25	6658	48171.84	17.15	340.79	6001.98	6658	48171.84	20.27
10	2	3	442.56	7565.81	20599	46486.21	17.31	335.48	5639.94	20599	46486.21	20.48
15	3	1	753.02	13543.56	0	80689.83	15.47	548.95	9873.25	0	80689.83	19.50
15	3	2	650.37	11570.01	6658	71738.16	16.82	487.69	8644.10	6658	71738.16	20.48
15	3	3	654.13	11569.94	10199	71738.16	16.82	491.44	8643.87	10199	71738.16	20.48
15	3	1	794.24	14284.85	0	82480.47	15.41	573.61	10316.66	0	82480.47	19.36
15	3	2	533.54	9282.89	16378	61629.21	17.99	418.73	7218.01	16378	61629.21	21.53
15	3	3	499.44	8669.65	16378	58536.96	18.42	395.50	6800.26	16378	58536.96	21.73
15	3	1	639.16	11495.67	0	70167.92	17.00	477.38	8585.94	0	70167.92	20.79
15	3	2	470.06	8187.85	13941	56925.55	18.47	376.54	6505.76	13941	56925.55	21.96
15	3	3	425.47	7309.47	17934	52291.03	19.15	348.17	5919.24	17934	52291.03	22.40
15	3	1	916.21	16478.58	0	89291.26	14.85	646.87	11634.33	0	89291.26	18.71
15	3	2	723.60	12680.14	17482	76532.67	15.99	537.09	9325.58	17482	76532.67	19.94
15	3	3	622.83	10838.89	18987	68384.33	17.10	473.08	8145.68	18987	68384.33	20.68
15	3	1	814.49	14649.12	0	80510.62	16.16	583.76	10499.34	0	80510.62	19.71
15	3	2	734.91	13090.57	6658	73722.10	17.22	535.70	9507.57	6658	73722.10	20.26
15	3	3	691.81	12225.89	11333	70336.61	17.40	509.74	8951.30	11333	70336.61	20.60
20	4	1	986.73	17746.87	0	102328.81	16.37	717.66	12907.58	0	102328.81	19.98
20	4	2	782.63	13809.57	13941	87410.21	17.57	595.59	10445.54	13941	87410.21	20.98
20	4	3	652.52	11232.70	26327	75370.77	18.42	520.67	8970.75	20599	77254.21	21.87
20	4	1	1141.89	20537.57	0	112637.68	15.42	815.43	14665.92	0	112637.68	19.44
20	4	2	595.71	10401.16	16378	73629.03	18.81	485.11	8411.96	16378	73629.03	22.41
20	4	3	569.86	9936.19	16378	71391.17	19.00	467.83	8101.10	16378	71391.17	22.55
20	4	1	983.86	17695.38	0	104909.90	15.81	717.94	12912.59	0	104909.90	19.71
20	4	2	705.89	12382.68	16378	85299.70	17.49	560.16	9761.62	16378	85299.70	21.57
20	4	3	511.91	8733.36	24771	66212.61	19.56	434.59	7342.79	24771	66212.61	22.83
20	4	1	1186.66	21342.82	0	114310.47	15.43	839.54	15099.69	0	114310.47	19.17
20	4	2	552.46	9572.18	19043	71892.68	19.15	464.33	7987.22	19043	71892.68	22.53
20	4	3	498.75	8606.31	19043	66065.64	19.87	426.34	7303.91	19043	66065.64	22.81
20	4	1	861.59	15496.20	0	94818.14	16.93	642.50	11555.81	0	94818.14	20.63
20	4	2	697.99	12413.36	7340	80415.42	18.34	539.86	9569.42	7340	80415.42	21.59
20	4	3	538.94	9286.32	21281	67584.16	19.42	444.82	7593.52	21281	67584.16	22.44

C.4 Results with current and future battery over instances with 25 and 30 customers

$ C $	$ P $	p	Current Battery					Future Battery				
			Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)	Tot. Cost (€)	En. Cons. (kJ)	Tr. Dist. (m)	Dr. Dist. (m)	Av. Spe. (m/s)
25	5	1	1455.79	26183.23	0	145024.97	15.02	1038.61	18680.00	0	145024.97	19.11
25	5	2	840.45	14751.93	19043	102848.28	17.88	673.69	11752.70	19043	102848.28	21.90
25	5	3	738.87	12828.50	24089	94117.84	18.67	611.91	10545.08	24089	94117.84	22.42
25	5	1	1246.43	22417.84	0	132882.81	15.65	911.48	16393.49	0	132882.81	19.79
25	5	2	932.64	16367.22	21281	105561.24	17.72	719.26	12529.44	21281	105561.24	21.34
25	5	3	807.19	14014.50	26327	95293.98	18.62	641.91	11070.58	24822	95558.18	21.90
25	5	1	1197.36	21535.19	0	128445.18	16.04	879.02	15809.64	0	128445.18	20.00
25	5	2	737.08	12892.78	19043	92305.19	18.95	602.25	10467.67	19043	92305.19	22.25
25	5	3	614.52	10592.02	24089	82123.71	19.80	528.70	9048.41	24089	82123.71	22.98
25	5	1	1447.67	26037.24	0	142916.63	15.26	1032.16	18563.98	0	142916.63	19.28
25	5	2	790.35	13850.80	19043	97506.37	18.37	636.73	11087.97	19043	97506.37	22.02
25	5	3	673.17	11662.56	23266	86768.35	19.11	561.55	9655.05	23266	86768.35	22.59
25	5	1	1284.97	23111.00	0	130785.16	16.21	929.90	16724.85	0	130785.16	19.95
25	5	2	765.97	13412.36	19043	94936.02	18.69	620.50	10795.90	19043	94936.02	22.12
25	5	3	661.29	11433.20	24089	85007.41	19.67	555.89	9633.86	19043	85354.41	22.57
30	6	1	1690.90	30411.96	0	168317.68	15.48	1209.68	21756.91	0	168317.68	19.41
30	6	2	991.41	17517.93	16378	120154.05	18.12	788.14	13862.08	16378	120154.05	21.87
30	6	3	849.12	14811.36	24089	108023.18	19.13	702.89	12181.43	24089	108023.18	22.50
30	6	1	1660.76	29869.84	0	165482.58	15.71	1188.69	21379.40	0	165482.58	19.46
30	6	2	976.34	17196.05	19043	120200.66	18.10	781.51	13691.86	19043	120200.66	21.86
30	6	3	863.73	15170.70	19043	109369.95	18.97	706.39	12340.79	19043	109369.95	22.32
30	6	1	1640.75	29509.81	0	163824.09	15.81	1176.76	21164.78	0	163824.09	19.59
30	6	2	1036.80	18334.34	16378	125496.39	17.71	821.40	14460.17	16378	125496.39	21.76
30	6	3	798.30	13884.31	24771	104765.82	19.20	671.46	11603.07	24771	104765.82	22.70
30	6	1	1498.31	26947.99	0	158189.49	15.81	1092.93	19656.98	0	158189.49	19.83
30	6	2	982.11	17299.77	19043	119546.81	18.26	783.76	13732.39	19043	119546.81	21.89
30	6	3	855.79	14931.44	24089	109094.52	18.98	707.92	12271.74	24089	109094.52	22.52
30	6	1	1779.30	32001.78	0	174611.22	15.07	1264.51	22743.05	0	174611.22	19.10
30	6	2	914.48	16070.44	19725	110772.18	18.83	733.87	12821.93	19725	110772.18	22.24
30	6	3	768.90	13355.47	24771	100724.59	19.41	647.07	11164.33	24771	100724.59	22.75