Contributions to rich vehicle routing problems

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Abstract

This thesis addresses rich routing problems within a logistics context. The first and major part of the thesis introduces a new location-routing problem, and discusses both modeling and solution approaches. The second part addresses the use of a vehicle routing problem in evaluating different supporting policies for electric vehicles.

Location-routing problems have become one of the most studied logistics problems during the past decade. Recent surveys on location-routing problems have addressed modeling and algorithmic issues as well as real-life applications, which include for example city logistics, postal and parcel delivery, and grocery distribution. In the first part of the thesis, motivated by an actual problem of a national postal service company, we introduce and define a new two-echelon location-routing problem (2E-LRP). The activities in the two echelons are organized into two waves: a delivery wave where products are sent from a single primary facility to customers through intermediate facilities, and a pickup wave where the flow of products is reversed. Each echelon has its own type of vehicles, and we model the synchronization of transshipments at the intermediate facilities. The model only considers temporal constraints, assuming that capacities are never binding; the vehicles are always large enough given the constraints on time. The resulting problem is a time-driven 2E-LRP with synchronization and sequential delivery and pickup waves. To the best of our knowledge, the problem being considered is original because it addresses a new variant of 2E-LRP that considers synchronization of transshipments and the sequence of delivery and pickup activities.

Because of the complexity of the problem, only small instances can be solved optimally, and large instances cannot even be solved with a feasible solution. Therefore, a heuristic approach is needed to tackle large-size real instances. We propose a decomposition-based heuristic for the problem and provide computational results for different sets of instances. In addition to the solution approach, we propose data-driven schemes for use in combination with the mathematical model. The aim of the schemes is to reduce the set of feasible solutions. The computational results of these schemes are provided for different sets of instances.

The scope of the second part of the thesis is to illustrate how a simple vehicle routing problem could be used to enhance economic evaluation procedures of supporting policies for electric vehicles. In some countries, governments have implemented supporting policies for the use of electric vehicles in urban freight transport. Few studies have addressed the impacts of policies supporting electric vehicles on logistics and society. To cast light on this topic, we establish a framework combining an optimization model (i.e., a vehicle routing problem) and economic analysis in order to determine the optimal decisions (i.e., purchase and routing of vehicles) of an individual logistics company, and the resulting changes in externalities and welfare in response to policies designed to support electric vehicles.

Keywords: two-echelon location-routing, synchronization, pickup and delivery waves, mixed-integer linear programming, electric vehicle, social welfare, urban freight policies, heterogeneous vehicle routing problem

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Chapter 1

Introduction

Logistics problems deal with strategic, tactical and operational decisions within distribution systems. Strategic decisions concern long-term issues such as decisions on type, number and location of facilities, as well as decisions on type and size of vehicle fleet. At the tactical level, typical decisions are on customer-visit frequencies and order type in a given time horizon. The operational level deals with distribution planning activities including vehicles and the drivers' schedules. At this level, short-term and daily decisions such as routing of vehicles are made.

Vehicle routing problems (VRPs) have been one of the most cited logistic problems in the literature during the five past decades. The original VRP was introduced in a paper by Dantzig and Ramser (1959) and it tackles tactical and operational level decisions. The VRP is defined in a distribution system where a given set of customers with delivery demands is served from a single facility using a given set of vehicles. The aim of the VRP is often to minimize total distance. In its standard form, each customer must be visited by exactly one vehicle and each vehicle performs a single trip starting and ending at a facility. The decisions in the VRP are to assign customers to each vehicle and to determine the order of customer visits by each vehicle.

In distribution systems design, decisions on facility locations (e.g., plants, depots, warehouses and hubs) are relevant due to their impact on total distribution costs and service measures. Despite the fact that such location decisions are often strategic, it is crucial to capture their interactions with the operation of the network. This has motivated a growing body of literature on location-routing problems (LRPs), which combine location and routing decisions. In the standard LRP, a given set of customers with known delivery demands is served from a set of potential facilities using a given set of vehicles. An opening cost is assigned to each facility. The aim is to minimize overall costs consisting of both routing and facility opening costs. The decisions in the LRP are to determine the locations of the facilities, to assign customers to each facility and to determine the vehicles' routes.

The combination of different features, such as vehicles capacities, routes lengths and time windows, has resulted in a variety of LRPs, as recently reviewed in survey papers by Nagy and Salhi (2007), Prodhon and Prins (2014) and Drexl and Schneider (2015). Among these, the literature on two-echelon location-routing problems (2E-LRPs) and its variants is scarce. The 2E-LRP is defined in a two-echelon distribution system. In two-echelon distribution systems, products are transported from origins (e.g., suppliers or production plants) to destinations (e.g., customers or retailers), through intermediate facilities (e.g., depots, cross-docks or distribution centers) where different operations such as storage, consolidation or transshipment occur. In 2E-LRPs, two echelons interact through intermediate facilities, where the first echelon consists of primary and intermediate facilities, and the second echelon consists of the intermediate facilities and customers. Each echelon has its own type of vehicles. The aim is to decide on location of central or intermediate facilities (or both), in addition to routing within each echelon. The main question that arises in a two-echelon distribution system is how to synchronize the flows of two echelons at intermediate facilities. The synchronization is important due to storage limitation at the intermediate facilities and time windows for visiting the customers. In its standard form, the 2E-LRP assumes that customers only require deliveries. However, in practice, customers often need both pickup and delivery. This may be the case in many real-life applications such as city logistics and postal and parcel delivery.

This thesis addresses rich vehicle routing problems within a logistics context. The term *rich vehicle routing* is associated with problems that incorporate some or all complex attributes of real-life applications. Some examples for such attributes are temporal constraints, sequence of distribution activities, fleet heterogeneity, diversity of policies, and environmental issues (Caceres-Cruz et al., 2015). Survey papers on rich vehicle routing problems are provided by Drexl (2012); Lahyani et al. (2015); Caceres-Cruz et al. (2015), and interested readers may refer to these papers

The first and bulk part of the thesis introduces a new location-routing problem and discusses both modeling and solution approaches. Motivated by an actual problem of the postal service company in Norway, we introduce a new 2E-LRP. The activities are organized in two waves: a delivery wave, where products are transported from a single primary facility to intermediate facilities and from intermediate facilities to customers, and a pickup wave, where the flow of products is reverse. The customers in each wave are served within individual time windows and the synchronization of transshipments at the intermediate facilities is respected. The decisions in the problem is to determine the locations of intermediate facilities and the vehicle routes at each echelon. We consider only time-related questions. This is typical for some postal and parcel delivery systems where the delivery and pickup of products outside densely populated areas are uniquely governed by time: when products are available at the primary facility, driving times to intermediate facilities, synchronization of vehicles at these facilities, and the delivery time to customers. And then the same sequence in the afternoon, ending with the latest arrival time of products at the primary facility. Within this framework, all vehicles are assumed to be large enough. Although this is not always true, it is most of the time. The resulting problem is a time-driven 2E-LRP with synchronization and sequential delivery and pickup waves. Most papers studying 2E-LRPs ignore the synchronization of transshipments at the intermediate facilities (Drexl and Schneider, 2015). To the best of our knowledge, time windows and synchronization have not been studied together in the literature on 2E-LRP and, in fact, a survey paper on two-echelon routing problems by Cuda et al. (2015) highlights these aspects as worthwhile to investigate. We provide a mixed-integer linear programming (MILP) formulation for the problem that we introduce.

Nagy and Salhi (2007) classified LRPs in terms of four key aspects; structure (i.e., standard hierarchical or non-standard hierarchical), type of input data (i.e., deterministic or stochastic), planning period (i.e., single- or multi-period), and solution methods (i.e., exact or heuristic). In standard hierarchical LRPs, facilities serve customers that are connected to the facilities by means of vehicle tours and no tour connects facilities. The main difference between standard and non-standard hierarchical LRPs is the incorporation of tour planning in different layers (i.e., echelons). Some example of non-standard LRPs are *transportation-location problem* (e.g., Cooper (1972); Klibi et al. (2010)) where the tour planning is not involved, *many-to-many location-routing problem* (e.g., Nagy and Salhi (1998); Wasner and Zäpfel (2004)) where tour planning is involved in both inter-facilities routing and between customers and facilities routing, *vehicle routing-allocation problem* (e.g., Beasley and Nascimento (1996)) where inter-facilities tour planning is involved but tour planning between customers and facilities is excluded, and *multi-level location-routing problem* that may include tour-planning within each layer. Based on the classification of LRPs provided by Nagy and Salhi (2007), the problem that we introduce in the thesis is categorized as *deterministic single-period non-standard hierarchical* LRP.

The 2E-LRP and its variants are very hard optimization problems and seldom investigated (Prodhon and Prins, 2014). Due to the complexity of the problem, only very small 2E-LRP instances can be solved using exact approaches. Therefore, heuristics are required to obtain appropriate solutions in acceptable running times on the large instances that can be found in practical applications. In this thesis, we propose a *decomposition-based heuristic* for the time-driven 2E-LRP with synchronization and sequential delivery and pickup waves.

The decomposition-based heuristic decomposes the problem into three phases: 1) choosing the facility configuration, 2) assigning the customers to the chosen facilities and 3) solving the routing sub-problem. We perform numerical experiments to check the performance of the decomposition-based heuristic in terms of the solution quality and computational time for different sets of instances. We compare the effect of the first phase of the proposed approach on the solution quality to the common approach used in the literature for facility configuration.

Besides the solution approach, we propose different schemes that work in combination with the MILP formulation. The aim of the schemes is to reduce the feasible solution space by removing routes that are unlikely to be part of high quality solutions. Through numerical experiments, we check the effect of schemes on reducing the set of feasible solutions for different sets of instances.

Logistics problems (e.g., vehicle routing problems, location-routing problems) usually focus on distribution cost minimization (e.g., facility opening costs, routing costs). Incorporating sustainability issues in logistics problems poses the challenging field of *green logistics*, which has received considerable attention from researchers in recent decades (Lin et al., 2014). Green logistics concern environmental, ecological and social issues as well as other conventional economic costs within distribution systems. The aim of green logistics is to obtain a sustainable distribution system by considering environmentally sensitive transportation policies. Such policies encourage companies to use *green vehicles* (i.e., vehicles with less negative environmental effects) such as electric vehicles (EV) for transportation needs.

Contrary to the first part of the thesis where we address different aspects of an actual problem through an optimization model, in the second part of the thesis, we do not aim to introduce a new routing problem but the scope is to illustrate how a simple vehicle routing problem could be used to enhance economic evaluation procedures of supporting policies for electric vehicles. Despite growing research interest in urban freight transport, there have been few studies addressing the impacts of EV-supporting policies on logistics and society. As a contribution to cover the gap, we establish a framework that combines an optimization model (i.e., a vehicle routing problem) and economic analysis to evaluate the impacts of EV-supporting policies on an individual company's logistics decisions (i.e., vehicle routing and purchase) and corresponding changes in externality and welfare.

In the reminder of this chapter, we explain the actual problem that motivated us to introduce the new 2E-LRP, we review the literature related to the new problem and outline the contributions of the thesis before presenting an overview of the dissertation.

1.1 Motivation

Our main motivation comes from an actual problem arising in *Posten Norge*, the national postal service company in Norway. This company provides mail and package delivery services via two main brands: *Posten* and *Bring*. Posten focuses on serving post offices and small post centers located in selected local supermarkets, while Bring focuses on business customers such as private companies and organizations in the Nordic area. A major concern for all postal service companies is to provide customers with on-time services while using resources efficiently. The most notable obstacle in Norway is the geographical location of customers. Norway is a relatively long country, with an intricate geography including more than 25,000 km of coastline and a number of small towns in urban and rural regions. Providing coverage across the whole country poses a challenge to postal service companies.

The main facilities for a postal service company are terminals. Posten Norge has nineteen terminals spread around Norway, as shown in Figure 1.1. Each customer is assigned to a unique terminal. A terminal is a place where goods, previously picked up from customers, are sorted before being delivered to the final customers. All goods must pass through a terminal for data capturing purposes.

Customers located close to a terminal are served directly from the terminal. For customers farther away (i.e., typically located in rural areas), it is inefficient to serve them directly from the terminal. It would be too expensive to use small vehicles as the number of necessary vehicles would be very large due to time windows of visiting customers and limited speed of vehicles. Large vehicles, on the other hand, would have limitations in rural areas due to features such as narrowness or steepness of roads, as well as the distances between customers; a full large vehicle would take far too long to deliver all its goods within the time windows. One reasonable solution to this problem is to establish reloading points between the terminal and customers. These points serve as locations where goods are unloaded from large vehicles, coming from the terminal and reloaded onto small vehicles, departing to customers. Posten Norge is currently looking for the optimal location of reloading points (RPs) associated to each of its terminals. Figure 1.2 illustrates the geographical distribution of customers and potential sites of RPs for a specific terminal. The square represents the terminal, the triangles are the potential sites for reloading points, and the grey dots are customers.

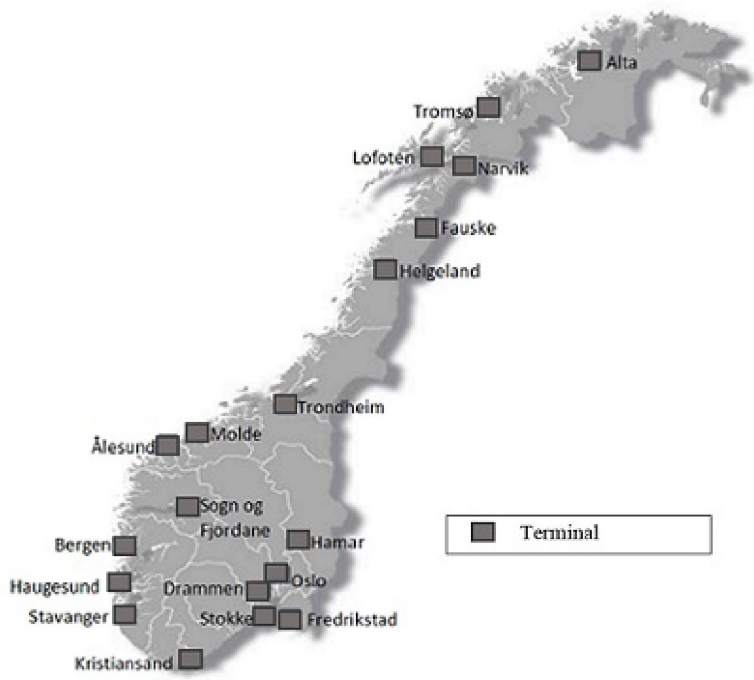


Figure 1.1: Geographical distribution of terminals within Norway

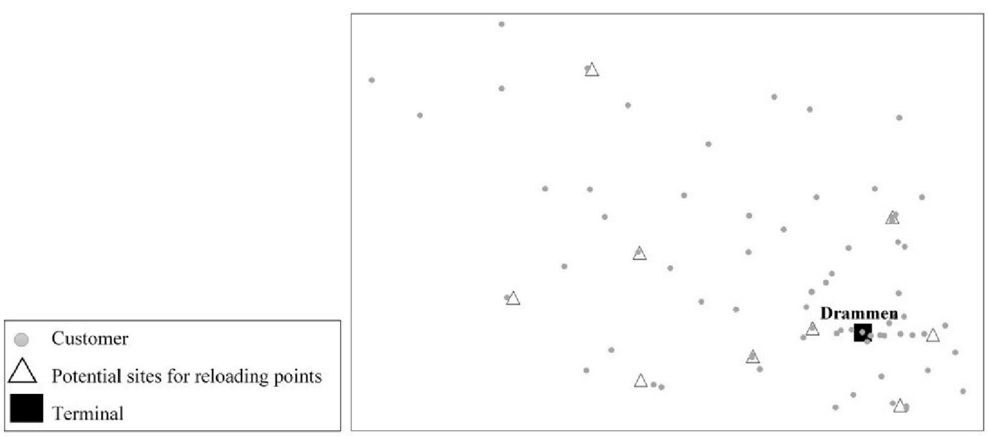


Figure 1.2: Geographical distribution of customers and potential sites of RPs for the Drammen terminal

1.2 Literature review

The literature on two-echelon routing problems can be split in two classes: the 2E-LRP and two-echelon vehicle routing problems (2E-VRP). Interested readers are referred to recent surveys (Drexl and Schneider, 2015; Prodhon and Prins, 2014; Cuda et al., 2015). In a 2E-VRP, the set of primary and intermediate facilities is given (i.e., there is no decision on the location of facilities) and the aim is to decide on vehicles routes in both echelons.

Both 2E-LRP and 2E-VRP can be applied to many real-life problems such as city logistics and postal and parcel delivery. In the literature, city logistics is probably the most cited application. Here we examine the relevant literature on two-echelon routing problems, in the context of postal service design and city logistics and we focus on papers that specifically consider what is important to us; temporal considerations, such as synchronization, time windows, and sequencing of deliveries and pickups.

A small body of literature addresses the application of LRPs on parcel delivery. Among these, the papers by Bruns et al. (2000); Wasner and Zäpfel (2004); Winkenbach et al. (2015, 2016) are worth mentioning. Bruns et al. (2000) investigated the problem of postal service networks. In their problem, the distribution network consists of three echelons and four levels. The first level consists of post offices. The second and the third levels consist of parcel processing centers and delivery bases, respectively. The fourth level consists of customers with delivery demands. The parcels are delivered from post offices to parcel processing centers and then to delivery bases, and from the delivery bases to customers. Although the original problem is a multi-echelon LRP, it is converted to an LRP by fixing the locations of the parcel processing centers and allocating delivery bases to parcel processing centers. The customers are partitioned into different zones, and the routing costs for each zone are approximated. In this manner, the LRP is reduced to a facility location problem, where the aim is to decide on the location of the delivery bases and allocation of customer zones to delivery bases. Wasner and Zäpfel (2004) studied a problem posed by a parcel delivery service provider in Austria. In their problem, the customers have both delivery and pickup demands. The pickup and delivery flows of products between customers must pass through hubs. A central hub with known location is given, and all other hubs are connected to each other through the central hub. The problem is considered as a hub-location vehicle routing problem, where the aim is to decide on the location of the hubs excluding the central hub as well as the inter-hub and hub-to-customer routing. The main difference between *hub-location routing problems* and LRPs is that in the former, besides the interactions between hub facilities and customers, the interactions (i.e., flow) between the hubs themselves is considered (Aykin, 1995), while this is not the case for the latter. In a recent paper, Winkenbach et al. (2015) developed an optimization model for the national postal operator in France. The optimization model enables decision makers to establish single-echelon or two-echelon (or both) systems in order to serve customers demanding different types of products. The aim of the optimization model is to identify the optimal number and locations of facilities at each echelon, the optimal sizes and shapes of areas assigned to each facility, and the optimal fleet size. The minimal routing costs of the vehicles are approximated with regards to different constraints involving the vehicle capacity and maximum route length. The approximation formula is used in the proposed MILP formulation for the 2E-LRP. They tested the validity of the approximation formula and observed high-quality solutions within a reasonable time for large-scale instances.

Regarding the temporal aspects in 2E-LRP, there are few papers in the literature. Nikbakhsh and Zegordi (2010) considered a 2E-LRP where soft time windows are applied to serving customers with a penalty for violation. The aim of the problem is to decide the location of intermediate facilities as well as routing of vehicles in both echelons. The synchronization of transshipments at intermediate facilities is not considered. They proposed a three-index MILP formulation while showing how to compute a lower bound for the problem and provided a two-stage heuristic.

A few papers in the literature address the application of two-echelon routing (e.g., 2E-VRP, 2E-LRP) in city logistics (e.g., Crainic et al. (2011) and Perboli et al. (2011)). In two-echelon (also known as two-tiered) city logistic problems, the first echelon involves primary vehicles with larger capacities delivering products from primary facilities located on the outskirts of the city to intermediate facilities where products are transferred to secondary vehicles with smaller capacities performing the intermediate facilities-to-customers delivery routes. In the context of city logistics, different variants such as synchronization of transshipment at intermediate facilities, and time windows, can be adapted. Crainic et al. (2009) introduced a new problem class within two-echelon city logistics problems that consider vehicle departure scheduling, strict time synchronization of transshipment at intermediate facilities, and the time windows of customers. The problem concerns the selection of routes and scheduling of departures for the vehicles in each echelon, as well as the selection of delivery routes for the customer demands from the primary facilities through intermediate facilities to the final customer. They provided a general mathematical formulation for the problem. Crainic et al. (2012) discussed methodological and managerial challenges related to the integration of different types of traffic strategies within the two-echelon city logistics problem. They considered three types of traffic strategies: customer-to-customer (c2c), customer-to-external zone (c2e), and external zone-to-customer (e2c). The c2c strategy concerns the traffic of vehicles between customers inside city limit. The c2e strategy incorporates traffic of vehicles from customers inside the city limit to zones outside the city limit. The e2c strategy deals with traffic of vehicles from zones outside the city limit to customers inside. Customers can have both delivery and pickup demands, and this makes the integration of different strategies complex. In order to avoid interlacing the pickup and delivery operations, they introduced a simple strategy, called *pseudo-backhaul*, where a route must be completed before the next route starts. Following the concepts related to integration of three types of traffic strategies (Crainic et al., 2012), Crainic et al. (2016) formally introduced and defined the new variant of 2E-VRP, where they considered different variants such as multiple routes of vehicles, synchronization of transshipment at facilities, sequences of delivery and pickup operations, and time dependency of travel. Vehicles perform multiple routes; each route consists of a sequence of visits at facilities and customers at given time moments. The multiple routes of each vehicle follow the pseudo-backhaul strategy. The routes serving the c2c requests follow the last-in-first-out rule, and the strict time synchronization at facilities is considered.

Regarding the sequence of delivery and pickup activities, Parragh et al. (2008) classified the vehicle routing problems into two main classes. The first class is denoted as vehicle routing problems with backhauls, where delivery customers are served in the linehaul and pickup customers are served in the backhaul. The significance of this problem comes from using the free capacity in vehicles when returning (backhaul) to the facilities. Two main variants of vehicle routing with backhauls are *vehicle routing with clustered backhaul*, where all linehauls are before backhauls, and *vehicle routing with mixed linehauls and backhauls*, where any sequence of linehauls and backhauls is permitted. The second class deals with transportation of products between delivery and pickup locations and is denoted as pickup and delivery vehicle routing problems. The pseudo-backhaul strategy considered by Crainic et al. (2016) is different from the problem considered in this thesis with respect to the sequence of delivery and pickup activities. In the former, although the multiple routes of the vehicles follow the pseudo-backhaul strategy, the last-in-first-out rule applied to visiting c2c requests may cause a route performing such requests consist of a sequence of visits at delivery and pickup customers that does not follow the rules in the vehicle routing problem with backhaul. The pickup and delivery waves in the problem considered in this thesis are similar to linehauls and backhauls in vehicle routing problems with clustered backhauls (Goetschalckx and Jacobs-Blecha, 1989), where all deliveries must be made before the pickups as dictated by our motivation example.

Regarding the related literature, the problem that we consider is original since it addresses a new variant of 2E-LRP that incorporates synchronization of transshipment and sequence of delivery and pickup activities.

1.3 Contributions

The contributions of the thesis are listed as follows:

- We define a new problem called *time-driven 2E-LRP with synchronization and sequential delivery and pickup* and provide a MILP formulation for this problem.
- We propose a decomposition-based heuristic for the time-driven 2E-LRP with synchronization and delivery and pickup wave. Through the numerical experiments we provide computational results for instances using actual data from a national postal service company, as well as some experimental instances. The provided sets of instances can also be adapted to be used in other similar problems.
- We propose three schemes in order to reduce the set of feasible solutions and provide the computational results in order to check the effect of the schemes on different sets of instances.
- We establish a framework combining an optimization model and an economic analysis to evaluate potential operational, financial, and environmental effects of EV-supporting policies in urban freight transport. Through the framework, we determine the optimal behaviour of an individual logistics company (i.e., vehicle purchase choice and vehicles' routing plan) in response to policies, and corresponding changes in externality and welfare.

1.4 Outline

The remainder of the dissertation is organized as follows. Chapter 2 describes the new 2E-LRP and provides the mathematical formulation. Chapter 3 proposes the *decomposition-based heuristic* for the described problem in Chapter 2. Chapter 4 provides the four sets of instances and analyzes the computational results obtained from the *decomposition-based* *heuristic*. Chapter 5 proposes three schemes in order to reduce the set of feasible solutions, and checks to what extent the schemes help with finding better solutions in less time for the sets of instances provided in Chapter 4. Chapter 6 extends the problem discussed in Chapter 2 to incorporate the vehicles capacity, multiple trips for vehicles, and location decisions on terminals. Chapter 7 provides a framework combining an optimization model and economic analysis for evaluating the effect of EV-supporting policy changes on resulted welfare. Chapter 8 concludes the thesis, and discusses possible future research directions.

Chapter 2

The model

Motivated by the actual problem discussed in Chapter 1, here we introduce and define a new two-echelon location-routing problem (2E-LRP). The problem is defined within a two-echelon distribution system, where the first echelon comprises a single terminal as the primary facility and reloading points (RPs) as intermediate facilities, and the second echelon consists of RPs and customers. There are two waves: delivery, where products are transported from the terminal to RPs and from RPs to customers; and pickup, where the flow of products is reversed. The customers in each wave are served within individual time windows, and the synchronization of transshipments at the RPs is respected.

Location-routing problems are normally constrained by time and capacity. We consider only time-related questions. This is typical for some postal and parcel delivery systems where the delivery and pickup of products outside densely populated areas are uniquely governed by time: when products are available at the terminal, driving times to intermediate facilities, synchronization of vehicles at these facilities, and the delivery time to customers. And then the same sequence in the afternoon, ending with the latest arrival time of products at the terminal. Within this framework, all vehicles are assumed to be large enough. Although this is not always true, it is most of the time. This means that one (large) vehicle is enough to deliver products to the intermediate facilities. However, because of the driving time, the arrival at RPs leaves very little time for deliveries in the second echelon. Thus, there is a tradeoff between time spent in this echelon and the number of vehicles. For delivery to customers, the available time is limited, and the number of deliveries (and later pickups) that can be made imply that vehicles are never full. This also means that each vehicle in this second echelon makes only one tour because there is no reason to go back to the intermediate facilities. This could be a pure delivery tour, pure pickup tour, or as is the case most of the time, a combined tour where pickups follow deliveries. This is what *time-driven* means: the problem is only governed by time, not volume and capacity.

The rest of this chapter is organized as follows. Section 2.1 describes the time-driven 2E-LRP with synchronization and sequential delivery and pickup waves. Section 2.2 presents a mixed-integer linear programming (MILP) formulation for the problem.

2.1 Problem description

We consider a two-echelon distribution system consisting of three levels. The first level contains a single terminal. The second level consists of RPs as intermediate facilities, while the third level consists of customers. The first echelon comprises the terminal and RPs, and the second echelon comprises the RPs and customers. The following notation is used.

We assume a single *product*; this is typically postal packages. The *terminal* is the primary facility; it is generally located in an urban area and is a place where products previously picked up from customers are sorted before being delivered to customers. The products must pass through the terminal for data capturing purposes. *Primary vehicles* are large vehicles that transport products within the first echelon. *Secondary vehicles* are smaller vehicles that transport products within the second echelon. *RPs* are intermediate facilities that are meeting points for primary and secondary vehicles so that they can transfer products. The products can be stored in RPs for short periods to be transferred between primary and secondary vehicles. No other operations, such as long-term storage or any other processes that may change the shape and form of products, take place at the RPs. *Customers* are the final destinations within the distribution system. For postal systems, these are typically post offices, post in stores, companies, or individuals.

Here, we only consider customers located far away from the terminal; this is typical in rural areas. Customers that live close to the terminal, which is typical for more densely populated areas, are served directly from the terminal and are therefore not covered by the two-echelon model.

It is inefficient to serve these rural customers directly from the terminal. It is too expensive to use secondary vehicles because the necessary number of vehicles is very large; a large number of small vehicles will need to travel a long way, and they will not be full even though they are small because they would have very limited time for the actual delivery. On the other hand, primary vehicles would encounter limitations in rural areas such as narrow or steep roads as well as the distances between customers. A full primary vehicle will take far too long to deliver all of its products. Hence, it is beneficial to establish RPs as locations where products are unloaded from primary vehicles coming from the terminal and reloaded onto secondary vehicles departing to customers. In this manner, primary vehicles can efficiently transport large volumes from the terminal to the RPs, and secondary vehicles can efficiently handle smaller volumes of products in rural areas, which generally include narrow or steep roads. Organizing these different vehicles in two echelons may also be an environmentally friendly solution, as pointed out by Mancini (2013).

The customers are served in two waves: delivery and pickup. In the *delivery wave*, products are sent from the terminal to RPs by primary vehicles and from RPs to customers by secondary vehicles. In the *pickup wave*, products collected from customers are sent to RPs by secondary vehicles and then from RPs to the terminal by primary vehicles. We model the switch from delivery to pickup by letting a secondary vehicle pass from a delivery customer to a pickup customer once at most; the reverse is never allowed. Time windows for visiting the customers in each wave are also given. These can be used in two different ways.

First, they can be used to ensure that not only does each vehicle perform deliveries before pickups but also that *all* deliveries take place before any pickup. Second, time windows can naturally also be used to express that certain customers must be served within specific customer-defined time windows.

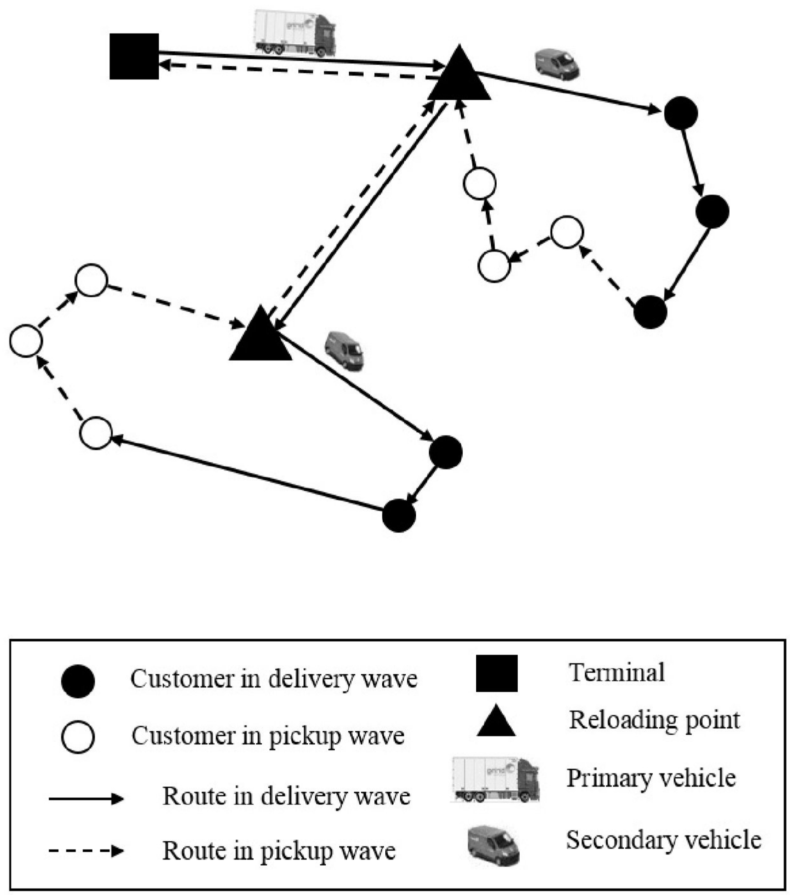


Figure 2.1: Illustration of the first and second echelons

Figure 2.1 illustrates an example of the two echelons. The square represents the terminal, and the triangles are the RPs. The routes in the delivery wave are illustrated with solid lines, while the routes in the pickup wave are illustrated with dashed lines. The black circles represent customers in the delivery wave, and the white circles are customers in the pickup wave. Primary and secondary vehicles make tours within their echelons. Each secondary vehicle is associated with a single RP. As illustrated in Figure 2.1, a secondary vehicle may perform only deliveries, only pickups, or both. In the latter situation, all deliveries must be made before the pickups. Synchronization between primary and secondary vehicles must be respected. That is, a secondary vehicle cannot depart from an RP in the delivery wave before a primary vehicle with its products has arrived. Likewise, in the pickup wave, a primary vehicle cannot depart from an RP until all of its pickup products have arrived.

Travel times are assumed to be deterministic and known. Splitting orders is not allowed but would not be optimal in any case given the assumptions because the problem is only governed by time, not volume and capacity. Even though, physically, a delivery and pickup customer may be the same entity, they are viewed as different here; there is no use in this model knowing whether or not customers in the two waves are the same or different. It is assumed that the fleet of vehicles for each type is homogeneous. There is a given earliest departure time for primary vehicles from the terminal. There is also a given latest return time to the terminal; all primary vehicles must return to the terminal before this time.

The goal is to find the optimal locations of RPs among a given set of potential sites while minimizing costs for opening RPs and paying the fleet and actual transportation costs. Note that the focus is on the problem of a single terminal whose location is given; the decisions on locations are for RPs only.

2.2 Model formulation

In this section, we present an arc-based MILP formulation for the time-driven 2E-LRP with synchronization and sequential delivery and pickup waves. The problem is formulated in a continuous time framework, and the time-frame of the model is set to one day.

We define the problem on a directed graph $G(V, A)$, where the set V contains the nodes and the set A contains the arcs. $V = V^1 \cup V^2$, where $V^1 = O \cup R$ is the set of nodes in the first echelon; O is the singleton set containing the terminal, and R is the set of potential sites for RPs. The set $V^2 = R \cup J^D \cup J^P$ is the set of nodes in the second echelon, where J^D is the set of customers in the delivery wave and J^P is the set of customers in the pickup wave. $A = A^1 \cup A^2$, where $A^1 = \{(i,j)|i \in O \cup R, j \in O \cup R, i \neq j\}$ is the set of arcs in the first echelon and $A^2 = \{(i,j)|i \in V^2, j \in V^2 \backslash \{\{(g,h)|g \in J^P, h \in J^D\} \cup \{(m,n)|m \in R, n \in R\}\}$ is the set of arcs in the second echelon. A^2 is defined so that no arc exists from a node $g \in J^P$ to a node $h \in J^D$ because no customer in the pickup wave is visited before a customer in the delivery wave. No arcs exist between two different RPs in the second echelon. T^e_{ij} represents the travel time between node i and node j in echelon e, $\forall (i,j) \in A^e, e \in E$. $E = \{1,2\}$ is the set of echelons and A^e is the set of arcs in echelon $e \in E$. c^e_{ij} is the travel cost of traversing arc $(i,j) \in A^e$.

Each RP $r \in R$ has a fixed cost of opening f_r. $J = J^D \cup J^P$ is the set of customers. Each customer $j \in J$ is visited only once, and it must be visited within its time window $[a_j, b_j]$, where a_j and b_j are the earliest and latest times, respectively, for visiting node $j \in J$. L is the set of primary vehicles, and K is the set of secondary vehicles. $\mathcal{T}^{zero}$ is the earliest time that a primary vehicle can depart from the terminal. $\mathcal{T}^{fin}$ is the latest time that a primary vehicle can come back to the terminal. f^e is the fixed usage cost of a vehicle in echelon $e \in E$.

The following decision variables are used. The location decision variable $z_r \in \{0,1\}, \forall r \in R$ is equal to 1 if RP r is open and 0 otherwise.

The routing decision variables x^1_{ijl} and x^2_{ijk} are for the first and second echelons, respectively. $x^1_{ijl} \in \{0,1\}, \forall (i,j) \in A^1, l \in L$ is equal to 1 if arc (i,j) is traversed by primary vehicle l and 0 otherwise. $x^2_{ijk} \in \{0,1\}, \forall (i,j) \in A^2, k \in K$ is equal to 1 if arc (i,j) is traversed by secondary vehicle k and 0 otherwise.

The time decision variables are defined as follows. $t^1_{il} \geq 0, \forall i \in V^1, l \in L$ is the time at which a primary vehicle visits node i. $t^{end}_l \geq 0, \forall l \in L$ is the time at which primary vehicle l returns to the terminal. $t^2_i \geq 0, \forall i \in J$ is the time at which node i is visited. $t^d_{rk} \geq 0, \forall r \in R, k \in K$ is the departure time of a secondary vehicle from RP r. $t^a_{rk} \geq 0, \forall r \in R, k \in K$ is the arrival time of secondary vehicle k to RP r.

The distribution variable $u_{rkl} \in \{0,1\}, \forall r \in R, k \in K, l \in L$ is defined as equal to 1 if secondary vehicle k meets the primary vehicle l at RP r and 0 otherwise.

Table 2.1 summarizes the sets, parameters, and decision variables used in the MILP formulation.

Table 2.1: Sets, parameters, and variables used in the MILP model

Sets and parameters	**Description**
O	singleton set containing the terminal, $O = \{o\}$
$\mathcal{T}^{zero}$	earliest time a primary vehicle can depart from the terminal
$\mathcal{T}^{fin}$	latest time a primary vehicle can come back to the terminal
R	set of potential RPs
f_r	fixed cost of opening RP r, $\forall r \in R$
E	set of echelons, $E = \{1, 2\}$
A^e	set of arcs in echelon e, $\forall e \in E$
T^e_{ij}	travel time between node i and node j in echelon e, $\forall (i,j) \in A^e, e \in E$
c^e_{ij}	travel cost of traversing arc (i,j) in echelon e, $\forall (i,j) \in A^e, e \in E$
J^D	set of customers in the delivery wave
J^P	set of customers in the pickup wave
J	set of all customers ($J = J^D \cup J^P$)
a_j	earliest arrival time at node j, $\forall j \in J$
b_j	latest arrival time at node j, $\forall j \in J$
L	set of primary vehicles
K	set of secondary vehicles
f^e	fixed usage cost of a vehicle in echelon e, $\forall e \in E$
M	a sufficiently large number
Variables	**Description**
$z_r \in \{0,1\}$	binary variable equal to 1 if RP r is open and 0 otherwise, $\forall r \in R$
$x^1_{ijl} \in \{0,1\}$	binary variable equal to 1 if arc (i,j)
	is traversed by primary vehicle l and 0 otherwise, $\forall l \in L, (i,j) \in A^1$
$t^1_{il} \geq 0$	time at which primary vehicle l visits node i, $\forall l \in L, i \in V^1$
$t^{end}_l \geq 0$	time at which primary vehicle l returns to the terminal, $\forall l \in L$
$x^2_{ijk} \in \{0,1\}$	binary variable equal to 1 if arc (i,j)
	is traversed by secondary vehicle k and 0 otherwise, $\forall k \in K, (i,j) \in A^2$
$t^2_i \geq 0$	time at which node i is visited, $\forall i \in J$
$t^d_{rk} \geq 0$	departure time of secondary vehicle k from RP r, $\forall r \in R, k \in K$
$t^a_{rk} \geq 0$	arrival time of secondary vehicle k to RP r , $\forall r \in R, k \in K$
$u_{rkl} \in \{0,1\}$	binary variable equal to 1 if secondary vehicle k meets with primary vehicle l
	for reloading at RP r and 0 otherwise, $\forall r \in R, k \in K, l \in L$

The model is formulated as follows.

$$\begin{aligned} \min \quad & \sum_{r \in R} f_r z_r + \sum_{(i,j) \in A^1} \sum_{l \in L} c^1_{ij} x^1_{ijl} + \sum_{(i,j) \in A^2} \sum_{k \in K} c^2_{ij} x^2_{ijk} \\ & + \sum_{(o,j) \in A^1} \sum_{l \in L} f^1 x^1_{ojl} + \sum_{r \in R} \sum_{j \in V^2} \sum_{k \in K} f^2 x^2_{rjk} \end{aligned} \tag{2.1}$$

The objective function (2.1) consists of five components. The first component is the opening costs of the RPs. The second and third components are the routing costs in the first and second echelons, respectively. The fourth and fifth components are the fixed costs of the primary and secondary vehicles, respectively. We assume that the sets of vehicles are given, but, since we use fixed cost ($f^e, \forall e \in E$), the mathematical formulation actually allows us to determine the optimal fleet size. Because the time-frame of the model is set to one day, all costs in the objective function are projected on a daily basis.

The constraints can be classified as follows: routing in the first and second echelons, time calculation and route continuity of the first and second echelons, time windows, and synchronization.

Constraints

$$x^1_{irl} \leq z_r \quad \forall i \in V^1, r \in R, l \in L \tag{2.2}$$

$$\sum_{r \in R} x^1_{orl} \leq 1 \quad \forall l \in L \tag{2.3}$$

$$x^1_{irl} \leq \sum_{(o,r) \in A^1 : r \in R} x^1_{orl} \quad \forall i \in V^1, l \in L \tag{2.4}$$

$$\sum_{j \in V^1} x^1_{jil} = \sum_{j \in V^1} x^1_{ijl} \quad \forall i \in V^1, l \in L \tag{2.5}$$

Constraints (2.2), (2.3), (2.4), and (2.5) are routing constraints imposed at the first echelon. Constraints (2.2) ensure that a primary vehicle can visit an RP only if the RP is open. Constraints (2.3) dictate that a primary vehicle cannot depart from the terminal to more than one RP. Constraints (2.4) state that a primary vehicle can visit an RP only if it has departed from the terminal. Constraints (2.5) make sure that the number of arcs entering a node in the first echelon must be the same as the number of arcs exiting the same node.

$$x^2_{rjk} \leq z_r \quad \forall r \in R, k \in K, j \in J \tag{2.6}$$

$$\sum_{r \in R} \sum_{j \in J} x^2_{rjk} \leq 1 \quad \forall k \in K \tag{2.7}$$

$$\sum_{i \in V^2} \sum_{k \in K} x^2_{ijk} = 1 \quad \forall j \in J \tag{2.8}$$

$$\sum_{j \in J} x^2_{rjk} = \sum_{j \in J} x^2_{jrk} \quad \forall r \in R, k \in K \tag{2.9}$$

$$\sum_{i \in V^2} x^2_{ijk} = \sum_{i \in V^2} x^2_{jik} \quad \forall j \in J, k \in K \tag{2.10}$$

Constraints (2.6), (2.7), (2.8), (2.9), and (2.10) are routing constraints imposed at the second echelon. Constraints (2.6) make sure that a secondary vehicle can depart from an RP only if the RP is open. Constraints (2.7) state that a secondary vehicle cannot depart from more than one RP. Constraints (2.8) ensure that each customer $j \in J$ is served by exactly one secondary vehicle. Constraints (2.9) and (2.10) dictate that the number of arcs entering a node in the second echelon must be the same as the number of arcs exiting the same node.

$$t^1_{ol} \geq \mathcal{T}^{zero} - M(1 - \sum_{r \in R} x^1_{orl}) \quad \forall l \in L \tag{2.11}$$

$$t^1_{rl} \geq t^1_{il} + T^1_{ir} - M(1 - x^1_{irl}) \quad \forall l \in L, i \in V^1, r \in R \tag{2.12}$$

$$t^{end}_l \geq t^1_{rl} + T^1_{ro} - M(1 - x^1_{rol}) \quad \forall l \in L, r \in R \tag{2.13}$$

$$t^{end}_l \leq \mathcal{T}^{fin} + M(1 - \sum_{r \in R} x^1_{rol}) \quad \forall l \in L \tag{2.14}$$

$$t^1_{rl} \leq M \sum_{i \in V^1} x^1_{irl} \quad \forall r \in R, l \in L \tag{2.15}$$

$$t^{end}_l \leq M \sum_{r \in R} x^1_{rol} \quad \forall l \in L \tag{2.16}$$

Constraints (2.11), (2.12), (2.13), (2.14), (2.15), and (2.16) are time calculation constraints in the first echelon. These constraints impose route continuity in the first echelon. Constraints (2.11) state that the departure time of vehicle $l \in L$ from the terminal must respect the earliest departure time from the terminal, $\mathcal{T}^{zero}$. Constraints (2.12) calculate the time that a primary vehicle arrives at the RP. Constraints (2.13) calculate the time that a primary vehicle comes back to the terminal. Constraints (2.14) make sure that the arrival time of vehicle $l \in L$ to the terminal respects the latest return time to the terminal, $\mathcal{T}^{fin}$. Constraints (2.15) make sure that the arrival time of a primary vehicle at the RP can be positive only if the primary vehicle visits the RP. Constraints (2.16) ensure that the returning time of a primary vehicle to the terminal can be positive only if the primary vehicle visits some RPs.

$$t_j^2 \geq t_{rk}^d + T_{rj}^2 - M(1 - x_{rjk}^2) \quad \forall k \in K, r \in R, j \in J \tag{2.17}$$

$$t_j^2 \geq t_i^2 + T_{ij}^2 - M(1 - x_{ijk}^2) \quad \forall i, j \in J, k \in K \tag{2.18}$$

$$t_{rk}^a \geq t_i^2 + T_{ir}^2 - M(1 - x_{irk}) \quad \forall k \in K, r \in R, i \in V^2 \tag{2.19}$$

$$t_{rk}^d \leq M \sum_{i \in J} x_{rik}^2 \quad \forall r \in R, k \in K \tag{2.20}$$

$$t_{rk}^a \leq M \sum_{i \in J} x_{rik}^2 \quad \forall r \in R, k \in K \tag{2.21}$$

$$t_j^2 \geq a_j \quad \forall j \in J \tag{2.22}$$

$$t_j^2 \leq b_j \quad \forall j \in J \tag{2.23}$$

Constraints (2.17), (2.18), (2.19), (2.20), and (2.21) are time calculation constraints in the second echelon and impose route continuity. Constraints (2.17) calculate the arrival time of a secondary vehicle to the first node after it visits RP r. Constraints (2.18) calculate the arrival time of secondary vehicle k at customer j. Constraints (2.19) calculate the time that secondary vehicle k comes back to RP r. Constraints (2.20) ensure that the departure time of a secondary vehicle from an RP can be positive only if the secondary vehicle departs from the RP to some nodes. Constraints (2.21) ensure that the returning time of a secondary vehicle to an RP can be positive only if the secondary vehicle departs from the RP. Time calculation constraints (2.17), (2.18), and (2.19) implicitly avoid sub-tours (Desrosiers et al., 1984). Constraints (2.22) and (2.23) define the time windows.

$$t_{rk}^{d} \geq t_{rl}^{1} - M(1 - u_{rkl}) \quad \forall r \in R, k \in K, l \in L \tag{2.24}$$

$$t_{rl}^{1} \geq t_{rk}^{a} - M(1 - u_{rkl}) \quad \forall r \in R, k \in K, l \in L \tag{2.25}$$

$$\sum_{j \in J^P} \sum_{i \in V^2} x_{jik}^{2} \leq M \sum_{r \in R} \sum_{l \in L} u_{rkl} \quad \forall k \in K \tag{2.26}$$

$$u_{rkl} \leq \sum_{i \in V^1} x_{irl}^{1} \quad \forall r \in R, k \in K, l \in L \tag{2.27}$$

$$u_{rkl} \leq \sum_{j \in J^D} x_{rjk}^{2} \quad \forall r \in R, k \in K, l \in L \tag{2.28}$$

$$u_{rkl} \leq \sum_{j \in J^P} x_{jrk}^{2} \quad \forall r \in R, k \in K, l \in L \tag{2.29}$$

$$\sum_{j \in J^D} \sum_{i \in V^2} x_{jik}^{1} \leq M \sum_{r \in R} \sum_{l \in L} u_{rkl} \quad \forall k \in K; \tag{2.30}$$

$$\begin{aligned} z_r \in \{0,1\} \quad \forall r \in R; \quad u_{rkl} \in \{0,1\} \quad \forall r \in R, k \in K, l \in L; \\ x_{ijl}^{1} \in \{0,1\} \quad \forall (i,j) \in A^1, l \in L; \quad x_{ijk}^{2} \in \{0,1\} \quad \forall (i,j) \in A^2, k \in K; \\ t_{il}^{1} \geq 0 \quad \forall i \in V^1, l \in L; \quad t_{l}^{end} \geq 0 \quad \forall l \in L; \quad t_{i}^{2} \geq 0 \quad \forall i \in J; \quad t_{rk}^{d}, t_{rk}^{a} \geq 0 \quad \forall r \in R, k \in K. \end{aligned} \tag{2.31}$$

Constraints (2.24), (2.25), (2.26), (2.27), (2.28), (2.29), and (2.30) impose synchronization of primary and secondary vehicles. Constraints (2.24) state that a secondary vehicle cannot depart from an RP with delivery demands before a primary vehicle loads it. Constraints (2.25) make sure that a primary vehicle cannot depart from an RP with pickup demands before a secondary vehicle loads it. Constraints (2.26) state that, if secondary vehicle k picks up from at least one customer, it must load at least one primary vehicle.

Constraints (2.27), (2.28), and (2.29) imply that the reloading between primary vehicle l and secondary vehicle k at RP r cannot happen unless both visit RP r in either the delivery or pickup wave.[1] Constraints (2.30) state that, if a secondary vehicle k delivers to at least one customer, it must be loaded from at least one primary vehicle. Finally, constraints (2.31) define the domain of the variables.

[1]Note that, in the implementation of the model, we defined and used a dummy set for the set of RPs in the pickup wave which duplicates the set R in order to distinguish between the delivery and pickup waves. For the sake of ease in readability, we do not present this dummy set in the formulation.

Chapter 3

The solution approach

The two-echelon location-routing problem (2E-LRP) is a difficult optimization problem because it combines two non-deterministic polynomial-time (NP) hard problems: facility location and vehicle routing. Attacking such a hard problem head on is not feasible when the instances reach a certain size. In fact, the results obtained with commercial solvers show that only small instances are solved optimally, and large instances are not even solved with a feasible solution. Therefore, a heuristic approach is required to tackle large-size real instances. In this chapter, we propose a *decomposition-based heuristic* for the time-driven 2E-LRP with synchronization and sequential delivery and pickup waves. The solution approach decomposes the original problem into three main phases: choosing the intermediate facility configuration, assigning customers to the intermediate facilities, and solving the routing sub-problem.

In solution approaches for LRPs, the choice of facility configuration has a considerable effect on the solution quality because it changes the vehicle routes and distribution costs. Choosing the facility configuration becomes more technically challenging when there are a large number of potential sites for facilities and the facility opening costs are considerably lower than the routing costs. In heuristics for LRPs, a common approach is to start with an initial facility configuration that is chosen either randomly or based on a criterion (e.g., opening cost, closeness to customers) and to change the facility configuration during the diversification phase of the search procedure. The operators in the diversification phase close or open facilities in order to explore different facility configurations. Such operators have been used in different heuristics for LRPs (e.g., the tabu search by Albareda-Sambola et al. (2005)) and for the 2E-LRP (e.g., the adaptive large neighborhood search by Contardo et al. (2012) and variable neighborhood search by Schwengerer et al. (2012)).

In the first phase of the decomposition-based heuristic, we generate an RP plan that provides RP configurations in each main iteration of the algorithm. The RP plan consists of all RP configurations with single RP, the RP configuration containing all RPs, and a subset of RP configurations containing i RPs, $2 \leq i \leq |R|$ with lower values of a pre-defined score, where $|R|$ is the cardinality of the set of potential sites for RPs. For each RP configuration containing i RPs, $2 \leq i \leq |R|$, the score is calculated based on three terms: 1) the sum of the RP opening costs, 2) the average traveling time between RPs and customers, and 3) the sum of the traveling time between any two RPs. Whenever the cardinality of RP configurations increases by one, we examine additional RP configurations that are not included in the RP plan if we obtain a lower value for the objective function (i.e., sum of RP opening costs, routing costs, and fixed vehicle costs). The additional RP configurations are chosen randomly. For example, if we obtain a solution with a lower value for the objective function with RP configurations containing three RPs compared to the ones with two RPs, we examine additional RP configurations containing three RPs that are not included in the RP plan.

In the second phase, for a given RP configuration, the customers are assigned to the RPs by an assignment model. In the third phase, for a given RP configuration and customer assignment, we solve the routing sub-problem as follows. We generate a feasible solution for the first echelon. We consider two types of feasible solutions for the first echelon: i) a solution containing back and forth routes between the terminal and RPs, and ii) a solution obtained by using the nearest neighbor heuristic. Given the feasible solution for the first echelon, we generate a pool of feasible routes for the second echelon and solve the routing sub-problem at the second echelon using a set-partitioning model. The aim of the set-partitioning model is to minimize the routing and fixed usage costs of vehicles at the second echelon. The set-partitioning model provides the best routes from the pool of feasible routes and the corresponding routing and vehicle fixed costs. We define *sub-iteration* in the algorithm as the number of iterations that the pool of feasible routes for the second echelon is updated. In each sub-iteration, the pool of feasible routes is updated by the generation of new routes using neighborhood search and the set-partitioning model is solved. This is iterated for a given number of sub-iterations and we save the solution with the lowest value for routing and fixed usage costs at the second echelon. In the next main iteration, we choose another RP configuration in the RP plan and follow the second and third phases of the algorithm. The algorithm stops after all RP configurations in the RP plan are examined and the best found solution (i.e., the one that provides the lowest value for sum of RP opening costs, routing costs, and fixed vehicle costs) is saved.

The third phase of the decomposition-based heuristic is similar to a column generation approach. In the standard column generation approach (Desaulniers et al., 2006; Lübbecke and Desrosiers, 2005), the routes (i.e., columns) are generated via a sub-problem (e.g., shortest path problem, knapsack problem). Then, the generated routes are given to the master problem (i.e., set-partitioning formulation) in order to find the best routes. This procedure is iterated until a stop criterion is met. Column generation approaches for the LRP have been used in previous literature. Among them, the papers by Akca et al. (2009) and Contardo et al. (2013) are worth mentioning. Contardo et al. (2013) formulated the LRP as a set-partitioning problem and introduced inequalities in order to strengthen the relaxed linear program. The problem is solved by column generation, where the master problem is a set-partitioning formulation and the sub-problem is a capacitated shortest path problem. However, both approaches proposed by Akca et al. (2009) and Contardo et al. (2013) cannot solve large instances in a reasonable amount of computational time.

The main difference between our approach and standard column generation is the generation of columns (routes). In the latter, the routes are generated via the sub-problem, while in the former the routes are generated heuristically via a neighborhood search. In this manner, we hope to get fairly good solutions with less computational time than the standard column generation technique.

3.1 Decomposition-based heuristic

This section explains the three phases of the algorithm. The problem is decomposed into three main phases. In the first phase, the RP configuration is determined with the RP plan. In the second phase, for a given RP configuration, the customers are assigned to the RPs by an assignment model. In the third phase, the routing sub-problem is solved.

3.1.1 Phase 1: Choosing RP configuration

The RP plan $P = \bigcup_{i \in R} P_i$ is generated to provide the RP configuration in each main iteration of the decomposition-based heuristic. P_i is the subset of RP configurations containing i RPs with lower values for $\mathcal{S}_p$. $\mathcal{S}_p$ is the score of RP configuration $p \in P_i$ and is calculated as follows:

$$\mathcal{S}_p = \lambda_1 \frac{\sum_{r \in p} f_r}{\sum_{p \in P_i} \sum_{r \in p} f_r} + \lambda_2 \frac{\sum_{r \in p} AT_r}{\sum_{p \in P_i} \sum_{r \in p} AT_r} - \lambda_3 \frac{\sum_{r \in p} \sum_{r' \in p} T^2_{rr'}}{\sum_{p \in P_i} \sum_{r \in p} \sum_{r' \in p} T^2_{rr'}} \quad \forall p \in P_i \tag{3.1}$$

AT_r is the average traveling time between RP r and customers and is calculated as follows:

$$AT_r = \frac{\sum_{j \in J^P \cup J^D} T^2_{rj}}{|J^D| + |J^P|} \quad \forall r \in R \tag{3.2}$$

where T^2_{rj} is the traveling time between RP $r \in R$ and customer $j \in J$.

In equation (3.1), λ_1, λ_2, and λ_3 are given parameters between zero and 1. In order to acquire a unit-invariant score, each term in equation (3.1) is divided by the sum of the same values for all RP configurations. The first term is the sum of the opening costs of RP configuration $p \in P_i$ compared to the sum of the same costs for all RP configurations in P_i. The second term is the average traveling time between RPs and customers in RP configuration $p \in P_i$ compared to the sum of the same values for all RP configurations in P_i. The third term is the sum of traveling times between any two RPs for RP configuration $p \in P_i$ compared to the sum of the same values for all RP configurations in P_i. The lower values for the first two terms provide a lower score for the RP configuration. The third term provides a higher score for an RP configuration containing two or more close RPs to each other. RP configuration $p \in P_i$ with a lower value for $\mathcal{S}_p$ is assigned a higher rank (i.e., the RP configuration with the lowest score is the best).

The cardinality of set P_i is assumed to be proportional to the occurrence probability of choosing i RPs and is calculated with equation (3.3). P_i contains $|P_i|$ RP configurations with higher ranks (i.e., with lower values for $\mathcal{S}_p$).

$$|P_i| = \lceil \frac{\binom{|R|}{1}}{\sum_{i=1}^{|R|} \binom{|R|}{i}} N \rceil \quad 1 < i \leq |R| \tag{3.3}$$

All RP configurations containing a single RP and configurations containing all RPs are explored (i.e.,$|P_1| = |R|$ and $|P_{|R|}| = 1$).

N is a given parameter for calculating $|P_i|$, and $N \leq 2^{|R|}$ is assumed. $\lceil . \rceil$ is the ceiling sign.

$|P_i^A|$ additional RP configurations $p \notin P_i$ are examined only if a better solution is obtained for RP configurations containing i RPs compared to RP configurations containing $i-1$ RPs; in other words, $\min_{p \in P_i} F_p < \min_{p' \in P_{i-1}} F_{p'}, 2 \leq i \leq |R|$, where F_p is the total cost consisting of the sum of RP opening costs, routing costs, and fixed vehicle costs for RP configuration p. Subset P_i^A includes the RP configurations containing i RPs, $2 \leq i \leq |R|$ not belonging to P_i. In order to diversify the search space, RP configurations in P_i^A are randomly chosen. The cardinality of subset P_i^A is calculated as $|P_i^A| = \lceil \eta |P_i| \rceil, 2 \leq i \leq |R|$, where $0 \leq \eta \leq 1$ is a given parameter.

3.1.2 Phase 2: Customer assignment to the RPs

In the second phase, for a given RP configuration, the customers are assigned to RPs with the assignment model. We define the sets, parameters, and decision variables used in the assignment model as follows. J is the set of customers. ORP is the set of RPs in a given RP configuration. c_{rj}^2 is the traveling cost from RP $r \in ORP$ to customer $j \in J$. The binary decision variable $\chi_{rj} \in \{0, 1\}$ is defined as equal to 1 if customer $j \in J$ is assigned to RP $r \in ORP$, and zero otherwise. Table 3.1 summarizes the sets, parameters, and decision variables used in the assignment model.

Table 3.1: Sets, parameters, and decision variables used in the assignment model

Sets, parameters	**Description**
J	set of all customers
ORP	set of RPs in a given RP configuration
c_{rj}^2	traveling cost from RP r to customer j
Variables	**Description**
$\chi_{rj} \in \{0, 1\}$	binary variable, equal to 1 if customer j is assigned to RP r, zero otherwise

The assignment model is formulated as follows:

$$\min \sum_{r \in ORP} \sum_{j \in J} c_{rj}^2 \chi_{rj} \tag{3.4}$$

Constraints

$$\sum_{r \in ORP} \chi_{rj} = 1 \quad \forall j \in J \tag{3.5}$$

$$\sum_{j \in J} \chi_{rj} \geq 1 \quad \forall r \in ORP \tag{3.6}$$

$$\chi_{rj} \in \{0, 1\} \quad \forall r \in R, j \in J \tag{3.7}$$

The objective function (3.4) minimizes the sum of traveling costs between RPs and customers. Constraints (3.5) dictate that each customer is visited exactly once. Constraints (3.6) dictate that each RP $r \in ORP$ serves at least one customer. Constraints (3.7) define the domain of variables.

3.1.3 Phase 3: Solving routing sub-problem

In the third phase of the decomposition-based heuristic, the routing sub-problem is solved given the RP configuration and customer assignment for the RPs. A feasible solution S is generated for the first echelon. Each route $s \in S$ starts from the terminal and ends at the terminal.

Each route in the first echelon is represented below.

$$o, i_1, \ldots, i_n, j_1, \ldots, j_m, o \quad \forall i_1, \ldots, i_n \in ORPD, \; j_1, \ldots, j_m \in ORPP \tag{3.8}$$

where o represents the terminal and $ORPD$ is the set of RPs in the delivery wave, where its elements are the same as the elements in ORP. $ORPP$ is the set of RPs in the pickup wave, where each element in set $ORPP$ has a corresponding element in set $ORPD$. The feasible solution S consists of routes where any node $i \in ORPD \cup ORPP$ is visited once at most. No node $i \in ORPP$ is visited before node $j \in ORPD$ on route $s \in S$. Two types of feasible solutions are considered for the first echelon: *i)* a solution containing back and forth routes between the terminal and RPs, and *ii)* a solution obtained by using the nearest neighbor heuristic that is generated by adding the nearest node to the last visited node $j \in ORPD \cup ORPP$ on the route until all nodes are visited.

The starting time (i.e., departure time from terminal) of each route $s \in S$ is set as T^{zero}. The length of each route $s \in S$ must respect the maximum length of the route in the first echelon (i.e., $T^{fin} - T^{zero}$).

$$l_s^1 \leq T^{fin} - T^{zero} \quad \forall s \in S \tag{3.9}$$

l_s^1 is the length of route $s \in S$ and is calculated as follows:

$$l_s^1 = \sum_{i,j \in s} T_{ij}^1 \quad \forall s \in S \tag{3.10}$$

where T_{ij}^1 is the traveling time between node i and node j.

c_s^1 is the cost of route $s \in S$ and is calculated as follows:

$$c_s^1 = \sum_{i,j \in s} c_{ij}^1 \quad \forall s \in S \tag{3.11}$$

$F_p^1(S)$ is the fixed costs of vehicles and routing costs for the feasible solution S for a given RP configuration p. It is calculated as follows:

$$F_p^1(S) = f^1 n_s + \sum_{s \in S} c_s^1 \quad \forall p \in P \tag{3.12}$$

where n_s is the number of routes in feasible solution S and f^1 is the fixed cost of the primary vehicle.

Each route $s \in S$ gives the maximum length of routes in the second echelon that originates from RP $r \in ORP$, $\mathcal{L}_r$. $\mathcal{L}_r$ is calculated as follows:

$$\mathcal{L}_r = \min_{s \in S}\{\mathcal{L}_r(s)\} \quad \forall r \in ORP \tag{3.13}$$

$\mathcal{L}_r(s)$ is the maximum length of routes in the second echelon that originates from RP $r \in ORP$ on route $s \in S$ and is calculated as follows:

$$\mathcal{L}_r(s) = (T^{fin} - \Phi^s_{M(r)} T^{'}(M(r), o)) - (T^{zero} + \Phi^s_r T^{'}(o, r)) \quad \forall s \in S, r \in ORPD, M(r) \in ORPP \tag{3.14}$$

$T^{'}(i,j)$ is the sum of traveling times for the arcs between node i and node j in a route, $\forall i, j \in O \cup ORPD \cup ORPP$. $M(r)$ is the corresponding element of element $r \in ORPD$ in the set $ORPP$. Φ^s_i is a binary parameter equal to 1 if node i is included on route s and zero otherwise, $\forall s \in S, i \in ORPD \cup ORPP$.

Given the feasible solution S for the first echelon, a pool of feasible routes $\mathcal{K} = \bigcup_{r \in ORP} \mathcal{K}_r$ is generated for the second echelon. $\mathcal{K}_r$ is the set of routes that originates from RP $r \in ORP$. Each route $k \in \mathcal{K}_r$ in the second echelon starts from RP $r \in ORP$ and ends at the same RP.

Each route $k \in \mathcal{K}$ is illustrated as follows:

$$r, \ldots, i, j, \ldots, r$$

Each node $j \in J^D \cup J^P$ is visited once at most on route $k \in \mathcal{K}$. No node $j \in J^D$ is visited after node $i \in J^P$ on route $k \in \mathcal{K}$. l^2_k is the length of route $k \in \mathcal{K}$ and is calculated as follows:

$$l^2_k = \sum_{i,j \in k} T^2_{ij} \quad \forall k \in \mathcal{K} \tag{3.15}$$

T^2_{ij} is the traveling time between node i and node j, $\forall i, j \in J^D \cup J^P \cup ORP$. The starting time (i.e., departure time from the terminal) of route $k \in \mathcal{K}_r, \forall r \in ORP$ is set equal to zero. The length of route $k \in \mathcal{K}_r, \forall r \in ORP$ must respect the maximum length of routes originating from RP r, $\mathcal{L}_r$.

Each route $k \in \mathcal{K}$ must be feasible regarding the time windows of visiting customers. Note that, when time windows are rather tight (i.e., without intersections) for customers, this may lead to an infeasible solution. In order to avoid such a situation, the time windows for visiting the customers in each wave are assumed to be the same for all customers. $TW_D = [e^D, l^D]$ is the time window for visiting customers in the delivery wave, and $TW_P = [e^P, l^P]$ is the time window for visiting customers in the pickup wave. e^D and l^D are the earliest and latest times, respectively, that customers can be visited in the delivery wave. e^P and l^P are the earliest and latest times, respectively, that customers can be visited in the pickup wave. Following the sequence of deliveries and pickups described in Section 2.1, $e^P \geq l^D$ is obtained. This means that no pickup takes place before the latest time of the deliveries.

There are two cases for checking the time windows regarding the type of route.

Case 1: Route $k \in \mathcal{K}$ contains only the delivery customers

Consider route $k \in \mathcal{K}$, which contains only the delivery customers, as illustrated below.

$$r, i_1, \ldots, i_n, r \quad \forall i_1, \ldots, i_n \in J^D, r \in ORP$$

where i_1 and i_n represent the first and last customers, respectively, on route $k \in \mathcal{K}$. In this case, the difference between the time that the last customer on the route is visited and the departure time from RP $r \in ORP$ must not be greater than $l^D - e^D$.

$$\mathcal{T}_{i_n} \leq l^D - e^D \tag{3.16}$$

where $\mathcal{T}_{i_n}$ is the time that the last delivery customer i_n on the route is visited.

Case 2: Route $k \in \mathcal{K}$ contains both delivery and pickup customers

Consider a mixed route $k \in \mathcal{K}$ that contains both delivery and pickup customers, as illustrated below.

$$r, i_1, \ldots, i_n, j_1, \ldots, j_m, r \quad \forall i_1, \ldots, i_n \in J^D,\ j_1, \ldots, j_m \in J^P, r \in ORP$$

where $i_1, \ldots, i_n$ are delivery customers and $j_1, \ldots, j_m$ are pickup customers. The time window for delivery customers is checked as in case 1. In order to check the time windows constraints for pickup customer, one of the cases given below may hold:

- If $\mathcal{T}_{j_1} > l^P$, the route is infeasible.
- If $e^P \leq \mathcal{T}_{j_1} \leq l^P$, check if $\mathcal{T}_{j_2}, \ldots, \mathcal{T}_{j_m} \leq l^P$.
- If $\mathcal{T}_{j_1} < e^P$, set $\mathcal{T}_{j_1} = e^P$ and check if $\mathcal{T}_{j_2}, \ldots, \mathcal{T}_{j_m} \leq l^P$.

If a route contains only pickup customers, it can be viewed as a special case of case 2 where the set of delivery customers is empty.

The number of iterations should be reduced if the initial iteration starts from a good pool of feasible routes rather than the construction of an arbitrary one. However, there is a tradeoff between the effort (i.e., time) required to generate a good pool of feasible routes and the resulting reduction in the overall running time. We chose the nearest neighbor heuristic in order to generate the initial pool of feasible routes. Rosenkrantz et al. (1977) compared the performance of three construction heuristics for the traveling salesman problem: farthest insertion, nearest insertion, and nearest neighbor. They showed that the nearest neighbor consumes less computational effort in order to create good routes than the other two.

The initial pool of feasible routes for the second echelon, $\mathcal{K}_{initial}$, is generated as follows. First, routes containing a single customer are generated. Then, routes containing two customers are generated by inserting the nearest customer to the last customer in routes containing a single customer. Then, the nearest customer is inserted to the last customer in the routes containing two customers. Customers continue to be inserted into the routes until all of them are inserted or the route is no longer feasible regarding the time windows and maximum length of the route $\mathcal{L}_r$.

Given $\mathcal{K}_{initial}$, the set-partitioning model is solved. The set-partitioning model provides the best routes from the pool of feasible routes and the corresponding routing and vehicle fixed costs. In the next sub-iteration, the initial pool of feasible routes is updated by the generation of new routes using neighborhood search. This is iterated for I_{ns} times, where I_{ns} is the number of neighborhood search sub-iterations. The best found solution and the corresponding routing and vehicle fixed costs are saved for a given RP configuration p.

In order to speed up the solving of the routing sub-problem, we place an upper limit on the number of customers $|J^{max}|$ for route $k \in \mathcal{K}$. $|J^{max}|$ is equal to the number of customers on route $k_m \in \mathcal{K}_{initial}$, where k_m is the route containing the maximum number of customers. The number of customers on route $k \in \mathcal{K}$ is limited to not exceed upper bound $|J^{max}|$.

Set-partitioning model

We define the sets, parameters, and decision variables used in the set-partitioning model as follows. ORP is the set of RPs in a given RP configuration. J^D is the set of customers in the delivery wave. J^P is the set of customers in the pickup wave. $\mathcal{K}_r$ is the set of feasible routes originating from RP $r \in ORP$. $\mathcal{K} = \bigcup\limits_{r \in ORP} \mathcal{K}_r$ represents the pool of feasible routes. $\mathcal{F}_k$ is the cost of route $k \in \mathcal{K}$. f^2 is the fixed cost of using a secondary vehicle. The binary parameter $g_{jk} \in \{0, 1\}$ is defined as equal to 1 if customer $j \in J^D \cup J^P$ is on route $k \in \mathcal{K}$, and zero otherwise. The binary decision variable $\psi_k \in \{0, 1\}$ is defined as equal to 1 if route $k \in \mathcal{K}$ is chosen, and zero otherwise. Table 3.2 summarizes the sets, parameters, and decision variables used in the set-partitioning model.

Table 3.2: Sets, parameters, and variables used in the set-partitioning model

Sets and parameters	**Description**
ORP	set of RPs in the given RP configuration
J^D	set of customers in the delivery wave
J^P	set of customers in the pickup wave
$\mathcal{K}_r$	set of feasible routes originating from RP $r \in ORP$
$\mathcal{K}$	pool of feasible routes, $\mathcal{K} = \bigcup_{r \in ORP} \mathcal{K}_r$
$\mathcal{F}_k$	cost of route $k \in \mathcal{K}$
f^2	fixed cost of using a secondary vehicle
$g_{jk} \in \{0, 1\}$	binary parameter; equal to 1 if customer j, $j \in J^D \cup J^P$ is on route $k \in \mathcal{K}$, zero otherwise
Variables	**Description**
$\psi_k \in \{0, 1\}$	binary variable; equal to 1 if route $k \in \mathcal{K}$ is chosen, zero otherwise

The set-partitioning model is formulated as follows.

$$\min \sum_{k \in \mathcal{K}} \mathcal{F}_k \psi_k + \sum_{k \in \mathcal{K}} \psi_k f^2 \tag{3.17}$$

Constraints

$$\sum_{k \in \mathcal{K}} g_{jk} \psi_k = 1 \quad \forall j \in J^D \cup J^P \tag{3.18}$$

$$\sum_{k \in \mathcal{K}_r} \psi_k \geq 1 \quad \forall i \in ORP \tag{3.19}$$

$$\psi_k \in \{0, 1\} \quad \forall k \in \mathcal{K} \tag{3.20}$$

The objective function (3.17) consists of two components. The first component is the sum of the routing costs in the second echelon. The second component is the fixed costs of the secondary vehicles. Constraints (3.18) dictate that each customer $j \in J^D \cup J^P$ is visited exactly once. Constraints (3.19) dictate that at least one route is chosen from RP $i \in ORP$. Constraints (3.20) define the domain of variables.

$F_p^2(\mathcal{K}) = \sum_{k\in\mathcal{K}} \mathcal{F}_k\psi_k + \sum_{k\in\mathcal{K}} \psi_k f^2$ is the routing and fixed vehicle costs of the pool of feasible routes $\mathcal{K}$ for RP configuration $p \in P$.

Neighborhood search is used on the pool of feasible routes. In each sub-iteration, the neighborhoods generate feasible routes, and this procedure is repeated for I_{ns} sub-iterations. After each sub-iteration, the set-partitioning model is solved, and the corresponding value for $F_p^2(\mathcal{K})$ is saved. Whenever a better solution is obtained (i.e., a lower value for $F_p^2(\mathcal{K})$ using the neighborhoods), the pool of feasible routes is replaced with the one that gives the better solution.

Figure 3.1 illustrates the steps of neighborhood search on the pool of feasible routes in the second echelon.

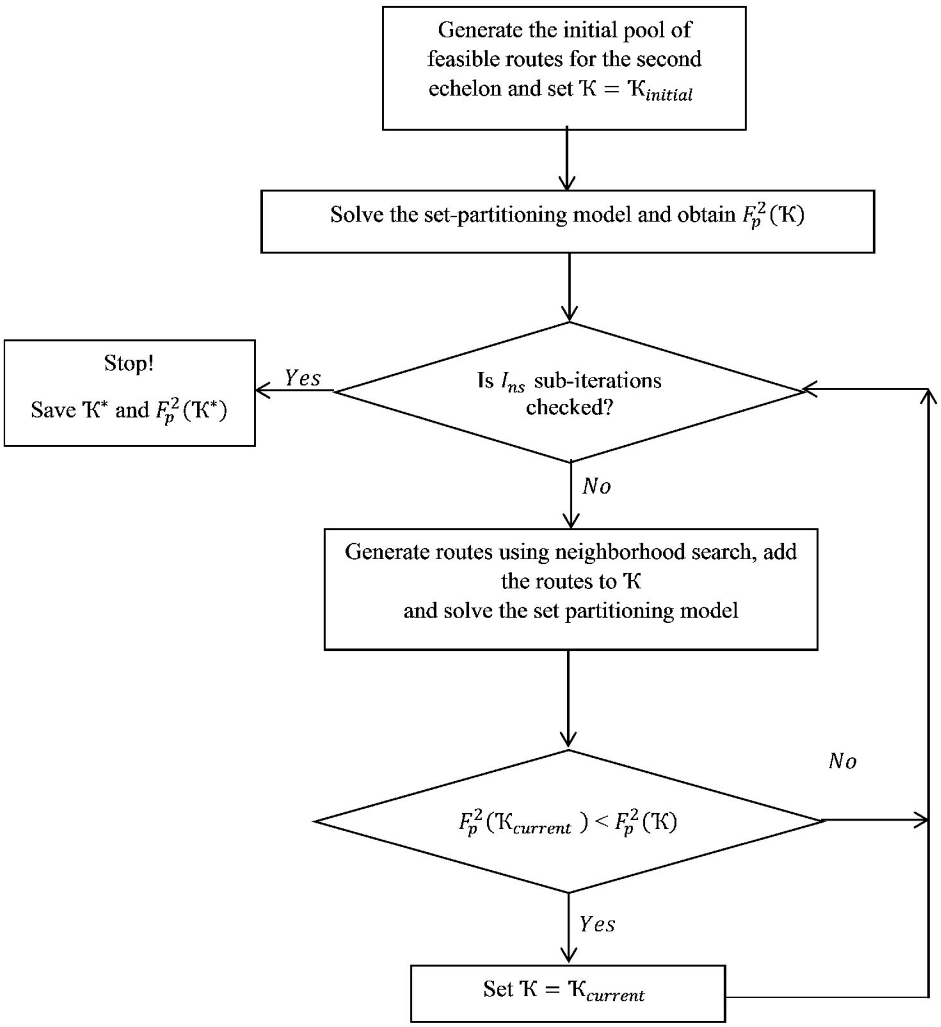


Figure 3.1: Steps of neighborhood search on the pool of feasible routes in the second echelon

Neighborhood search on pool of routes in the second echelon

We consider four neighborhoods: *inter-route interchange*, *inter-route shuffle*, *nearest insertion* and *two-point crossover*. The inter-route interchange and inter-route shuffle neighborhoods are used for intensification of the search space. The nearest insertion and two-point crossover neighborhoods are used for diversification of the search space.

The proportions of neighborhoods are given parameters. $0 \leq \%iri \leq 1$ is the proportion of the *inter-route interchange* neighborhood. $0 \leq \%irs \leq 1$ is the proportion of the *inter-route shuffle* neighborhood. $0 \leq \%ni \leq 1$ is the proportion of the *nearest insertion* neighborhood. $0 \leq \%tpc \leq 1$ is the proportion of the *two-point crossover* neighborhood. It is assumed that $\%iri + \%irs + \%ni + \%tpc = 1$. The neighborhoods are explained below.

inter-route interchange The inter-route interchange neighborhood is an adaptation of the two-interchange neighborhood by Savelsbergh (1985) for use in the decomposition-based heuristic. The inter-route interchange neighborhood randomly chooses $\%iri|\mathcal{K}|$ routes from the pool of feasible routes $\mathcal{K}$, where $|\mathcal{K}|$ is the cardinality of set $\mathcal{K}$. In each route, two customers are chosen randomly, and their positions are interchanged. The chosen customers are either delivery or pickup customers.

inter-route shuffle The inter-route shuffle neighborhood is similar to the edge-exchange neighborhood (Bräysy and Gendreau, 2005) and arc interchange neighborhood (Albareda-Sambola et al., 2007), where one or more edges on a route are replaced. The inter-route shuffle neighborhood randomly chooses $\%irs|\mathcal{K}|$ routes containing two or more customers. For each chosen route, two points are chosen randomly, and the order of customers located between the two points is shuffled. The two points are chosen within either delivery or pickup customers.

nearest insertion The nearest insertion neighborhood randomly chooses $\%ni|\mathcal{K}|$ routes containing two or more customers. For each chosen route, a point is chosen randomly, and a number of non-visited customers (i.e., customers that are not included in the chosen route) are inserted into the route. The route ends at the same RP where it starts from. The insertion of non-visited customers follows the nearest neighbor heuristic.

two-point crossover The two-point crossover operator used in the genetic algorithm is adapted for use in the decomposition-based heuristic. The two-point crossover neighborhood randomly chooses $\%tpc|\mathcal{K}|$ pairs of routes (i.e., parent routes). Each pair of routes starts from an RP and ends at the same RP. For each parent route, two points are randomly chosen, where the points are located either between delivery or pickup customers. The new route (i.e., offspring route) is generated by merging two strings, where each string consists of customers located between the two points on each parent route.

In the first half of the neighborhood search sub-iterations I_{ns}, the aim is to diversify the search space. Thus, higher proportions are assigned to the nearest insertion and two-point crossover neighborhoods compared to the inter-route interchange and inter-route shuffle neighborhoods. In the second half of the neighborhood search sub-iterations, the aim is to intensify the search space. Thus, higher proportions are assigned to the inter-route interchange and inter-route shuffle neighborhoods compared to the nearest insertion and two-point crossover neighborhoods.

After I_{ns} sub-iterations, the best found solution $s^* \in S^*, k^* \in \mathcal{K}^*$ and the corresponding total cost $F_p = F_p^1(S^*) + F_p^2(\mathcal{K}^*) + \sum_{r \in p} f_r$ are saved for a given RP configuration $p \in P$.

In the next main iteration, the other RP configuration $p \in P$ is chosen, and the second and third phases of the decomposition-based heuristic are followed. Whenever the number of RPs increases by one, the increase is checked to see if it leads to better solution. In other words, if condition (3.21) is satisfied, $|P_i^A|$ additional RP configurations $p \notin P_i$ are examined.

$$\min_{p \in P_i} F_p < \min_{p' \in P_{i-1}} F_{p'}, 2 \leq i \leq |R| \tag{3.21}$$

The overall best found solution and its corresponding total cost $F_{p^*} = F_{p^*}^1(S^*) + F_{p^*}^2(\mathcal{K}^*) + \sum_{r \in p^*} f_r$ are saved at the end of the algorithm. The stop criterion for the algorithm is the number of main iterations (i.e., $\sum_{i=1}^{|R|} |P_i| + \sum_{i=2}^{|R|} |P_i^A|$).

The steps of the decomposition-based heuristic are illustrated in Figure 3.2. The sets and parameters used in the decomposition-based heuristic are explained in Table 3.3.

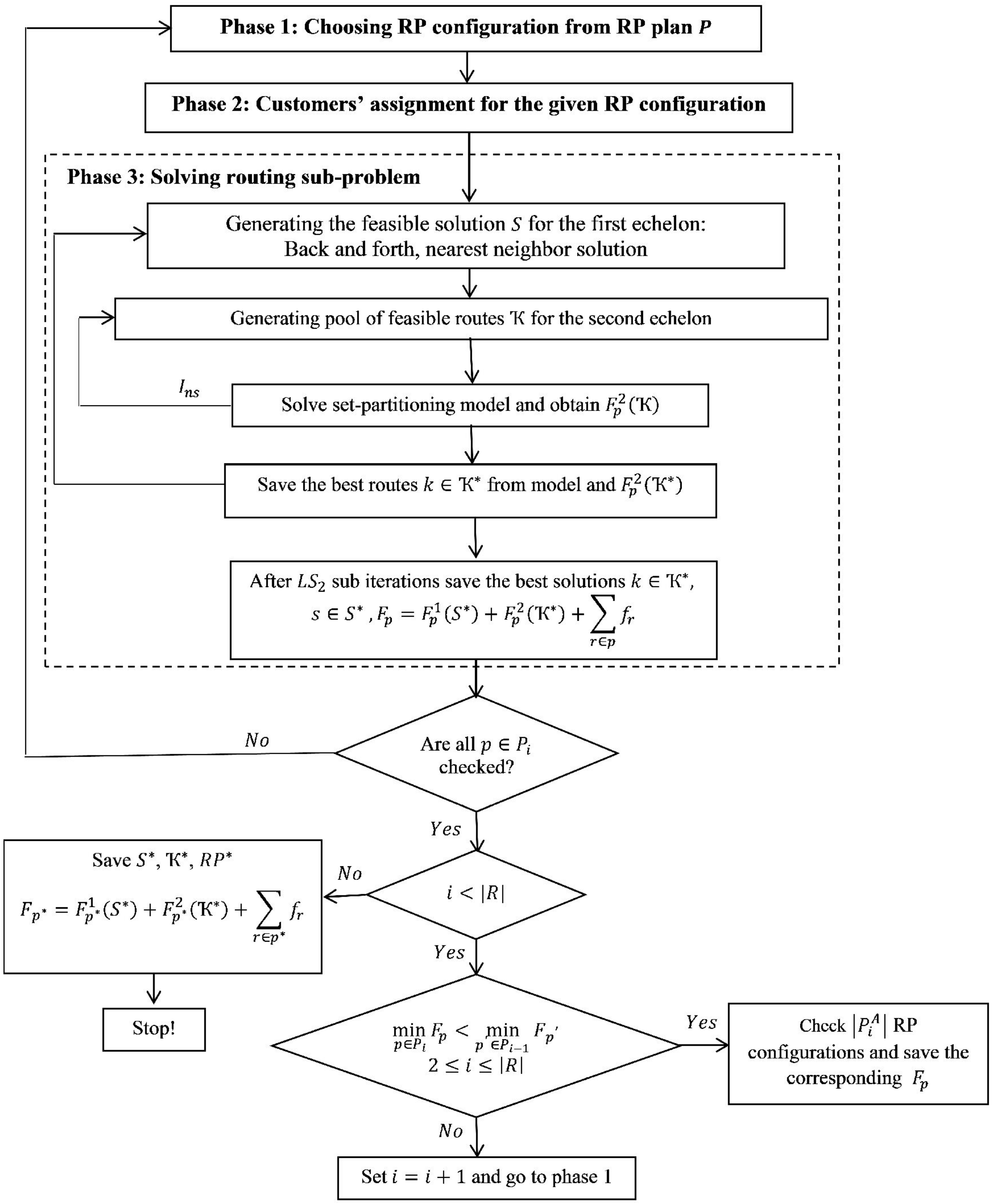


Figure 3.2: Steps of the decomposition-based heuristic

Table 3.3: Sets and parameters used in the decomposition-based heuristic

Sets and parameters	**Description**
P_i	subset of RP configurations containing i RPs, $\forall i \in R$
P_i^A	subset of RP configurations containing i RPs not belonging to P_i, $2 \leq i \leq \|R\|$
η	coefficient used to calculate the cardinality of set P_i^A
$\lambda_1, \lambda_2, \lambda_3$	coefficients used to calculate $\mathcal{S}_p$
N	minimum number of main iterations
S	feasible solution for the first echelon
$\mathcal{K}$	pool of feasible routes for the second echelon
$TW_D = (e^D, l^D)$	time window for visiting customers in the delivery wave
$TW_P = (e^P, l^P)$	time window for visiting customers in the pickup wave
$\mathcal{T}_i$	time of visiting node i, $\forall i \in J^D \cup J^P$
I_{ns}	number of neighborhood search sub-iterations
	for the pool of routes in the second echelon $\mathcal{K}$
$\|J^{max}\|$	upper bound for the number of customers on route $k \in K$
$0 \leq \%iri \leq 1$	proportion of the inter-route interchange neighborhood
$0 \leq \%irs \leq 1$	proportion of the inter-route shuffle neighborhood
$0 \leq \%ni \leq 1$	proportion of the nearest insertion neighborhood
$0 \leq \%tpc \leq 1$	proportion of the two-point crossover neighborhood

In this chapter we have proposed a three-phase decomposition-based heuristic for the 2E-LRP with synchronization and sequential delivery and pickup. In the following chapter, we provide computational results for different sets of instances using actual data, as well as some experimental instances.

Chapter 4

Numerical experiments

In this chapter, we provide the computational results for different sets of instances generated from actual data as well as some experimental instances. In order to check the quality of the solutions and computational effort, we compared the results obtained by the decomposition-based heuristic with the results obtained from solving the mixed-integer linear programming (MILP) formulation provided in Chapter 2. In order to check the effect of diversification in the first phase of the heuristic on solution quality, we provided the solutions considering only the RP configuration with the lowest value for $\mathcal{S}_p$ within the RP plan. We checked the effect of the change in number of neighborhood search I_{ns} on the solution quality for different sets of instances. In order to compare the effect of RP configuration choices on solution quality, we modified the first phase of the proposed method by following the common approach used in the literature for choosing RP configurations and we compared the results. The MILP formulation was coded in AMPL using the solver CPLEX 12.6. For each instance, a time limit of 12 hours was considered. The decomposition-based heuristic was coded in Python 3.5 using the solver CPLEX 12.6. Both the MILP formulation and decomposition-based heuristic were coded on a computer with 4 CPU cores and 8 GB of RAM.

4.1 Sets of instances

We consider four different sets of instances: SI1, SI2, SI3, and SI4. The first set of instances (SI1) is generated based on the actual data of Posten Norge. The difference between SI1 and the other three sets of instances is in the traveling time. For SI1, the traveling times are obtained from real data; for SI2, SI3, and SI4, the traveling times are proportional to the corresponding Euclidean distances.

In addition, the four sets of instances differ regarding the customer location distribution. For SI1, there is no specific pattern for the customer location distribution because the instances are randomly chosen among a large set of customers in a real dataset. In each set of instances SI2, SI3, and SI4, the customer location distribution has a specific pattern.

For SI1, seven different sizes are considered from 15 to 50. For SI2, SI3, and SI4, seven different sizes are considered from 15 to 70. For each size, four instances are considered: *a, b, c*, and *d*. The characteristics of the four sets of instances are provided in the appendix at the end of this chapter.

In the second set of instances (SI2), the terminal is located at the center of the plane, and the customers are located in different clusters far from the terminal. Figure 4.1 shows an example of a feasible solution for SI2.

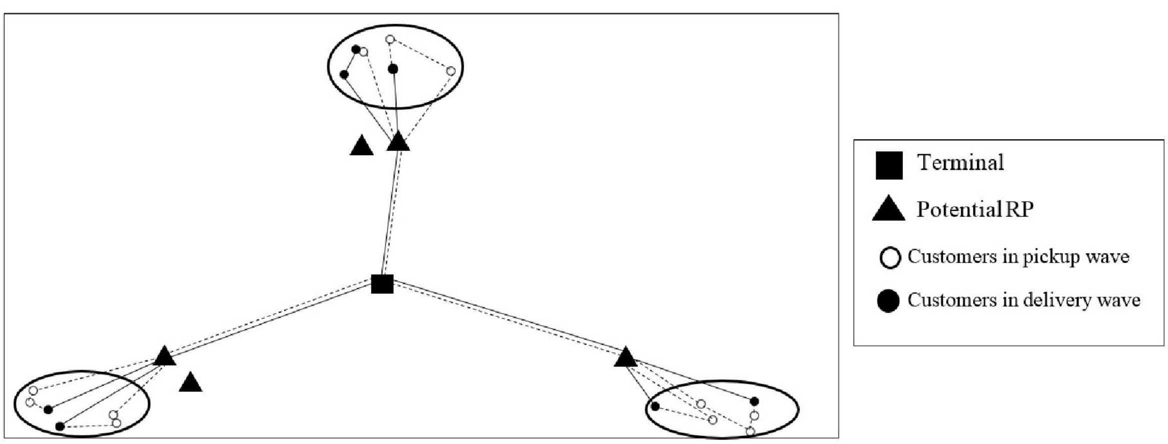


Figure 4.1: Feasible solution for SI2

In the third set of instances (SI3), the terminal is located at the center of the plane, and the customers are located uniformly around the terminal. Figure 4.2 shows an example of a feasible solution for SI3. Note that there are no customers in a circle around the depot. This is because the customers in this area are served directly from the depot and not via an RP.

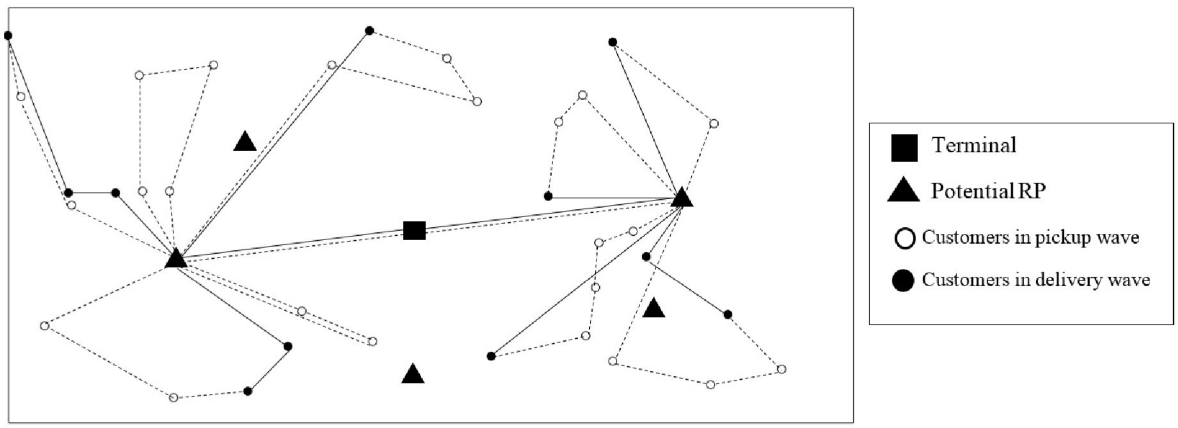


Figure 4.2: Feasible solution for SI3

In the fourth set of instances (SI4), the terminal is located in the corner of the plane, and the customers are located uniformly around the terminal. Again, however, a quarter of a circle close to the depot is excluded. Figure 4.3 shows an example of a feasible solution for SI4.

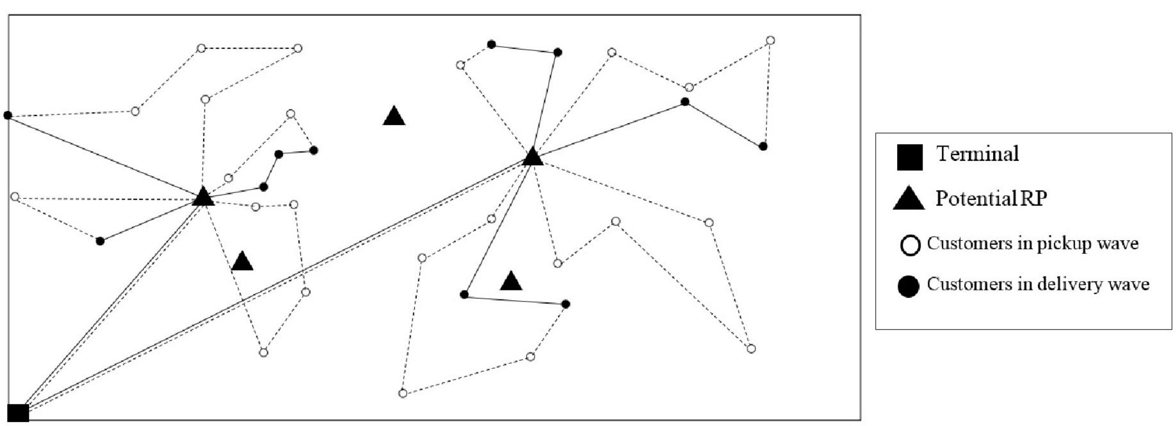


Figure 4.3: Feasible solution for SI4

4.2 Parameter setting

We set the parameters used in the decomposition-based heuristic according to the experimental tests. In the experimental tests, 28 instances were generated that are not included in the sets of instances explained above. We checked the improvement in the solution quality with changes in the parameters provided in Table 3.3 for the instances, and we determined the values that yielded the best performance. In order to diversify the search space, we assigned higher proportions to the nearest insertion and two-point crossover neighborhoods in the first half of the neighborhood search sub-iterations. The proportion values of the neighborhoods were set to $\%iri = 0.2, \%irs = 0.1, \%ni = 0.6, \%tpc = 0.1$ in the first half of the neighborhood search sub-iterations. In order to intensify the search space, we assigned higher proportions to the inter-route interchange and inter-route shuffle neighborhoods in the second half of the neighborhood search sub-iterations. The proportion values of the neighborhoods were set to $\%iri = 0.4, \%irs = 0.3, \%ni = 0.2, \%tpc = 0.1$ in the second half of the neighborhood search sub-iterations. The coefficients used to calculate the RP configurations scores $\mathcal{S}_p$ were set to $\lambda_1 = 1, \lambda_2 = 1$, and $\lambda_3 = 0.4$. The number of neighborhood search sub-iterations for the pool of routes was set to $I_{ns} = 30$. We set the values of $N = 10$ and $\eta = 0.3$ because they resulted in a good tradeoff between the running time and solution quality.

4.3 Computational results

Given the above parameters, the computational results for the four sets of instances SI1, SI2, SI3, and SI4 are provided here. Each instance was run once with the CPLEX solver. Because of the randomness incorporated in the decomposition-based heuristic, we performed five runs with the proposed method for each instance and determined the average and minimum objective function values. The results obtained by the lower bound for the presented problem are given here. We obtained the lower bound by relaxing the integrality in the

MILP formulation. In order to check the effect of diversification in the first phase of the decomposition-based heuristic, we only considered the RP configuration with the lowest value for $\mathcal{S}_p, \forall p \in P$ and followed the second and third phases of the decomposition-based heuristic. We performed five runs on each instance and determined the average values.

We used the gap to the best-known solution (GBK) in order to compare the values of the objective function generated by different approaches.

$$GBK_i = \frac{OF_i - \min OF_i}{\min OF_i} * 100 \tag{4.1}$$

where OF_i is the objective function value generated by approach i.

Table 4.1 reports the aggregated results obtained by different approaches. The details of the results are provided in Tables 4.7–4.10 in the appendix at the end of this chapter. Columns $\overline{GBK}_{MILP}$ and $\overline{CPU}_{MILP}$ represent the average GBK and time spent (in seconds), respectively, for instances obtained by solving the MILP. Headers $\overline{GBK}_{avg}$, $\overline{GBK}_{min}$, and $\overline{CPU}_{min}$ correspond to the average GBK, minimum GBK, and average time spent, respectively, for instances obtained from the decomposition-based heuristic. Header *# of BKS* represents the number of best-known solutions (BKSs) found by the decomposition-based heuristic. Column $\overline{GBK}_{NNS}$ corresponds to the average GBK for instances solved by the decomposition-based heuristic without the use of neighborhood search (i.e., $I_{ns} = 0$). Column $\overline{GBK}_{LB}$ represents the average GBK for instances obtained by the proposed lower bound. Header $\overline{GBK}_{RCLS}$ corresponds to the average GBK for instances obtained by considering the RP configuration with the lowest score of $\mathcal{S}_p, \forall p \in P$. In the column *Set*, the superscripts *S, M* refer to *small-* and *medium-size* instances containing 40 nodes or less, and the superscript *L* refers to *large-size* instances containing more than 40 nodes.

The decomposition-based heuristic was able to find the best-known solutions in 26 of 112 instances, including 11 small- and medium-size and 15 large-size instances. For the small- and medium-size instances, the average GBK with the decomposition-based heuristic was 4.23, and the average GBK obtained with CPLEX was 0.34. The average time spent on

Table 4.1: Aggregated results obtained by different approaches

Set	CPLEX		Decomposition-based heuristics						
	$\overline{GBK}_{MILP}$	$\overline{CPU}_{MILP}$	$\overline{GBK}_{avg}$	$\overline{GBK}_{min}$	$\overline{CPU}_{avg}$	#of BKS	$\overline{GBK}_{NNS}$	$\overline{GBK}_{RCLS}$	$\overline{GBK}_{LB}$
$SI1^{S,M}$	0.00	7592	6.68	4.69	295	0	21.1	22.0	-33.6
$SI2^{S,M}$	0.12	15385	2.06	1.22	296	2	26.1	4.9	-70.6
$SI3^{S,M}$	0.63	10625	3.11	1.61	10625	4	12.5	9.6	-37.8
$SI4^{S,M}$	0.62	7308	5.08	3.53	333	5	12.5	13.7	-26.8
Average	0.34	10228	4.23	2.76	2887		18.1	12.6	-42.2
$SI1^{L}$	1.58	34634	2.73	0.28	1455	3	30.5	21.8	-36.3
$SI2^{L}$	-	43200	1.12	0.00	3665	4	90.9	3.5	-72.4
$SI3^{L}$	-	43200	1.92	0.00	3108	4	18.7	9.4	-44.5
$SI4^{L}$	-	43200	2.22	0.00	3743	4	24.0	13.4	-37.2
Average	1.58	41058	2.00	0.07	2993		41.0	12.0	-47.6

^{S,M} restricted to instances containing 40 nodes or less
^{L} restricted to instances containing more than 40 nodes
total # of BKS by decomposition-based heuristic = 26/112

instances by the decomposition-based heuristic was 2887 s, which is almost one-fourth the time spent by the CPLEX solver. For the small- and medium-size instances, the lowest and highest gaps between the average GBK of the decomposition-based heuristic and the CPLEX solver were obtained with SI2 and SI1, respectively. The high gap in the average GBK for the two sets of instances was due to the difference in customer location distributions for the two sets. The customers in SI2 were located in clusters, while the customer location distribution in SI1 did not follow any specific pattern, and the randomness incorporated in the neighborhood search had less effect on the solution of the routing sub-problem for SI2 compared to SI1. For the large-size instances, the CPLEX solver was not able to find feasible solutions for SI2, SI3, and SI4. The average time spent on instances by the decomposition-based heuristic was 2993 s.

Based on the results provided in column $\overline{GBK}_{NNS}$, the quality of solutions obtained by the decomposition-based heuristic without neighborhood search was poor. The average GBK was 18.1 for the small- and medium-size instances and 41.0 for the large-size instances.

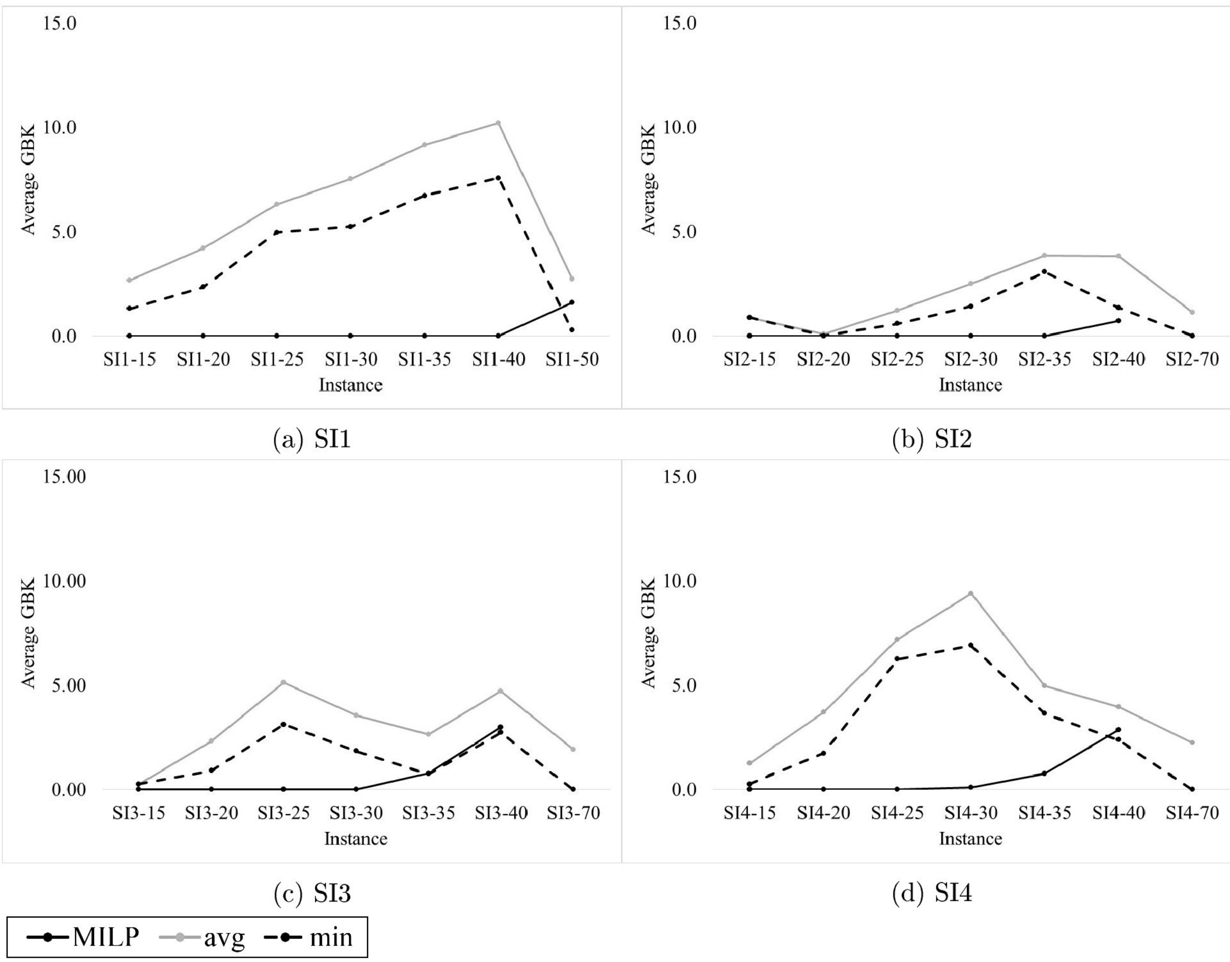
The average GBK with the decomposition-based heuristic considering the RP configuration with the lowest score was 12.6 for the small- and medium-size instances. However, the quality of the solutions was still lower than the best-known solution. This may be because only the RP configuration with the lowest value of $\mathcal{S}_p, \forall p \in P$ was considered; this does not necessarily provide the optimal RP configuration. The search space needed to be diversified by the consideration of more RP configurations in order to improve the solution quality.

The results with the proposed lower bound showed that the gap between the relaxed solutions and BKS was too high. The average GBK for the large-size instances was -47.6.

Figures 4.4a–4.4d compare the average GBK (i.e., average values out of four instances for each size) obtained by different approaches to the four sets of instances. The solid black line represents the average GBK for each size of instances obtained by solving the MILP. The gray and dashed black lines illustrate the average and minimum GBK for each size of instances obtained by the decomposition-based heuristic. As shown in these figures, the gap between the average GBK with the decomposition-based heuristic and by solving the MILP increased with the size of the instances until a size was reached where CPLEX was either unable to find a solution or provided solutions with lower quality compared to the proposed method (e.g., for instances in SI1, the size was 50). The gap was due to the random nature of neighborhoods used to solve the routing sub-problem.

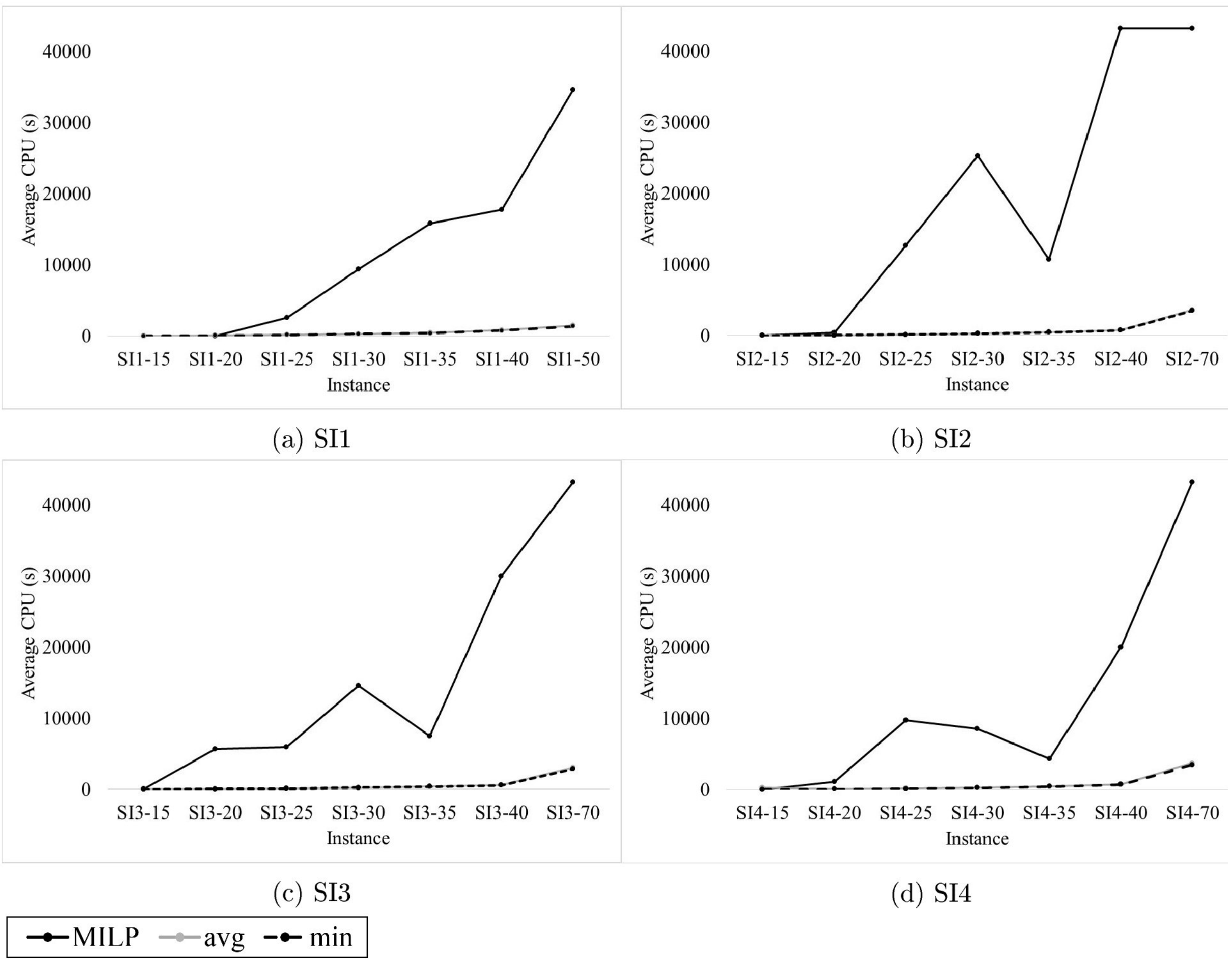
Figures 4.5a–4.5d illustrate the average times spent by different approaches on each size of the four sets of instances. As the size of the instances increased, the computational time of the decomposition-based heuristic was much less than that of the MILP. The time spent on instances by CPLEX did not always increase (e.g., the time spent on instances with a size of 35 was less than the time spent on a size of 30 for SI2). This is because CPLEX stopped solving some instances owing to the limited memory.

We checked the effect of the number of neighborhood search sub-iterations I_{ns} on the solution quality and computational time. We chose 28 instances of sizes between 15 and 70 nodes. For each size, we chose four instances, including one from each set of instances. We



(a) SI1 (b) SI2 (c) SI3 (d) SI4

Figure 4.4: Average GBK obtained by different approaches to the four sets of instances



(a) SI1

(b) SI2

(c) SI3

(d) SI4

Figure 4.5: Average CPUs obtained by different approaches to the four sets of instances

considered three levels: $I_{ns} = 10, I_{ns} = 30$, and $I_{ns} = 50$. We set the other parameters of the decomposition-based heuristic as described in Section 4.2.

GBK was calculated by using equation (4.1) for the three levels of I_{ns}. Table 4.2 lists the aggregated results obtained for different levels of I_{ns}. The detailed results are provided in Table 4.11 of the appendix. Columns $\overline{GBK}$ and $\overline{CPU}$ in Table 4.2 correspond to the average GBK and time spent on each set of instances, respectively.

The improvement in solution quality was marginal when the number of local search sub-iterations was increased from 30 to 50 (i.e., average $\overline{GBK}$ changed from 0.74 to 0.00), while there was a notable gap between the obtained solution quality with $I_{ns} = 10$ and $I_{ns} = 50$. The average times spent at $I_{ns} = 10$ and $I_{ns} = 30$ were almost one-fifth and half, respectively, the time spent at $I_{ns} = 50$. This confirms that a reasonable value was chosen for I_{ns} (i.e., 30 sub-iterations) when the parameters were set in order to obtain good-quality solutions within a reasonable amount of computational time. Figure 4.6 compares the average time spent on each size of instances for the three levels of I_{ns}. The dashed black line represents the results with $I_{ns} = 10$. The gray and solid black lines represent the results with $I_{ns} = 30$ and $I_{ns} = 50$, respectively.

Table 4.2: Aggregated results for different numbers of local search sub-iterations

	$\overline{GBK}$			$\overline{CPU}$		
Set	I_{ns}=10	I_{ns}=30	I_{ns}=50	I_{ns}=10	I_{ns}=30	I_{ns}=50
SI1	3.96	0.64	0.00	234	562	1029
SI2	2.29	0.36	0.00	385	906	1873
SI3	4.36	1.01	0.00	344	715	1830
SI4	3.63	0.94	0.00	416	837	2159
Average	3.56	0.74	0.00	345	755	1723

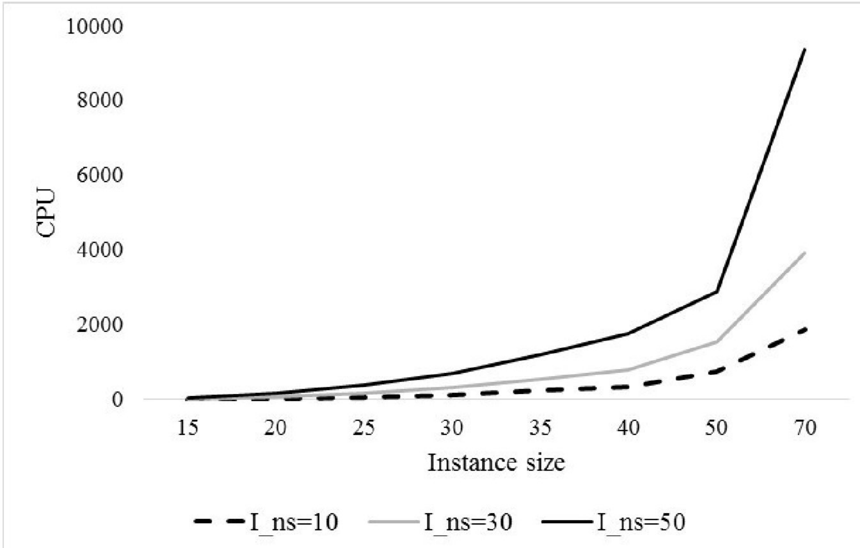


Figure 4.6: CPU comparison for the different numbers of neighborhood search sub-iterations

Finally, we modified the first phase of the decomposition-based heuristic by following the common approach used in the solution methods in the literature for location-routing problems (LRPs), and we compared the results obtained by the original method and modified method.

The common approach in the literature is to start with an initial facility configuration (chosen either randomly or the one with the lowest opening costs) and to explore different facility configurations by using different neighborhoods. Such neighborhoods open, close, and switch facilities during the search procedure (e.g., *open plant, close plant, and switch plant* neighborhoods in Albareda-Sambola et al. (2005) and *satellite removal, satellite swap, or satellite opening* operators in Contardo et al. (2012)).

Figure 4.7 illustrates the steps of the modified decomposition-based heuristic. This starts with the RP configuration having the lowest score S_p (i.e., with the highest rank). The second and third phases are the same as those for the original decomposition-based heuristic. We explored different RP configurations using the three neighborhoods: *open, close and switch plant* (i.e., RP in the presented problem) proposed by Albareda-Sambola et al. (2005). During the search procedure, the *close plant* neighborhood is explored first.

If no admissible move using *close plant* is found or the RP configuration consists of one RP, *switch plant* is explored. The *open plant* neighborhood is only explored when no admissible move is found with the other two neighborhoods. The maximum number of main iterations of the algorithm was set as the stopping condition.

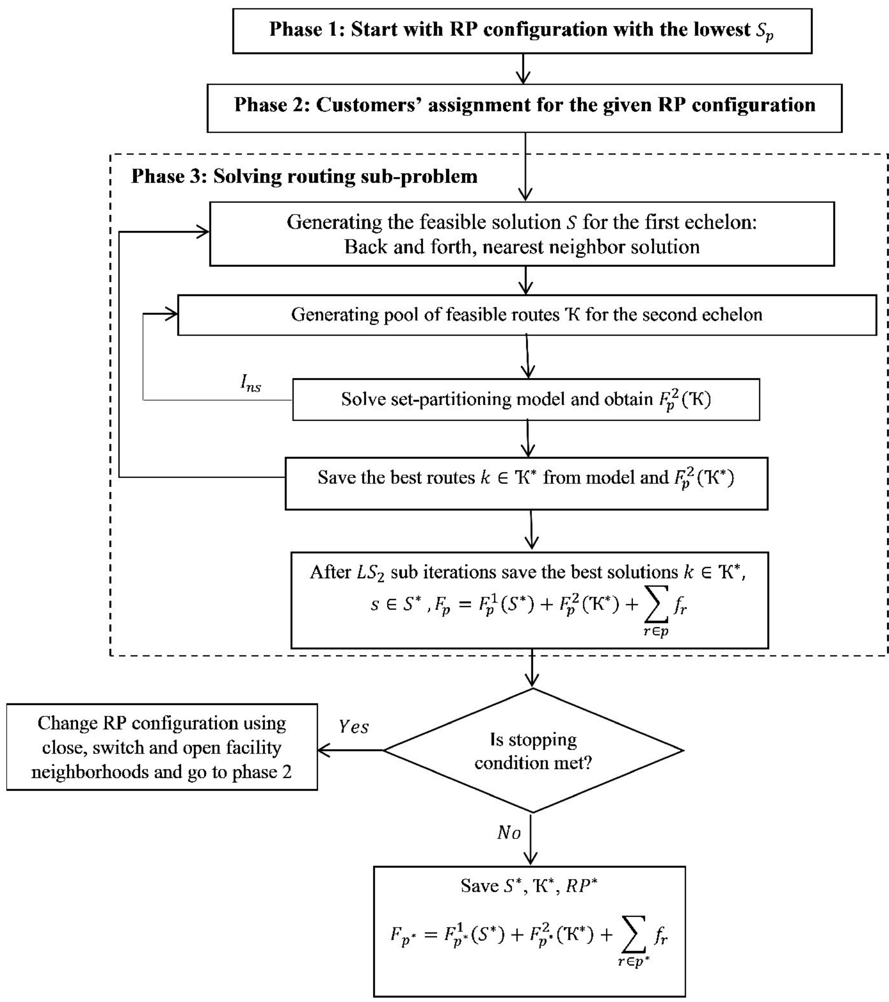


Figure 4.7: Steps of the modified decomposition-based heuristic

We considered thirty instances from SI1, SI2, SI3, and SI4. The instances were chosen randomly. The maximum number of main iterations was set to 10 for both the original and modified decomposition-based heuristics. For the original decomposition-based heuristic, we set $N = 10 - |R| - 1$ and $\eta = 0$. The values of the other parameters were set as provided in Section 4.2. We performed five runs of both the original and modified methods on each instance. We define $\sigma = \dfrac{OF_{DBH}}{OF_{MDBH}}$ in order to compare the solution qualities obtained by the two methods, where OF_{DBH} and OF_{MDBH} correspond to the objective function values obtained by the original and modified decomposition-based heuristics, respectively. A value of unity for σ implies that the obtained solution is the same for both methods. A value less than unity for σ indicates that better solutions were obtained with the original decomposition-based heuristic than with the modified decomposition approach. Figure 4.8 compares the solution qualities obtained from the original and modified decomposition-based heuristics. The solid line represents $\sigma = 1$. Because the second and third phases were the same in both the original and modified decomposition-based heuristics, differences in the obtained solutions were only due to the RP configurations explored by each method. We obtained solutions with lower or equal values of the objective function for 20 out of 30 instances with the original decomposition-based heuristic. This implies that, for a given number of iterations, the original decomposition-based heuristic explores RP configurations that provide better-quality solutions.

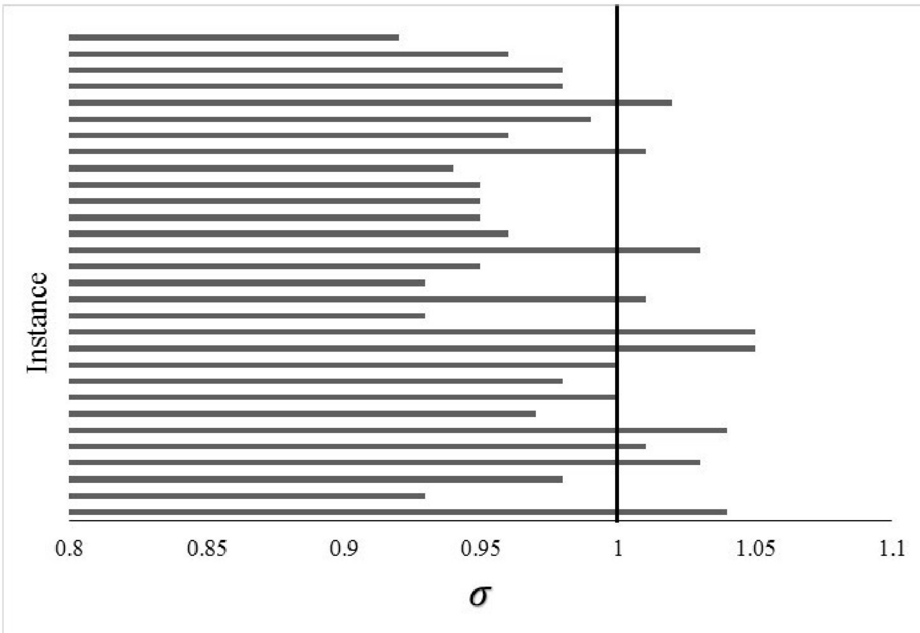


Figure 4.8: Comparison between solution qualities of original and modified decomposition-based heuristics

In Chapter 5, we introduce different schemes that are used in combination with the MILP formulation in order to reduce the set of feasible solutions and check to what extent the schemes help to find better solutions in less time.

4.4 Appendix: characteristics of sets of instances and details of results

This appendix provides the characteristics of the four sets of instances and details for some of results that are summarized in Section 4.3.

Tables 4.3–4.6 provide the characteristics of the instances in SI1, SI2, SI3, and SI4. In these tables, $|R|$ is the number of potential sites for RPs, $|J^P|$ is the number of customers in the pickup wave, and $|J^D|$ is the number of customers in the delivery wave. $|O|$ is the cardinality of singleton set O. The size of the instances refers to the total number of nodes.

Each row of Tables 4.3–4.6 represents four different instances with the same size: *a, b, c*, and *d*. Set R was the same for all instances.

Table 4.3: Characteristics of instances in SI1

Instance	|R|	$\|J^P\|$	$\|J^D\|$	$\|O\|$	Number of nodes
SI1-15 (a,b,c,d)	5	7	2	1	15
SI1-20 (a,b,c,d)	5	10	4	1	20
SI1-25 (a,b,c,d)	5	13	6	1	25
SI1-30 (a,b,c,d)	5	17	7	1	30
SI1-35 (a,b,c,d)	5	20	9	1	35
SI1-40 (a,b,c,d)	5	23	11	1	40
SI1-50 (a,b,c,d)	5	29	15	1	50

Table 4.4: Characteristics of instances in SI2

Instance	|R|	$\|J^P\|$	$\|J^D\|$	$\|O\|$	Number of nodes
SI2-15 (a,b,c,d)	5	7	2	1	15
SI2-20 (a,b,c,d)	5	10	4	1	20
SI2-25 (a,b,c,d)	5	13	6	1	25
SI2-30 (a,b,c,d)	5	17	7	1	30
SI2-35 (a,b,c,d)	5	20	9	1	35
SI2-40 (a,b,c,d)	5	23	11	1	40
SI2-70 (a,b,c,d)	5	39	25	1	70

Table 4.5: Characteristics of instances in SI3

Instance	|R|	$\|J^P\|$	$\|J^D\|$	$\|O\|$	Number of nodes
SI3-15 (a,b,c,d)	5	7	2	1	15
SI3-20 (a,b,c,d)	5	10	4	1	20
SI3-25 (a,b,c,d)	5	13	6	1	25
SI3-30 (a,b,c,d)	5	17	7	1	30
SI3-35 (a,b,c,d)	5	20	9	1	35
SI3-40 (a,b,c,d)	5	23	11	1	40
SI3-70 (a,b,c,d)	5	39	25	1	70

Table 4.6: Characteristics of instances in SI4

Instance	|R|	$\|J^P\|$	$\|J^D\|$	$\|O\|$	Number of nodes
SI4-15 (a,b,c,d)	5	7	2	1	15
SI4-20 (a,b,c,d)	5	10	4	1	20
SI4-25 (a,b,c,d)	5	13	6	1	25
SI4-30 (a,b,c,d)	5	17	7	1	30
SI4-35 (a,b,c,d)	5	20	9	1	35
SI4-40 (a,b,c,d)	5	23	11	1	40
SI4-70 (a,b,c,d)	5	39	25	1	70

Table 4.7–4.10 report the detailed results obtained by the decomposition-based heuristic for the four sets of instances. In these tables, column (BKS) corresponds to the best-known solution. Column RP corresponds to the location decision obtained in the best-known solution. Header *gap to optimality* represents the gap to optimality as reported by the CPLEX solver. The * symbol in the column *out of memory* indicates that the memory limit was exceeded. Column GBK_{MILP} represents GBK obtained by solving MILP for each instance. Columns GBK_{avg} and GBK_{min} correspond to the average and minimum GBK, respectively, obtained from five runs with the decomposition-based heuristic for each instance. Column GBK_{NNS} corresponds to GBK obtained by the decomposition-based approach without neighborhood search for each instance. Header CPU_{MILP} stands for the time spent (in seconds) on each instance by the CPLEX solver. Headers CPU_{avg} and CPU_{min} stand for the average and minimum times spent, respectively, for the five runs on each instance with the decomposition-based heuristic.

Table 4.11 reports the details of results obtained at three levels for I_{ns}. Headers GBK and CPU represent the gap to the best-known solution and time spent at each level of I_{ns}, respectively, for each instance.

Table 4.7: Detailed results for SI1

			$MILP$										
Instance	BKS	RP	GTO	Out of memory	GBK_{MILP}	GBK_{avg}	GBK_{min}	GBK_{NNS}	GBK_{RCLS}	GBK_{LB}	CPU_{MILP}	CPU_{avg}	CPU_{min}
SI1-15a	9270.4	3	0.0		0.0	2.4	1.1	6.9	8.2	-32.7	18	21	20
SI1-15b	6342.4	1	0.0		0.0	1.9	0.6	33.5	53.4	-21.2	4	23	21
SI1-15c	6234.2	4	0.0		0.0	3.0	1.4	7.9	32.8	-37.3	10	23	19
SI1-15d	5563.3	2	0.0		0.0	3.3	2.1	15.5	18.5	-34.0	6	25	21
Average			0.0		0.0	2.7	1.3	16.0	28.2	-31.3	9.6	23.1	20.3
SI1-20a	12027.8	2,3	0.0		0.0	1.8	0.5	2.6	11.3	-30.9	11	63	60
SI1-20b	10462.4	4,5	0.0		0.0	4.9	3.7	10.3	10.3	-36.7	26	71	65
SI1-20c	9333.1	1	0.0		0.0	5.1	2.1	13.3	35.3	-29.7	30	75	70
SI1-20d	10597.6	3	0.0		0.0	5.1	3.1	20.6	16.4	-33.4	56	63	61
Average			0.0		0.0	4.2	2.4	11.7	18.3	-32.7	31.1	67.9	64.0
SI1-25a	11148.3	4	0.0		0.0	5.6	5.4	15.9	15.8	-36.6	2578	152	141
SI1-25b	9067.7	1,3	0.0		0.0	7.4	5.7	19.3	25.3	-40.9	56	158	143
SI1-25c	10033.1	4	0.0		0.0	5.7	3.7	34.6	36.2	-37.3	3587	155	150
SI1-25d	14904.8	4	0.0		0.0	6.6	5.0	8.8	13.8	-27.4	4116	137	129
Average			0.0		0.0	6.3	5.0	19.7	22.8	-35.6	2584.2	150.4	140.8
SI1-30a	13826.5	1,3	8.8	*	0.0	6.7	4.5	13.1	24.2	-39.0	7464	269	259
SI1-30b	12007.6	3	15.9	*	0.0	7.5	5.9	27.5	16.6	-39.2	6269	312	275
SI1-30c	13628.2	1,5	19.2	*	0.0	4.4	2.6	23.5	17.9	-42.0	3530	305	297
SI1-30d	12770.5	4	0.0		0.0	11.6	7.9	26.9	31.7	-27.7	20284	268	254
Average			11.0		0.0	7.5	5.2	22.7	22.6	-37.0	9386.7	288.4	271.3
SI1-35a	15018.3	3,4	6.0	*	0.0	8.4	6.4	11.5	18.2	-30.9	5240	459	297
SI1-35b	14557.2	3,4	5.4	*	0.0	9.3	7.3	24.4	10.4	-27.2	11260	478	413
SI1-35c	17747.9	4	2.8		0.0	9.5	6.9	24.4	12.0	-27.5	43200	450	413
SI1-35d	15243.2	4	18.6	*	0.0	9.4	6.3	30.8	21.6	-35.3	3599	461	401
Average			8.2		0.0	9.2	6.7	22.8	15.6	-30.2	15824.8	462.1	381.0
SI1-40a	15246.3	3,5	21.4	*	0.0	12.3	9.2	33.4	25.3	-38.7	5821	778	754
SI1-40b	16362.5	2	8.0	*	0.0	3.3	3.0	15.8	19.8	-37.4	15955	751	714
SI1-40c	11669.4	4	13.9	*	0.0	11.9	8.4	45.8	28.7	-36.6	5887	790	751
SI1-40d	14987.2	4	7.3		0.0	13.3	9.7	40.9	24.1	-25.8	43200	784	761
Average			12.7		0.0	10.2	7.6	34.0	24.5	-34.6	17715.6	775.7	745.0
SI1-50a	21782.0	4,5	-		-	3.2	0.0	31.7	35.2	-32.4	43200	1409	1154
SI1-50b	20418.0	3,5	-		-	3.5	0.0	27.3	18.8	-41.1	43200	1515	1470
SI1-50c	22083.0	3,5	28.2	*	3.2	1.0	0.0	27.8	6.2	-37.8	32193	1452	1416
SI1-50d	21940.0	3,4	21.3	*	0.0	3.3	1.1	35.1	26.8	-34.1	19942	1444	1421
Average			24.8		1.6	2.7	0.3	30.5	21.8	-36.3	34633.8	1454.8	1365.3

Table 4.8: Detailed results for SI2

			$MILP$										
Instance	BKS	RP	GTO	Out of memory	GBK_{MILP}	GBK_{avg}	GBK_{min}	GBK_{NNS}	GBK_{RCLS}	GBK_{LB}	CPU_{MILP}	CPU_{avg}	CPU_{min}
SI2-15a	6068.9	1,3	0.0		0.0	0.0	0.0	3.6	1.9	-66.3	22.7	21.8	20.0
SI2-15b	6020.3	2,3	0.0		0.0	1.8	1.8	1.9	1.8	-65.2	15.9	21.4	20.0
SI2-15c	6305.7	2,3	0.0		0.0	0.0	0.0	2.1	4.5	-64.6	12.3	21.6	21.0
SI2-15d	6353.3	1,3	0.0		0.0	1.7	1.7	1.7	2.1	-65.8	17.8	19.5	17.0
Average			0.0		0.0	0.9	0.9	2.3	2.6	-65.5	17.2	21.1	19.5
SI2-20a	6493.0	1,3	0.0		0.0	0.1	0.0	7.4	0.2	-58.3	49.0	68.5	65.0
SI2-20b	6210.0	2,3	0.0		0.0	0.0	0.0	10.5	0.0	-61.9	27.1	70.3	68.0
SI2-20c	6493.0	2,3	0.0		0.0	0.2	0.0	7.1	1.1	-56.7	37.3	69.5	65.0
SI2-20d	6398.0	1,3	0.0		0.0	0.0	0.0	1.8	1.2	-62.3	1568.0	70.5	68.0
Average			0.0		0.0	0.1	0.0	6.7	0.6	-59.8	420.4	69.7	66.5
SI2-25a	6730.5	1,3	23.3	*	0.0	1.5	0.8	13.8	2.5	-79.1	19629.8	144.8	142.0
SI2-25b	6963.4	2,3	0.0		0.0	1.4	1.0	29.8	3.5	-74.0	20735.6	147.0	141.0
SI2-25c	6857.6	1,3	27.9	*	0.0	0.8	0.2	20.1	2.8	-78.0	4438.2	147.8	140.0
SI2-25d	6660.9	2,3	35.6	*	0.0	1.1	0.3	18.9	1.6	-77.0	5797.7	165.8	161.0
Average			21.7		0.0	1.2	0.6	20.7	2.6	-77.0	12650.3	151.3	146.0
SI2-30a	6983.5	1,3	9.5		0.0	1.4	0.7	22.1	1.7	-74.9	43200.0	242.5	236.0
SI2-30b	6836.7	2,3	44.6	*	0.0	2.3	1.5	18.3	2.5	-79.1	10869.5	308.4	300.0
SI2-30c	6982.6	1,3	24.4	*	0.0	2.8	1.0	41.8	4.1	-75.0	9599.6	306.3	299.0
SI2-30d	6863.5	2,3	0.0		0.0	3.5	2.5	37.3	6.7	-75.2	37399.2	309.0	300.0
Average			19.6		0.0	2.5	1.4	29.9	3.7	-76.0	25267.1	291.5	283.8
SI2-35a	7136.4	1,3	38.7	*	0.0	6.5	5.5	56.6	9.7	-67.4	10181.7	492.8	475.0
SI2-35b	6933.2	2,3	48.0	*	0.0	3.3	2.1	37.9	6.3	-75.9	7822.8	522.0	464.0
SI2-35c	7290.1	2,3	47.9	*	0.0	3.2	2.8	37.8	5.0	-72.8	4833.7	470.0	456.0
SI2-35d	7207.9	1,3	43.8	*	0.0	2.4	1.8	41.0	14.9	-70.6	20170.2	447.5	412.0
Average			44.6		0.0	3.9	3.1	43.3	9.0	-71.7	10752.1	483.1	451.8
SI2-40a	7092.2	2,5	44.7		0.0	3.7	2.7	49.2	3.9	-76.7	43200.0	805.5	765.0
SI2-40b	6997.2	1,3	50.6		0.0	3.1	2.7	45.1	16.8	-76.8	43200.0	861.3	815.0
SI2-40c	7312.0	1,5	43.0		2.1	6.9	0.0	59.3	12.1	-68.3	43200.0	701.8	679.0
SI2-40d	7641.0	2,5	-		-	1.6	0.0	62.4	11.4	-71.6	43200.0	677.3	651.0
Average			46.1		0.7	3.8	1.4	54.0	11.1	-73.4	43200.0	761.4	727.5
SI2-70a	8875.0	2,3	-		-	3.4	0.0	95.1	3.3	-72.4	43200.0	3509.0	3261.0
SI2-70b	8617.0	1,3	-		-	0.3	0.0	78.9	0.5	-76.4	43200.0	4087.0	3927.0
SI2-70c	9092.0	2,3	-		-	0.3	0.0	93.1	7.6	-71.0	43200.0	3401.8	3198.0
SI2-70d	8791.0	2,3	-		-	0.5	0.0	96.2	2.6	-69.8	43200.0	3662.0	3552.0
Average			-		-	1.1	0.0	90.9	3.5	-72.4	43200.0	3664.9	3484.5

Table 4.9: Detailed results for SI3

			$MILP$										
Instance	BKS	RP	GTO	Out of memory	GBK_{MILP}	GBK_{avg}	GBK_{min}	GBK_{NNS}	GBK_{RCLS}	GBK_{LB}	CPU_{MILP}	CPU_{avg}	CPU_{min}
SI3-15a	8826.0	1	0.0		0.0	0.0	0.0	8.0	7.2	-39.9	56	20	18
SI3-15b	6836.0	3	0.0		0.0	0.0	0.0	1.3	17.9	-40.1	15	21	19
SI3-15c	8099.1	3	0.0		0.0	0.0	0.0	2.3	3.6	-42.8	35	21	19
SI3-15d	7984.5	1	0.0		0.0	1.1	1.1	7.4	14.3	-40.5	32	20	19
Average			0.0		0.0	0.3	0.3	4.8	10.8	-40.8	34.6	20.3	18.8
SI3-20a	9933.2	1	0.0		0.0	4.2	2.9	17.8	18.2	-34.2	7066	57	55
SI3-20b	9128.0	3	10.8	*	0.0	1.8	0.0	7.6	8.5	-40.1	5666	57	52
SI3-20c	9931.5	1,4	12.5	*	0.0	0.4	0.3	3.1	0.1	-42.8	4759	58	53
SI3-20d	8568.6	1,4	8.7	*	0.0	2.9	0.4	11.6	8.5	-43.0	5145	62	61
Average			8.0		0.0	2.3	0.9	10.0	8.8	-40.0	5659.0	58.5	55.3
SI3-25a	10971.0	2,5	9.8	*	0.0	6.1	3.2	12.1	15.0	-34.9	5094	129	121
SI3-25b	9566.1	2,3	14.6	*	0.0	4.8	2.5	8.6	8.7	-40.7	5818	143	135
SI3-25c	10323.8	1,5	20.6	*	0.0	5.1	2.9	10.8	2.1	-42.9	3802	137	130
SI3-25d	11472.0	2,4	0.0		0.0	4.5	3.9	8.6	11.9	-29.2	8935	129	120
Average			11.2		0.0	5.1	3.1	10.0	9.4	-36.9	5912.5	134.2	126.5
SI3-30a	10816.1	1,4	13.4	*	0.0	3.3	1.8	15.7	19.2	-37.1	6826	237	220
SI3-30b	12540.6	1,4	5.9	*	0.0	4.5	2.4	13.8	9.2	-33.2	37849	236	225
SI3-30c	12209.6	1,5	14.6	*	0.0	2.2	1.0	13.5	5.1	-35.1	6378	250	241
SI3-30d	13394.6	1,4	8.5	*	0.0	4.2	2.3	11.3	14.0	-33.4	7369	241	220
Average			10.6		0.0	3.6	1.9	13.6	11.9	-34.7	14605.5	240.9	226.5
SI3-35a	12018.0	2,5	26.4	*	2.4	1.4	0.0	11.4	1.6	-43.3	8630	420	412
SI3-35b	13525.5	2,4	14.2	*	0.0	5.8	2.8	22.9	14.3	-34.4	8966	419	411
SI3-35c	14891.2	2,3	26.1	*	0.0	1.7	0.2	16.7	3.0	-40.9	5598	400	393
SI3-35d	14559.0	1,4	28.1	*	0.8	1.7	0.0	9.4	14.7	-37.9	6958	396	380
Average			23.7		0.8	2.7	0.7	15.1	8.4	-39.1	7537.8	408.5	399.0
SI3-40a	15280	2,4	-		-	1.6	0.0	17.0	5.2	-40.0	43200	616	606
SI3-40b	14536	2,5	22.8	*	0.0	2.2	0.4	20.2	8.0	-37.2	26091	576	545
SI3-40c	14575	2,5	15.1		0.0	11.3	10.5	26.0	16.3	-27.5	43200	551	535
SI3-40d	14623	2,4	26.6	*	8.9	3.7	0.0	22.7	4.6	-36.7	7521	599	584
Average			21.5		3.0	4.7	2.7	21.5	8.5	-35.3	30002.9	585.6	567.5
SI3-70a	21041.0	1,4	-		-	1.0	0.0	22.3	19.5	-42.8	43200	3041	2566
SI3-70b	22099.0	2,3,4	-		-	2.2	0.0	11.5	5.1	-45.9	43200	3241	3101
SI3-70c	21639.0	1,2,5	-		-	1.5	0.0	14.7	5.2	-47.3	43200	3025	2741
SI3-70d	23231.0	2,3	-		-	3.0	0.0	26.2	7.9	-42.2	43200	3124	3050
Average			-		-	1.9	0.0	18.7	9.4	-44.5	43200.0	3107.8	2864.5

Table 4.10: Detailed results for SI4

			MILP										
Instance	*BKS*	*RP*	*GTO*	Out of memory	GBK_{MILP}	GBK_{avg}	GBK_{min}	GBK_{NNS}	GBK_{RCLS}	GBK_{LB}	CPU_{MILP}	CPU_{avg}	CPU_{min}
SI4-15a	5142.0	5	0.0		0.0	1.5	1.0	6.9	13.2	-41.5	12	24	22
SI4-15b	5517.6	5	0.0		0.0	1.0	0.0	12.9	16.7	-37.5	8	21	19
SI4-15c	5819.0	3	0.0		0.0	1.0	0.0	4.7	9.1	-35.0	22	20	19
SI4-15d	4608.3	4	0.0		0.0	1.7	0.0	2.7	30.0	-36.7	9	1169	22
Avergae			0.0		0.0	1.3	0.3	6.8	17.2	-37.7	12.8	308.4	20.5
SI4-20a	7941.7	1,4,5	0.0		0.0	4.0	2.2	16.9	4.8	-23.2	19	70	65
SI4-20b	9623.7	4,5	0.0		0.0	3.7	2.0	11.5	12.9	-13.2	44	63	61
SI4-20c	10062.8	2,4	0.0		0.0	3.2	0.7	5.8	9.2	-26.9	4380	64	62
SI4-20d	8574.2	1,3	0.0		0.0	3.9	2.1	9.0	12.4	-15.4	20	70	67
Avergae			0.0		0.0	3.7	1.7	10.8	9.8	-19.7	1115.4	66.4	63.8
SI4-25a	10751.7	1,5	0.0		0.0	7.1	6.2	13.3	11.3	-24.7	24437	149	141
SI4-25b	10188.2	1,5	0.0		0.0	8.2	7.1	9.8	15.4	-17.7	4825	154	148
SI4-25c	11336.6	4,5	6.4	*	0.0	7.1	6.3	9.3	13.1	-24.2	4875	159	152
SI4-25d	10456.7	1,5	0.0		0.0	6.3	5.3	17.5	15.3	-19.9	5108	154	148
Avergae			1.6		0.0	7.2	6.2	12.5	13.8	-21.6	9811.3	154.0	147.3
SI4-30a	11485.8	2,3,4	7.1	*	0.0	9.5	7.3	23.8	21.9	-20.7	6903	261	245
SI4-30b	12122.0	1,3	16.7	*	0.3	1.1	0.0	10.3	16.0	-26.9	6608	288	275
SI4-30c	11792.1	4,5	19.6	*	0.0	17.0	12.3	29.0	34.9	-29.3	3243	252	242
SI4-30d	11957.9	4,5	9.4	*	0.0	10.1	8.0	17.2	13.1	-22.1	17471	293	278
Avergae			13.2		0.1	9.4	6.9	20.1	21.5	-24.7	8556.1	273.0	260.0
SI4-35a	13257.6	2,3	15.0	*	0.0	12.9	11.6	20.8	14.5	-26.4	4631	456	442
SI4-35b	14182.0	2,3,4	20.8	*	0.5	0.9	0.0	3.5	7.0	-34.3	4987	475	425
SI4-35c	14617.1	1,4,5	22.8	*	0.0	5.3	2.9	11.2	10.1	-31.9	3786	457	448
SI4-35d	15190.0	1,2,3	19.0	*	2.5	0.7	0.0	6.8	5.8	-27.4	3980	452	440
Avergae			19.4		0.8	5.0	3.6	10.6	9.4	-30.0	4346.0	459.9	438.8
SI4-40a	14990.0	2,4	-		-	1.9	0.0	15.5	7.9	-30.1	-	705	681
SI4-40b	14355.1	4,5	18.3		0.0	1.9	1.4	15.9	8.4	-27.4	43200	796	775
SI4-40c	14308.3	4,5	11.4	*	0.0	10.9	8.1	17.7	16.7	-21.4	9708	724	699
SI4-40d	15365	1,3	35.2	*	8.6	1.1	0.0	8.4	9.2	-30.7	7115	732	721
Avergae			21.6		2.9	4.0	2.4	14.4	10.5	-27.4	20007.8	739.2	719.0
SI4-70a	23355.0	2,3	-		-	2.5	0.0	26.0	17.8	-33.9	43200	3897	3750
SI4-70b	23628.0	2,3,4	-		-	0.5	0.0	21.4	9.9	-40.8	43200	3740	3266
SI4-70c	20737.0	1,3	-		-	4.3	0.0	24.9	14.2	-35.9	43200	3713	3389
SI4-70d	22774.0	2,3	-		-	1.7	0.0	23.7	11.5	-38.2	43200	3620	3415
Avergae			-		-	2.2	0.0	24.0	13.4	-37.2	43200.0	3742.7	3455.0

Table 4.11: Detailed results for different numbers of local search sub-iterations

	GBK			*CPU*		
Instance	I_{ns}=10	I_{ns}=30	I_{ns}=50	I_{ns}=10	I_{ns}=30	I_{ns}=50
SI1-15c	5.90	2.01	0.00	12	39	61
SI1-20c	3.01	0.00	0.00	39	116	194
SI1-25c	9.54	0.85	0.00	79	239	421
SI1-30a	1.16	0.00	0.00	150	434	752
SI1-35b	2.36	0.93	0.00	259	755	1324
SI1-40b	4.23	0.35	0.00	362	805	1572
SI1-50c	1.52	0.34	0.00	741	1545	2878
Average	3.96	0.64	0.00	234	562	1029
SI2-15a	0.00	0.00	0.00	12	36	63
SI2-20d	1.81	0.00	0.00	34	81	178
SI2-25c	3.55	0.00	0.00	74	168	403
SI2-30a	1.91	0.61	0.00	125	315	656
SI2-35c	2.20	0.35	0.00	236	520	1269
SI2-40d	3.62	0.35	0.00	338	870	1948
SI2-70c	2.95	1.17	0.00	1878	4350	8594
Average	2.29	0.36	0.00	385	906	1873
SI3-15b	0.00	0.00	0.00	10	20	51
SI3-20c	0.44	0.00	0.00	30	60	153
SI3-25d	6.41	0.73	0.00	66	148	340
SI3-30c	4.47	0.39	0.00	125	255	684
SI3-35a	7.10	3.05	0.00	211	424	1089
SI3-40d	3.31	0.00	0.00	296	650	1625
SI3-70a	8.80	2.88	0.00	1671	3450	8869
Average	4.36	1.01	0.00	344	715	1830
SI4-15a	2.17	1.92	0.00	12	25	66
SI4-20b	4.70	0.61	0.00	34	72	178
SI4-25c	3.48	0.46	0.00	76	168	426
SI4-30a	5.23	0.00	0.00	141	305	735
SI4-35d	0.00	0.00	0.00	234	481	1155
SI4-40a	5.74	2.36	0.00	376	824	1965
SI4-70a	4.11	1.22	0.00	2041	3982	10591
Average	3.63	0.94	0.00	416	837	2159

Chapter 5

Schemes for the model

In this chapter, we propose three data-driven schemes that we use in combination with the mixed-integer linear programming (MILP) formulation provided in Chapter 2. The idea of the schemes is to remove routes that are unlikely to be part of high-quality solutions. We expect to get promising solutions in less time when the schemes are used. The first scheme removes the set of *long arcs* connecting pairs of far apart nodes from the original set of arcs. The idea is similar to the *filtering rule* used in granular tabu search (Toth and Vigo, 2003). The *granularity threshold* is defined in order to distinguish long arcs and calculated based on the sparseness of the graph. In the first scheme, we use a simple criterion based on the notion of farness to distinguish long arcs (i.e., the arcs that connect two far nodes from each other) and we remove such long arcs from the original set of arcs in the second echelon. The other two types of schemes are new and, to the best of our knowledge, have not been addressed in the literature.

5.1 Reducing the set of feasible solutions

We define the three schemes below. In the first scheme, *long arcs* (i.e., arcs connecting pairs of far apart nodes) are removed from arcs set of the second echelon, A^2. The second scheme implies that customers that are close to each other must be served from the same opened RP, while the third scheme implies that any pair of customers that are close to each other, but far from an opened RP, must be on the same tour. For the second and third schemes, we define additional constraints, while for the first scheme we just modify the set of arcs in the second echelon from A^2 to $A^{2'}$, where in $A^{2'}$ we exclude the long arcs in A^2. In order to analyze the three schemes, we define new terms as follows.

Farness: Two nodes i and j are far apart if the direct travel time between them is greater than $\alpha \cdot \max\{T\}$, where α is a given parameter, and $\max\{T\}$ is the maximum travel time between any two nodes among all pairs of nodes in set A^2.

Closeness: Two nodes i and j are close to each other if the direct travel time between them is less than $\beta \cdot \max\{T\}$, where β is a given parameter.

We define the following subsets of arcs.

LongArcs: All pairs of nodes that are far apart in the second echelon.

$$LongArcs = \{(i,j) \in A^2 | T^2_{ij} > \alpha \cdot \max\{T\}\}$$

CloseCustomers: All pairs of nodes that are close to each other in the second echelon.

$$CloseCustomers = \{(i,j) | i,j \in J, 0 < T^2_{ij} < \beta \cdot \max\{T\}\}$$

The different schemes are as follows.

(a) **No secondary vehicle k traverses arc $(i,j) \in A^2$ if nodes i and j are far from each other.**

Here, we define set $A^{2'}$ and we use it instead of set A^2 in the MILP formulation (i.e., (2.1)–(2.31));

$$A^{2'} = \{(i,j) \in A^2 | (i,j) \notin LongArcs\}$$

(b) **Customers close to each other must be served from the same RP.**

We define the binary variables y_{rj} below.

$$y_{rj} = \begin{cases} 1 & \text{if customer } j \text{ is served from RP } r, \forall r \in R, j \in J \\ 0 & \text{otherwise} \end{cases}$$

$$\sum_{i \in V^2} x^2_{rik} + \sum_{i \in V^2} x^2_{ijk} \leq 1 + y_{rj} \quad \forall r \in R, k \in K, j \in J \tag{5.1}$$

$$\sum_{i \in V^2} x^2_{rik} + \sum_{i \in V^2} x^2_{ijk} + M(1 - \sum_{i \in V^2} x^2_{ijk}) \geq 2y_{rj} \quad \forall r \in R, k \in K, j \in J \tag{5.2}$$

Constraints (5.1) and (5.2) ensure that customer j is served from RP r (i.e., $y_{rj} = 1$) if it is visited by a vehicle that departs from RP r (i.e., $\sum_{i \in V^2} x^2_{rik} = 1$ and $\sum_{i \in V^2} x^2_{ijk} = 1$). With y_{rj} from (5.1) and (5.2), if two customers i and j are close to each other, they must be served from the same RP:

$$y_{rj} = y_{ri} \quad \forall r \in R, (i,j) \in \mathit{CloseCustomers} \tag{5.3}$$

(c) **Any pair of customers close to each other, while far from an opened RP, must be served on the same tour. Note that this does not apply if the pair of customers is close to an opened RP; in that case, they may or may not be on the same tour.**

$$\sum_{h \in V^2} x^2_{hik} \geq \frac{1}{2}\Big(\sum_{r \in RF_j} y_{rj} + \sum_{r \in RF_i} y_{ri}\Big) - M\Big(1 - \sum_{h \in V^2} x^2_{hjk}\Big) \;\; \forall k \in K, (i,j) \in \mathit{CloseCustomers} \tag{5.4}$$

Here, RF_i is the set of RPs far from node $i \in J$.

It is worth reflecting on what we are doing. Assume for argument's sake that the problem is solved with a Benders-like algorithm and consider the use of optimality cuts. Such cuts remove feasible points that cannot be optimal. This is contrary to feasibility cuts (as well as faces, facets, and valid inequalities in discrete optimization), which only cut away points that are not feasible. In this chapter, we generate (explicitly or implicitly) inequalities that behave like optimality cuts; they distinctly cut away feasible points, but contrary to proper optimality cuts, they may also cut away the optimal solution. Hence, they can be seen as approximate (or heuristic) optimality cuts.

In addition, note that the schemes can be seen as a way to approximate the routing cost. The difference between the proposed schemes and most routing approximation formulas in the literature is that, in the latter, the routing costs are approximated based on Euclidean distances, while this is not true for the former. In the next section, we show the extent to which the schemes help with finding better solutions in a given amount of time or reducing the time to obtain a certain quality compared to not using the schemes. Because of the data-driven nature of schemes, infeasible solutions for the instances may be found. We perform numerical experiments to check the validity of the schemes in terms of finding feasible solutions given the best-known solutions for different sets of instances.

Note that even if the optimal solution is cut away, this is of minor importance if we can get better solutions than without the schemes, since optimal solutions are generally not available for larger instances. So apart from very small instances, we cannot check if the optimal solution is actually cut away. We can only check if the schemes lead to better solutions.

Finally, note that, although the presented model determines both RP locations and vehicle routes, only the first is of real interest. Hence, we shall not be too worried if the schemes change the optimal routing if they do not change the optimal RPs.

5.2 Numerical experiments

In the previous section, we defined different schemes to reduce the set of feasible solutions and hopefully reduce the solution time. In this section, we provide computational results for different sets of instances (SI). For each set of instances, we tested the schemes to see if they led to better solutions in less time. All computations were coded in AMPL using the solver CPLEX 12.6 on a computer with 24 CPU cores and 35 GB of RAM. For each instance, we considered a time limit of one hour.

5.2.1 Computational results

In this section, we provide the computational results for the four sets of instances provided in Section 4.1. In total, there are seven possible scheme combinations to examine: (a), (b), (c), (a, b), (a, c), (b, c), and (a, b, c). First, the three single schemes were implemented: (a), (b), and (c). The results for schemes (b) and (c) alone were of lower quality than those of scheme (a). Hence, for the sake of brevity, we only present the results for scheme (a) and the full set (a, b, c) here. Five different combinations were considered for each instance. The first combination was without the schemes (i.e., using the MILP formulation of Section 2.2). The second and third combinations were only with scheme (a), using two different levels for α. The fourth and fifth combinations used all three schemes (a, b, c) with two different choices for (α, β).

We checked the chosen values of α with scheme (a) and (α, β) with schemes (a, b, c) to see if they cut the feasible set of the solution space. The solutions were fixed as the best-known solutions (i.e., the values for BKSs in Tables 4.7–4.10), and we implemented MILP with the schemes for the four sets of instances. Feasible solutions were obtained for all instances using the schemes, which showed that the chosen values for α in scheme (a) and (α, β) for all three schemes did not cut the set of feasible solutions.

In order to compare the values of the objective function for the different combinations, we calculated the gap to the best-known solution (GBK) with equation (4.1).

In the appendix at the end of this chapter, we show all of the details of the results, particularly how the different combinations worked for each instance. We also discuss the results in some detail. In this section, we present the highlights of the results. An upper bound on the computational time of one hour was placed on all of the instances. For all but the smallest cases, this CPU time was spent. Hence, what is in fact being reported in most cases is the solution quality that could be obtained in one hour.

Tables 5.1–5.4 report the aggregated results for the five combinations of schemes on the four sets of instances. In these tables, header $\overline{GBK}$ represents the average GBK for each size of instances obtained with different combinations. The bold numbers correspond to the lowest value of GBK obtained out of the five combinations on each size of instances.

The average GBK for SI1 is reported in Table 5.1. Compared to the solutions without the schemes, the objective function values either got better or remained the same, on average, when scheme (a) or all of the schemes were used.

Note that a GBK of zero occurred only if that combination was best for *all* four instances for that size. The appendix details which combination produced the best result for each instance.

Table 5.1: Aggregated results for SI1 without and with the schemes

Instance	without schemes	Scheme: a		Schemes: a, b, and c	
α or (α, β)		0.8	0.7	(0.8,0.15)	(0.7,0.2)
	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$
SI1-15	0.00	0.00	0.00	0.00	0.00
SI1-20	0.00	0.00	0.00	0.00	0.00
SI1-25	0.00	0.00	0.00	0.00	0.00
SI1-30	0.04	0.03	**0.01**	0.03	0.04
SI1-35	3.23	**0.58**	0.91	0.78	2.26
SI1-40	13.75	5.74	**4.30**	4.90	4.57
SI1-50	-	-	-	-	-

Table 5.2: Aggregated results for SI2 without and with the schemes

Instance	without schemes	Scheme: a		Schemes: a, b, and c	
α or (α, β)		0.7	0.6	(0.7,0.1)	(0.6,0.15)
	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$
SI2-15	0.00	0.00	0.00	0.00	0.00
SI2-20	0.00	0.00	0.00	0.00	0.00
SI2-25	0.00	0.00	0.00	0.00	0.00
SI2-30	0.49	0.35	0.45	**0.13**	0.21
SI2-35	0.54	0.42	0.49	**0.10**	0.35
SI2-40	0.91	0.15	0.09	6.81	**0.00**
SI2-70	-	-	-	-	-

The average GBK for the instances in SI2, SI3, and SI4 are reported in Tables 5.2–5.4, respectively. For these sets of instances, with only scheme (a), the average GBK stayed the same or improved compared to the combination without the schemes. Note that, for both SI3 and SI4, the combined scheme was necessary in order to obtain feasible solutions to the larger instances.

Table 5.3: Aggregated results for SI3 without and with the schemes

Instance	without schemes	Scheme: a		Schemes: a, b, and c	
α or (α, β)		0.8	0.7	(0.8,0.15)	(0.7,0.2)
	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$
SI3-15	0.00	0.00	0.00	0.00	0.00
SI3-20	0.00	0.00	0.00	0.00	0.00
SI3-25	0.00	0.00	0.00	1.11	0.55
SI3-30	1.40	1.40	**0.45**	0.60	0.46
SI3-35	13.63	11.15	12.97	**2.15**	2.22
SI3-40	-	-	-	**0.00**	-
SI3-70	-	-	-	-	-

Table 5.4: Aggregated results for SI4 without and with the schemes

Instance	without schemes	Scheme: a		Schemes: a, b, and c	
α or (α, β)		0.8	0.7	(0.8,0.15)	(0.7,0.2)
	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$	$\overline{GBK}$
SI4-15	0.00	0.00	0.00	0.00	0.00
SI4-20	0.00	0.00	0.00	0.00	0.00
SI4-25	0.00	0.00	0.00	0.47	2.18
SI4-30	0.49	0.03	**0.00**	2.51	2.70
SI4-35	10.04	3.05	9.71	**0.89**	7.76
SI4-40	-	-	-	**0.00**	-
SI4-70	-	-	-	-	-

Generally speaking, with scheme (a), we obtained either lower or the same values for the objective function, on average, compared to the solutions without any scheme. When we used the combined scheme, feasible solutions could be found to some of the larger instances that were unsolvable without the schemes or with only scheme (a). This shows that schemes (b) and (c) work well together with scheme (a).

These results show that the gap between $\overline{GBK}$ of the best found solutions obtained by the schemes and the solutions without the schemes increased with the size of the instances.

The other notable finding is that the performance of the schemes depended on the customer distribution in the instance. For instances in SI1, SI3, and SI4, the gap between the best solution (i.e., with the lowest value of $\overline{GBK}$) with all schemes and the solution without schemes was higher compared to the results obtained for SI2. This implies that the schemes provided higher-quality solutions for the instances where customers were uniformly distributed on the plane (e.g., SI3 and SI4) compared to instances where the customers were located rather densely on specific parts of the plane (e.g., SI2).

5.2.2 Appendix: details of results without and with schemes

In this appendix, we present and discuss the details of the results that are summarized in Section 5.2.1. Tables 5.5–5.8 detail the results obtained from different combinations for four sets of instances. In these tables, column *CPU* represents the time spent (in seconds) on each instance in each combination. Column *Gap%* corresponds to the gap to optimality reported by the CPLEX solver. Column *GBK* corresponds to the GBK obtained by each combination for each instance. Finally, header *RP* represents the location decisions obtained by each combination for each instance. For scheme (a), two levels of α and two levels of (α, β) were used; see the table for actual values.

We start with SI1. The results are listed in Table 5.5. All small instances of sizes 15 and 20 were solved optimally in a shorter amount of time either with scheme (a) or the combined schemes, and the location decisions for all instances were the same as for the solutions without the schemes. For instances of size 25, the lowest average CPU time of 976 s was observed when only scheme (a) was used with $\alpha = 0.7$. For larger instances of sizes 35 and 40, the lowest average GBK was observed with either scheme (a) or the combined schemes.

For SI2, the results are listed in Table 5.6. The instances of sizes 20 and 25 were solved in a shorter amount of time with a GBK of zero when the combined schemes were used. With the combined schemes, a lower average GBK was also observed for larger instances of sizes 30 and 35. For instances of size 40, two more instances were solved with the lowest average GBK when a combined scheme with $(\alpha, \beta) = (0.6, 0.15)$ was used.

For SI3, see Table 5.7. For the instances of sizes 30 and 35, the average GBK decreased with either scheme (a) or the combined scheme.

Finally, consider SI4. As indicated by the results in Table 5.8, with $(\alpha, \beta) = (0.7, 0.2)$ for the combined schemes, the average CPU time for instances of 20 decreased from 920 to 54 s. The lowest average GBK of 0.89 was observed for instances of size 35 when a combined scheme with $(\alpha, \beta) = (0.8, 0.15)$ was used.

For both SI3 and SI4, one of the large instances of size 40 was solved with the combined scheme using $(\alpha, \beta) = (0.8, 0.15)$.

Table 5.5: Detailed results for SI1 without and with the schemes

	Without schemes				**Scheme: a**								**schemes: (a, b, c)**							
α or (α, β)					**0.8**				**0.7**				**(0.8,0.15)**				**(0.7,0.2)**			
Instance	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**
SI1-15a	19	0.0	0.00	r3	17	0.0	0.00	r3	13	0.0	0.00	r3	22	0.0	0.00	r3	14	0.0	0.00	r3
SI1-15b	5	0.0	0.00	r1	3	0.0	0.00	r1	4	0.0	0.00	r1	5	0.0	0.00	r1	7	0.0	0.00	r1
SI1-15c	32	0.0	0.00	r4	10	0.0	0.00	r4	9	0.0	0.00	r4	22	0.0	0.00	r4	17	0.0	0.00	r4
SI1-15d	10	0.0	0.00	r2	12	0.0	0.00	r2	8	0.0	0.00	r2	20	0.0	0.00	r2	9	0.0	0.00	r2
Average	17	0.0	0.00		11	0.0	0.00		8	0.0	0.00		17	0.0	0.00		12	0.0	0.00	
SI1-20a	22	0.0	0.00	r2,r3	18	0.0	0.00	r2,r3	17	0.0	0.00	r2,r3	23	0.0	0.00	r2,r3	22	0.0	0.00	r2,r3
SI1-20b	24	0.0	0.00	r4,r5	20	0.0	0.00	r4,r5	22	0.0	0.00	r4,r5	30	0.0	0.00	r4,r5	24	0.0	0.00	r4,r5
SI1-20c	25	0.0	0.00	r1	34	0.0	0.00	r1	33	0.0	0.00	r1	136	0.0	0.00	r1	21	0.0	0.00	r1
SI1-20d	176	0.0	0.00	r3	23	0.0	0.00	r3	71	0.0	0.00	r3	35	0.0	0.00	r3	24	0.0	0.00	r3
Average	62	0.0	0.00		24	0.0	0.00		36	0.0	0.00		56	0.0	0.00		**22**	0.0	0.00	
SI1-25a	2961	0.0	0.00	r4	3600	1.8	0.00	r4	177	0.0	0.00	r4	291	0.0	0.00	r4	326	0.0	0.00	r4
SI1-25b	64	0.0	0.00	r1,r3	67	0.0	0.00	r1,r3	272	0.0	0.00	r1,r3	144	0.0	0.00	r1,r3	178	0.0	0.00	r1,r3
SI1-25c	3600	3.1	0.00	r4	3600	3.7	0.00	r4	3161	0.0	0.00	r4	3600	3.7	0.00	r4	3600	2.7	0.00	r4
SI1-25d	406	0.0	0.00	r4	84	0.0	0.00	r4	293	0.0	0.00	r4	3256	0.0	0.00	r4	122	0.0	0.00	r4
Average	1758	0.8	0.00		1838	1.36	0.00		**976**	0.0	0.00		1823	0.9	0.00		1056	0.7	0.00	
SI1-30a	3600	7.4	0.00	r1,r3	3600	4.6	0.00	r1,r3	3600	4.3	0.00	r1,r3	3600	3.7	0.00	r1,r3	3600	9.9	0.00	r1,r3
SI1-30b	3600	11.0	0.16	r3	3600	10.8	0.13	r3	3600	7.1	0.00	r3	3600	4.2	0.11	r4	3600	10.2	0.18	r4
SI1-30c	3600	7.8	0.00	r4	3600	15.6	0.00	r4	3600	8.4	0.00	r4	3600	1.2	0.00	r4	3600	15.6	0.00	r4
SI1-30d	3600	3.5	0.00	r4	3600	3.5	0.00	r4	3600	4.5	0.03	r4	3600	3.5	0.00	r4	3600	4.3	0.00	r4
Average	3600	7.4	0.04		3600	8.62	0.03		3600	6.1	**0.01**		3600	3.2	0.03		3600	10.0	0.04	
SI1-35a	3600	10.7	1.64	r3,r4	3600	11.1	2.32	r1,r3	3600	7.7	0.00	r3,r4	3600	10.9	1.66	r3,r4	3600	13.9	5.22	r3,r5
SI1-35b	3600	14.1	3.04	r4	3600	10.4	0.00	r3,r4	3600	12.3	0.00	r3,r4	3600	11.7	0.00	r3,r4	3600	11.5	0.00	r3,r4
SI1-35c	3600	8.6	2.07	r4	3600	4.8	0.00	r3,r4	3600	12.0	2.86	r4,r5	3600	5.7	0.00	r3,r4	-	-	-	-
SI1-35d	3600	20.7	6.17	r2,r5	3600	11.7	0.00	r4	3600	15.5	0.79	r4	3600	17.2	1.45	r4	3600	17.9	1.56	r3,r4
Average	3600	10.1	3.23		3600	9.01	**0.58**		3600	11.9	0.91		3600	11.4	0.78		3600	14.5	2.26	
SI1-40a	3600	40.3	30.01	r3,r5	3600	18.8	0.00	r3,r5	3600	20.1	4.81	r3,r5	3600	16.0	1.67	r3,r5	3600	21.7	2.38	r3,r5
SI1-40b	3600	14.5	2.72	r3,r4	3600	15.4	0.00	r2,r3	3600	16.3	3.67	r1,r3	3600	13.5	1.13	r4	3600	22.1	15.50	r4
SI1-40c	3600	9.2	0.41	r4	3600	9.0	1.16	r4	3600	11.6	0.14	r4	3600	12.6	0.00	r4	3600	7.2	0.40	r4
SI1-40d	3600	26.3	21.85	r3,r5	3600	25.3	21.81	r3,r4	3600	14.5	8.56	r3,r4	3600	24.8	16.80	r3	3600	9.2	0.00	r4
Average	3600	22.6	13.75		3600	17.10	5.74		3600	15.6	**4.30**		3600	16.7	4.90		3600	15.0	4.57	
SI1-50a	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI1-50b	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI1-50c	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI1-50d	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Average	-	-	-		-	-	-		-	-	-		-	-	-		-	-	-	

Table 5.6: Detailed results for SI2 without and with the schemes

	Without the schemes				Scheme: a								Schemes: (a, b, c)							
α or (α,β)					0.7				0.6				(0.7,0.1)				(0.6,0.15)			
Instance	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**
SI2-15a	15	0.0	0.00	r1,r3	16	0.0	0.00	r1,r3	18	0.0	0.00	r1,r3	20	0.0	0.00	r1,r3	20	0.0	0.00	r1,r3
SI2-15b	17	0.0	0.00	r2,r3	17	0.0	0.00	r2,r3	12	0.0	0.00	r2,r3	23	0.0	0.00	r2,r3	32	0.0	0.00	r2,r3
SI2-15c	27	0.0	0.00	r2,r3	27	0.0	0.00	r2,r3	12	0.0	0.00	r2,r3	32	0.0	0.00	r2,r3	54	0.0	0.00	r2,r3
SI2-15d	47	0.0	0.00	r1,r3	38	0.0	0.00	r1,r3	22	0.0	0.00	r1,r3	43	0.0	0.00	r1,r3	52	0.0	0.00	r1,r3
Average	27	0.0	0.00		25	0.0	0.00		**16**	0.0	0.00		29	0.0	0.00		39	0	0.00	
SI2-20a	51	0.0	0.00	r1,r3	49	0.0	0.00	r1,r3	44	0.0	0.00	r1,r3	38	0.0	0.00	r1,r3	35	0.0	0.00	r1,r3
SI2-20b	100	0.0	0.00	r2,r3	95	0.0	0.00	r2,r3	52	0.0	0.00	r2,r3	107	0.0	0.00	r2,r3	43	0.0	0.00	r2,r3
SI2-20c	90	0.0	0.00	r2,r3	83	0.0	0.00	r2,r3	39	0.0	0.00	r2,r3	64	0.0	0.00	r2,r3	48	0.0	0.00	r2,r3
SI2-20d	3542	0.0	0.00	r1,r3	3457	0.0	0.00	r1,r3	1865	0.0	0.00	r1,r3	109	0.0	0.00	r1,r3	62	0.0	0.00	r1,r3
Average	946	0.0	0.00		921	0.0	0.00		500	0.0	0.00		80	0.0	0.00		**47**	0.00	0.00	
SI2-25a	3600	19.7	0.00	r1,r3	3600	17.8	0.00	r1,r3	3600	20.7	0.00	r1,r3	3505	0.0	0.00	r1,r3	3600	29.4	0.00	r1,r3
SI2-25b	3600	21.6	0.00	r2,r3	3600	23.2	0.00	r2,r3	3600	27.4	0.00	r2,r3	3600	22.4	0.00	r2,r3	352	0.0	0.00	r2,r3
SI2-25c	3600	22.5	0.00	r1,r3	3600	21.9	0.00	r1,r3	3600	24.4	0.00	r1,r3	3600	20.9	0.00	r1,r3	3600	21.5	0.00	r1,r3
SI2-25d	3600	22.2	0.00	r2,r3	3600	21.0	0.00	r2,r3	3600	22.4	0.00	r2,r3	207	0.0	0.00	r2,r3	3600	25.5	0.00	r2,r3
Average	3600	21.5	0.00		3600	21.0	0.00		3600	23.7	0.00		**2728**	10.8	0.00		2788	19.1	0.00	
SI2-30a	3600	35.5	1.18	r1,r3	3600	37.7	1.18	r1,r3	3600	34.6	1.18	r1,r3	3600	27.3	0.14	r1,r3	3600	23.2	0.00	r1,r3
SI2-30b	3600	37.0	0.03	r2,r3	3600	37.1	0.00	r2,r3	3600	33.0	0.00	r2,r3	3600	32.1	0.39	r2,r3	3600	39.2	0.03	r2,r3
SI2-30c	3600	29.5	0.00	r1,r3	3600	31.8	0.00	r1,r3	3600	28.4	0.00	r1,r3	3600	33.5	0.00	r1,r3	3600	40.6	0.05	r1,r3
SI2-30d	3600	41.0	0.77	r2,r3	3600	38.2	0.21	r2,r3	3600	39.6	0.62	r2,r3	3600	31.2	0.00	r2,r3	3600	37.5	0.77	r2,r3
Average	3600	35.8	0.49		3600	36.225	0.35		3600	33.9	0.45		3600	31.0	**0.13**		3600	35.1	0.21	
SI2-35a	3600	41.7	0.20	r1,r3	3600	41.7	0.20	r1,r3	3600	37.2	0.00	r1,r3	3600	44.0	0.34	r1,r3	3600	41.7	0.20	r1,r3
SI2-35b	3600	47.4	0.00	r2,r3	3600	47.4	0.00	r2,r3	3600	47.7	0.00	r2,r3	3600	44.1	0.06	r2,r3	3600	48.1	0.00	r2,r3
SI2-35c	3600	45.5	0.93	r2,r3	3600	45.6	0.93	r2,r3	3600	45.9	0.93	r2,r3	3600	33.1	0.00	r2,r3	3600	45.8	0.93	r2,r3
SI2-35d	3600	43.2	1.04	r1,r3	3600	41.2	0.53	r1,r3	3600	43.2	1.04	r1,r3	3600	31.6	0.00	r1,r3	3600	36.2	0.28	r1,r3
Average	3600	44.5	0.54		3600	44.0	0.42		3600	43.5	0.49		3600	38.2	**0.10**		3600	42.9	0.35	
SI2-40a	-	-	-	-	-	-	-	-	-	-	-	-	3600	59.4	6.57	r2,r3,r5	3600	46.4	0.00	r2,r3
SI2-40b	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI2-40c	3600	42.3	0.91	r1,r3	3600	36.3	0.15	r1,r3	3600	34.2	0.09	r1,r3	-	-	-	-	3600	31.3	0.00	r1,r3
SI2-40d	-	-	-	-	-	-	-	-	-	-	-	-	3600	59.9	7.06	r1,r4,r5	3600	54.3	0.00	r1,r3,r5
Average	3600	42.3	0.91		3600	36.3	0.15		3600	34.2	0.09		3600	44.3	6.81		3600	44.0	**0.00**	
SI2-70a	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI2-70b	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI2-70c	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI2-70d	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Average	-	-	-		-	-	-		-	-	-		-	-	-		-	-	-	

Table 5.7: Detailed results for SI3 without and with the schemes

	Without schemes				**Scheme: a**								**Schemes: (a, b, c)**							
α or (α, β)					**0.8**				**0.7**				**(0.8,0.15)**				**(0.7,0.2)**			
Instance	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**
SI3-15a	32	0.0	0.00	r1	34	0.0	0.00	r1	33	0.0	0.00	r1	24	0.0	0.00	r1	36	0.0	0.00	r1
SI3-15b	14	0.0	0.00	r3	15	0.0	0.00	r3	15	0.0	0.00	r3	16	0.0	0.00	r3	17	0.0	0.00	r3
SI3-15c	22	0.0	0.00	r3	21	0.0	0.00	r3	22	0.0	0.00	r3	31	0.0	0.00	r3	33	0.0	0.00	r3
SI3-15d	25	0.0	0.00	r1	24	0.0	0.00	r1	25	0.0	0.00	r1	25	0.0	0.00	r1	23	0.0	0.00	r1
Average	23	0.0	0.00		24	0.0	0.00		24	0.0	0.00		24	0.0	0.00		27	0.0	0.00	
SI3-20a	79	0.0	0.00	r1	79	0.0	0.00	r1	78	0.0	0.00	r1	231	0.0	0.00	r1	2204	0.0	0.00	r1
SI3-20b	3600	9.1	0.00	r3	3600	8.9	0.00	r3	3600	8.9	0.00	r3	3600	9.9	0.00	r3	3600	10.4	0.00	r3
SI3-20c	3600	13.6	0.00	r1,r4	3600	13.6	0.00	r1,r4	3600	13.7	0.00	r1,r4	3600	16.9	0.00	r1,r4	3600	12.3	0.00	r1,r4
SI3-20d	3600	2.2	0.00	r1,r4	3600	2.2	0.00	r1,r4	3600	2.0	0.00	r1,r4	3600	16.9	0.00	r1,r4	3600	8.9	0.00	r1,r4
Average	2720	6.2	0.00		2720	6.2	0.00		2720	6.1	0.00		2758	10.9	0.00		3251	7.9	0.00	
SI3-25a	3600	9.8	0.00	r2,r5	3600	9.7	0.00	r2,r5	3600	9.6	0.00	r2,r5	3600	15.1	0.00	r2,r5	3600	9.0	0.00	r2,r5
SI3-25b	3600	14.6	0.00	r2,r3	3600	14.6	0.00	r2,r3	3600	14.4	0.00	r2,r3	3600	20.9	2.80	r2,r4	3600	12.2	0.41	r2,r3
SI3-25c	3600	13.2	0.00	r1,r5	3600	13.3	0.00	r1,r5	3600	13.4	0.00	r1,r5	3600	18.3	0.00	r1,r5	3600	16.4	0.14	r1,r4
SI3-25d	3600	8.1	0.00	r2,r4	3600	8.0	0.00	r2,r4	3600	8.7	0.00	r2,r4	3600	13.9	1.64	r1,r4	3600	11.4	1.64	r1,r4
Average	3600	11.4	0.00		3600	11.4	0.00		3600	11.5	0.00		3600	17.1	1.11		3600	12.2	0.55	
SI3-30a	3600	15.8	0.00	r2,r4	3600	15.8	0.00	r2,r4	3600	15.3	0.00	r2,r4	3600	17.8	2.41	r1,r4	3600	18.1	0.00	r2,r4
SI3-30b	3600	10.0	0.05	r1,r4	3600	10.0	0.05	r1,r4	3600	10.6	0.43	r1,r4	3600	8.4	0.00	r1,r5	3600	12.3	0.62	r1,r4
SI3-30c	3600	22.6	5.57	r1,r4	3600	22.6	5.57	r1,r4	3600	18.7	1.35	r1,r4	3600	18.9	0.00	r1,r4	3600	18.4	1.22	r2,r5
SI3-30d	3600	13.1	0.00	r1,r4	3600	13.0	0.00	r1,r4	3600	12.4	0.00	r1,r4	3600	13.3	0.00	r1,r4	3600	13.1	0.00	r1,r4
Average	3600	15.4	1.40		3600	15.3	1.40		3600	14.3	**0.45**		3600	14.6	0.60		3600	15.5	0.46	
SI3-35a	3600	32.4	10.71	r1,r3	3600	32.4	10.71	r1,r3	3600	36.3	16.06	r1,r3	3600	32.5	6.90	r2,r4	3600	27.3	0.00	r1,r2,r5
SI3-35b	3600	22.8	6.85	r2,r4	3600	27.2	13.33	r2,r4	3600	28.3	15.12	r2,r4	3600	17.2	0.00	r2,r5	3600	20.6	4.44	r2,r5
SI3-35c	3600	47.4	29.10	r1,r2	3600	43.7	20.56	r1,r2	3600	43.7	19.96	r1,r2	3600	31.9	0.00	r2,r3	-	-	-	-
SI3-35d	3600	30.9	7.86	r1,r3	3600	25.7	0.00	r1,r5	3600	28.4	0.76	r1,r5	3600	25.2	1.71	r2,r5	-	-	-	-
Average	3600	33.4	13.63		3600	32.3	11.15		3600	34.2	12.97		3600	26.7	**2.15**		3600	23.9	2.22	
SI3-40a	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI3-40b	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI3-40c	-	-	-	-	-	-	-	-	-	-	-	-	3600	51.2	0.00	r1,r2,r3	-	-	-	-
SI3-40d	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Average	-	-	-		-	-	-		-	-	-		3600	51.2	**0.00**		-	-	-	
SI3-70a	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI3-70b	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI3-70c	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI3-70d	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Average	-	-	-		-	-	-		-	-	-		-	-	-		-	-	-	

Table 5.8: Detailed results for SI4 without and with the schemes

	Without the schemes				**Scheme: a**								**Schemes: (a, b, c)**							
α or (α, β)					**0.8**				**0.7**				**(0.8,0.15)**				**(0.7,0.2)**			
Instance	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**	**CPU**	**Gap%**	**GBK**	**RP**
SI4-15a	14	0.0	0.00	r5	14	0.0	0.00	r5	13	0.0	0.00	r5	21	0.0	0.00	r5	12	0.0	0.00	r5
SI4-15b	12	0.0	0.00	r5	13	0.0	0.00	r5	13	0.0	0.00	r5	17	0.0	0.00	r5	17	0.0	0.00	r5
SI4-15c	14	0.0	0.00	r3	15	0.0	0.00	r3	14	0.0	0.00	r3	19	0.0	0.00	r3	13	0.0	0.00	r3
SI4-15d	10	0.0	0.00	r4	11	0.0	0.00	r4	10	0.0	0.00	r4	19	0.0	0.00	r4	14	0.0	0.00	r4
Avergae	13	0.0	0.00		13	0.0	0.00		13	0.0	0.00		19	0.0	0.00		14	0.0	0.00	
SI4-20a	21	0.0	0.00	r1,r4,r5	21	0.0	0.00	r1,r4,r5	19	0.0	0.00	r1,r4,r5	29	0.0	0.00	r1,r4,r5	22	0.0	0.00	r1,r4,r5
SI4-20b	38	0.0	0.00	r4,r5	43	0.0	0.00	r4,r5	39	0.0	0.00	r4,r5	47	0.0	0.00	r4,r5	72	0.0	0.00	r4,r5
SI4-20c	3600	3.5	0.00	r2,r4	3600	5.2	0.00	r2,r4	3600	3.5	0.00	r2,r4	3600	2.7	0.00	r2,r4	85	0.0	0.00	r2,r4
SI4-20d	22	0.0	0.00	r1,r3	56	0.0	0.00	r1,r3	22	0.0	0.00	r1,r3	38	0.0	0.00	r1,r3	38	0.0	0.00	r1,r3
Avergae	920	0.9	0.00		930	1.3	0.00		920	0.9	0.00		929	0.7	0.00		**54**	0.0	0.00	
SI4-25a	3600	7.9	0.00	r1,r5	3600	7.4	0.00	r1,r5	3600	6.8	0.00	r1,r5	3600	10.4	1.79	r4,r5	3600	13.8	3.87	r1,r5
SI4-25b	3600	5.7	0.00	r1,r5	3600	5.7	0.00	r1,r5	3600	5.6	0.00	r1,r5	3600	2.7	0.07	r1,r3	3600	4.3	0.07	r1,r3
SI4-25c	3600	2.2	0.00	r4,r5	3600	2.1	0.00	r4,r5	3600	2.1	0.00	r4,r5	3600	3.7	0.00	r4,r5	3600	7.3	3.31	r4,r5
SI4-25d	2104	0.0	0.00	r1,r5	2042	0.0	0.00	r1,r5	1842	0.0	0.00	r1,r5	1342	0.0	0.00	r1,r5	3079	0.0	1.46	r1,r3
Avergae	3226	4.0	0.00		3211	3.8	0.00		**3160**	3.6	0.00		3035	4.2	0.47		3470	6.3	2.18	
SI4-30a	3600	7.2	0.00	r2,r3,r4	3600	7.0	0.00	r2,r3,r4	3600	7.3	0.00	r2,r3,r4	3600	10.2	0.14	r2,r3,r4	3600	14.3	0.67	r2,r3,r4
SI4-30b	3600	11.8	1.86	r1,r2,r3	3600	9.4	0.00	r1,r2,r3	3600	7.2	0.00	r1,r2,r3	3600	15.7	5.86	r1,r3	3600	17.5	4.52	r2,r3
SI4-30c	3600	13.5	0.12	r1,r2	3600	12.4	0.12	r1,r2	3600	13.1	0.00	r1,r2	3600	14.1	0.50	r2,r4	3600	18.6	2.36	r4
SI4-30d	3600	12.7	0.00	r4,r5	3600	12.5	0.00	r4,r5	3600	12.7	0.00	r4,r5	3600	16.1	3.53	r4	3600	12.7	3.27	r1
Avergae	3392	7.2	0.49		3600	10.3	0.03		3600	10.1	**0.00**		3600	14.0	2.51		3600	15.8	2.70	
SI4-35a	3600	20.6	2.75	r1,r3	3600	18.4	0.00	r1,r3	3600	20.6	2.75	r1,r3	3600	17.2	2.66	r1,r3	-	-	-	-
SI4-35b	3600	33.5	23.33	r4	3600	24.7	8.82	r4	3600	27.3	12.07	r4	3600	19.3	0.00	r4	-	-	-	-
SI4-35c	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI4-35d	3600	18.1	4.04	r4,r5	3600	14.6	0.33	r2,r3,r5	3600	25.4	14.30	r2,r3,r4,r5	3600	14.4	0.00	r4,r5	3600	20.9	7.76	r4
Avergae	3600	24.1	10.04		3600	19.2	3.05		3600	24.4	9.71		3600	17.0	**0.89**		3600	20.9	7.8	
SI4-40a	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI4-40b	-	-	-	-	-	-	-	-	-	-	-	-	3600	41.2	0.00	r2,r3	-	-	-	-
SI4-40c	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI4-40d	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Avergae	-	-	-		-	-	-		-	-	-		3600	41.2	**0.00**		-	-	-	
SI4-70a	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI4-70b	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI4-70c	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI4-70d	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Average	-	-	-		-	-	-		-	-	-		-	-	-		-	-	-	

Chapter 6

Extension

In this chapter, we generalize the problem described in Chapter 2 by considering the capacity of vehicles, multiple trips for vehicles, and decision on terminal locations.

A large body of literature on location-routing problems (LRPs) has addressed the capacity of vehicles (e.g., Barreto et al. (2007); Lopes et al. (2008); Gendron and Semet (2009)). Note that, by incorporating the vehicle capacity and time considerations, allowing vehicles to make multiple trips can be useful. For instance, consider the case where the vehicle capacity is small compared to customer demands and the time windows for visiting customers are rather loose. In such a case, a vehicle can visit customers over multiple trips where it pays a fixed cost for only the first trip, while the single-trip assumption for vehicles trivially leads to extra fixed costs.

Few papers in the literature on two-echelon location-routing problems (2E-LRPs) have addressed the subject of multiple primary facilities and decisions on their locations (e.g., Crainic et al. (2009) and Sterle (2009)). Decisions on the locations of primary facilities (e.g., platforms, terminals) are relevant, as highlighted by Cuda et al. (2015). In this chapter, we consider multiple terminals and decisions on their locations. In our motivation problem, there are some areas where the distribution of customers between two terminals is ambiguous, and the customer assignment to each terminal is not trivial. In such areas, the main decision is to assign customers to each terminal in order to reduce the total distribution costs. Within the multi-terminal setting, terminals may interact as follows: deliveries are transported from a terminal to a reloading point (RP), and the collected pickups from the same RP are transported to another terminal. Such interaction may occur when the fixed usage costs of the primary vehicles are high. This may increase the routing costs at both echelons but provides an efficient use of primary vehicle capacity.

6.1 Problem description

In this section, we only describe the changes to the original problem settings provided in Section 2.1 for the extended problem. The first level consists of terminals as primary facilities. The second level consists of RPs as intermediate facilities. The third level consists of customers. Figure 6.1 illustrates the two echelons, including multiple terminals. Both terminals and RPs are assumed to be uncapacitated. An opening cost is associated with each terminal and each RP. The capacity of primary vehicles is higher than that of secondary vehicles.

Each type of vehicle can perform multiple trips at each echelon. Each primary vehicle starts its first trip from a terminal and comes back to the same terminal after its last trip because they should be available at each terminal for the next day's activities. Each secondary vehicle starts its trip from an RP and returns to the same RP.

The demand of customers and travel times are assumed to be deterministic and known. The capacity of a secondary vehicle is assumed to be greater than the demand of each customer. Splitting orders is not allowed. The goal is to find the optimal locations of terminals and RPs among a given set of potential sites while minimizing costs for opening terminals, costs for opening RPs, costs of paying for the fleet, and actual transportation costs.

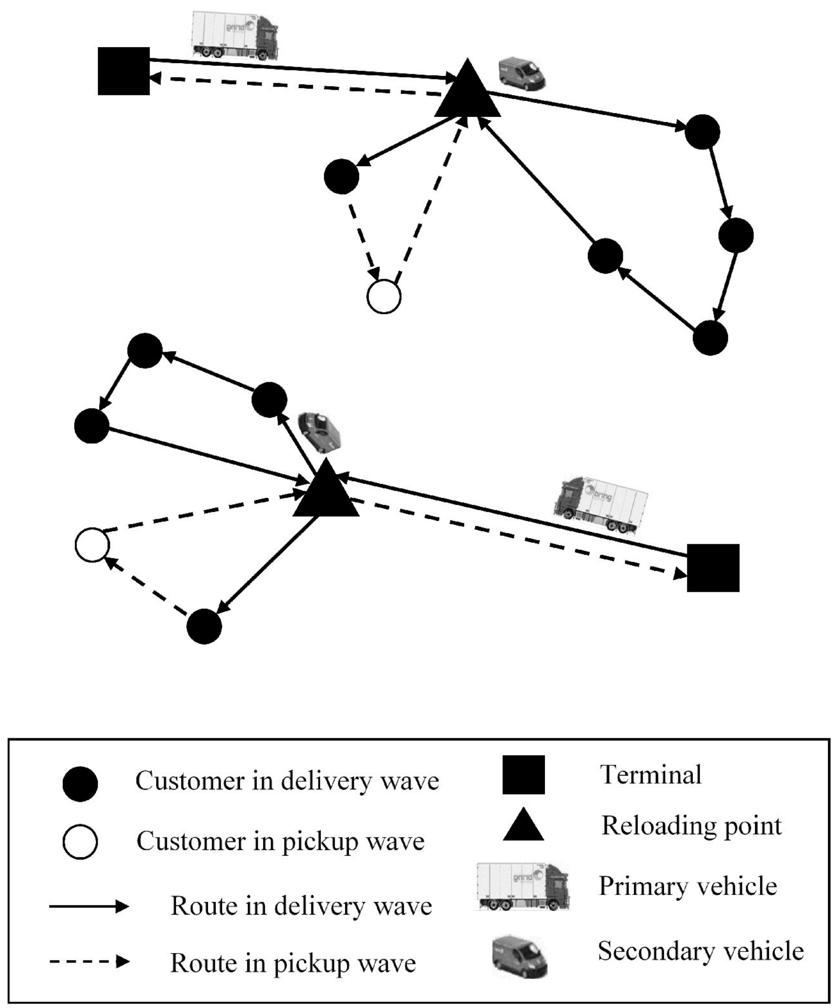


Figure 6.1: Illustration of a feasible solution for a 2E-LRP with multiple terminals

6.2 Model formulation

In this section, we use the arc-based mixed-integer linear programming (MILP) formulation described in Chapter 2 in order to extend the time-driven 2E-LRP with synchronization and sequential delivery and pickup waves by incorporating the vehicle capacities, multiple trips for vehicles, and decisions on terminal locations.

The new sets and parameters are defined as follows.

$V^1 = O \cup R$ is the set of nodes in the first echelon where O is the set of potential sites for terminals. $A^1 = \{(i,j)|i,j \in V^1, i \neq j\}$ is the set of arcs in the first echelon. Each terminal $o \in O$ has a fixed cost of opening $\mathcal{F}_o$. Each customer $j \in J$ has a known demand volume of d_j and is visited only once.

The set of primary vehicles L is defined as the union of subsets l_i; $L = \bigcup_i l_i$. We assume that $|l_i| = \mathcal{M}$, where $\mathcal{M}$ is the maximum number of trips that primary vehicle $l \in l_i$ can perform. The set of secondary vehicles K is defined as the union of subsets k_i; $K = \bigcup_i k_i$. We assume that $|k_i| = \mathcal{N}$, where $\mathcal{N}$ is the maximum number of trips that secondary vehicle $k \in k_i$ can perform. Each primary vehicle has a limited capacity of $\mathcal{Q}^1$. $\mathcal{Q}^2$ is the capacity of the secondary vehicle, and we assume that $d_j \leq \mathcal{Q}^2, \forall j \in J$. $\mathcal{T}_o^{zero}$ is the earliest time that a primary vehicle can depart from terminal $o \in O$. $\mathcal{T}_o^{fin}$ is the latest time that a primary vehicle can come back to terminal $o \in O$.

The new decision variables are defined as follows. The location decision variable $w_o \in \{0,1\}, \forall o \in O$ is equal to unity if terminal o is open and zero otherwise. Time decision variable $t_{ol}^{end} \geq 0, \forall o \in O, l \in L$ is the time at which primary vehicle l returns to terminal o. Itinerary variable $v_{il} \in \{0,1\}, \forall i \in J, l \in L$ is equal to unity if the demand of node $i \in J$ is transported at the first echelon by primary vehicle l and zero otherwise.

Table 6.1 summarizes the sets, parameters, and decision variables used in the MILP formulation.

Table 6.1: Sets, parameters, and variables used in the MILP model (multi-terminal)

Sets and parameters	**Description**
O	set of potential terminals
$\mathcal{F}_o$	fixed cost of opening terminal o, $\forall o \in O$
$\mathcal{T}_o^{zero}$	earliest time a primary vehicle can depart from terminal o, $\forall o \in O$
$\mathcal{T}_o^{fin}$	latest time a primary vehicle can come back to terminal o, $\forall o \in O$
R	set of potential RPs
f_r	fixed cost of opening RP r, $\forall r \in R$
E	set of echelons, $E = \{1, 2\}$
A^e	set of arcs in echelon e, $\forall e \in E$
T_{ij}^e	travel time between node i and node j in echelon e, $\forall (i,j) \in A^e, e \in E$
c_{ij}^e	travel cost of traversing arc (i,j) in echelon e, $\forall (i,j) \in A^e, e \in E$
J^D	set of customers in the delivery wave
J^P	set of customers in the pickup wave
J	set of all customers ($J = J^D \cup J^P$)
a_j	earliest arrival time at node j, $\forall j \in J$
b_j	latest arrival time at node j, $\forall j \in J$
d_j	demand of node j, $\forall j \in J$
K	set of secondary vehicles
L	set of primary vehicles
$\mathcal{M}$	maximum number of trips that can be performed by primary vehicle
$\mathcal{N}$	maximum number of trips that can be performed by secondary vehicle
$\mathcal{Q}^e$	capacity of vehicles in echelon e, $\forall e \in E$
f^e	fixed usage cost of a vehicle in echelon e, $\forall e \in E$
M	a sufficiently large number

Variables	**Description**
$w_o \in \{0,1\}$	binary variable equal to 1 if terminal o is open, 0 otherwise, $\forall o \in O$
$z_r \in \{0,1\}$	binary variable equal to 1 if RP r is open, 0 otherwise, $\forall r \in R$
$x_{ijl}^1 \in \{0,1\}$	binary variable equal to 1 if arc (i,j)
	is traversed by primary vehicle l, 0 otherwise, $\forall l \in L, (i,j) \in A^1$
$t_{il}^1 \geq 0$	time at which primary vehicle l visits node i, $\forall l \in L, i \in V^1$
$t_{o,l}^{end} \geq 0$	time at which primary vehicle l returns to terminal o,$\forall o \in O, l \in L$
$x_{ijk}^2 \in \{0,1\}$	binary variable equal to 1 if arc (i,j)
	is traversed by secondary vehicle k, 0 otherwise, $\forall k \in K, (i,j) \in A^2$
$t_i^2 \geq 0$	time at which node i is visited, $\forall i \in J$
$t_{rk}^d \geq 0$	departure time of secondary vehicle k from RP r, $\forall r \in R, k \in K$
$t_{rk}^a \geq 0$	arrival time of secondary vehicle k to RP r, $\forall r \in R, k \in K$
$u_{rkl} \in \{0,1\}$	binary variable equal to 1 if secondary vehicle k meets
	with primary vehicle l for reloading at RP r, 0 otherwise, $\forall r \in R, k \in K, l \in L$
$v_{il} \in \{0,1\}$	binary variable equal to 1 if demand of node i
	is transported at the first echelon by primary vehicle l, 0 otherwise, $\forall i \in J, l \in L$

The model is formulated as follows.

$$\begin{aligned} \min \quad & \sum_{o \in O} \mathcal{F}_o w_o + \sum_{r \in R} f_r z_r + \sum_{(i,j) \in A^1} \sum_{l \in L} c^1_{ij} x^1_{ijl} + \sum_{(i,j) \in A^2} \sum_{k \in K} c^2_{ij} x^2_{ijk} \\ & + \sum_{o \in O} \sum_{j \in V^1} \sum_{l \in L : l = l^1_i} f^1 x^1_{ojl} + \sum_{r \in R} \sum_{j \in V^2} \sum_{k \in K : k = k^1_i} f^2 x^2_{rjk} \end{aligned} \tag{6.1}$$

The objective function (6.1) consists of six components. The first component is the opening costs of terminals. The second component is the opening costs of RPs. The third and fourth components are routing costs in the first and second echelons, respectively. The fifth and sixth components are the fixed costs of primary and secondary vehicles, respectively. Because each vehicle can perform multiple trips, only the cost of the first trip performed by each vehicle is considered, where l^1_i is the first member in subset l_i and k^1_i is the first member in subset k_i.

The constraints can be classified as follows: routing for the first and second echelons, vehicle capacity for the first and second echelons, time calculation and route continuity for the first and second echelons, time windows, vehicle precedence, and synchronization constraints.

Constraints

$$x^1_{iol} \leq w_o \quad \forall i \in V^1, o \in O, l \in L \tag{6.2}$$

$$x^1_{irl} \leq \sum_{o \in O} \sum_{r \in R} x^1_{orl} \quad \forall i \in V^1, l \in L \tag{6.3}$$

$$x^1_{irl} \leq z_r \quad \forall i \in V^1, r \in R, l \in L \tag{6.4}$$

$$\sum_{r \in R} x^1_{orl} \leq 1 \quad \forall o \in O, l \in L \tag{6.5}$$

$$\sum_{j \in V^1} x^1_{jil} = \sum_{j \in V^1} x^1_{ijl} \quad \forall i \in V^1, l \in L \tag{6.6}$$

$$\sum_{l \in L} v_{il} = 1 \quad \forall i \in J \tag{6.7}$$

Constraints (6.2), (6.3), (6.4) , (6.5), (6.6), and (6.7) are routing constraints imposed at the first echelon.

Constraints (6.2) ensure that a primary vehicle can visit a terminal only if the terminal is open. Constraints (6.3) state that a primary vehicle can visit an RP only if it has departed from the terminal. Constraints (6.4) ensure that a primary vehicle can visit an RP only if the RP is open. Constraints (6.5) state that a primary vehicle cannot depart from the terminal to more than one RP. Constraints (6.6) ensure that the number of arcs entering node $i \in V^1$ in the first echelon must be the same as the number of arcs exiting the same node. Constraints (6.7) state that the demand of each customer is transported by exactly one primary vehicle.

The routing constraints for the second echelon remain the same as the constraints (2.6), (2.7), (2.8), (2.9), and (2.10).

$$\sum_{i \in J^D} d_i v_{il} \leq \mathcal{Q}^1 \quad \forall l \in L \tag{6.8}$$

$$\sum_{i \in J^P} d_i v_{il} \leq \mathcal{Q}^1 \quad \forall l \in L \tag{6.9}$$

$$\sum_{i \in V^2} \sum_{j \in J^D} d_j x^2_{ijk} \leq \mathcal{Q}^2 \quad \forall k \in K \tag{6.10}$$

$$\sum_{i \in V^2} \sum_{j \in J^P} d_j x^2_{ijk} \leq \mathcal{Q}^2 \quad \forall k \in K \tag{6.11}$$

Constraints (6.8) and (6.9) are primary vehicle capacity constraints and ensure that the volume transported by a primary vehicle must respect its capacity. Constraints (6.10) and (6.11) are secondary vehicle capacity constraints and dictate that the volume transported by a secondary vehicle has to be less than its capacity.

$$t^1_{ol} \geq \mathcal{T}^{zero}_o - M(1 - \sum_{r \in R} x^1_{orl}) \quad \forall o \in O, l \in L \tag{6.12}$$

$$t^1_{rl} \geq t^1_{il} + T^1_{ir} - M(1 - x^1_{irl}) \quad \forall l \in L, i \in V^1, r \in R \tag{6.13}$$

$$t^{end}_{ol} \geq t^1_{rl} + T^1_{ro} - M(1 - x^1_{rol}) \quad \forall o \in O, l \in L, r \in R \tag{6.14}$$

$$t^{end}_{ol} \leq \mathcal{T}^{fin}_o + M(1 - \sum_{r \in R} x^1_{rol}) \quad \forall o \in O, l \in L \tag{6.15}$$

$$t^1_{rl} \leq M \sum_{i \in V^1} x^1_{irl} \quad \forall r \in R, l \in L \tag{6.16}$$

$$t^{end}_{ol} \leq M \sum_{r \in R} x^1_{rol} \quad \forall o \in O, l \in L \tag{6.17}$$

Constraints (6.12), (6.13), (6.14), (6.15), (6.16), and (6.17) are time calculation constraints for the first echelon. These constraints impose route continuity in the first echelon and implicitly avoid sub-tours. Constraints (6.12) state that the departure time of vehicle $l \in L$ from terminal $o \in O$ must respect the earliest departure time from the terminal: $\mathcal{T}^{zero}_o$. Constraints (6.13) calculate the arrival time of primary vehicle l at RP r. Constraints (6.14) calculate the time that primary vehicle l comes back to terminal $o \in O$. Constraints (6.15) ensure that the arrival time of primary vehicle $l \in L$ to terminal $o \in O$ respects the latest return time to the terminal: $\mathcal{T}^{fin}_o$. Constraints (6.16) ensure that the arrival time of a primary vehicle at the RP can turn positive only if the primary vehicle visits the RP. Constraints (6.17) make sure that the returning time of a primary vehicle to terminal $o \in O$ can turn positive only if the primary vehicle visits some RPs.

Time calculation constraints for the second echelon remain the same as constraints (2.17), (2.18), (2.19), (2.20), and (2.21). The time window constraints are the same as constraints (2.22) and (2.23).

$$M(1 - \sum_{r \in R} x^1_{orl+1}) + t^1_{ol+1} \geq t^{end}_{ol} \quad \forall o \in O, l \in l_i : l < \mathcal{M} \tag{6.18}$$

$$\sum_{r \in R} x^1_{orl+1} \leq \sum_{r \in R} x^1_{orl} \quad \forall o \in O, l \in l_i : l < \mathcal{M} \tag{6.19}$$

$$M(1 - \sum_{i \in J} x^2_{rjk+1}) + t^d_{rk+1} \geq t^a_{rk} \quad \forall r \in R, k \in k_i : k < \mathcal{N} \tag{6.20}$$

$$\sum_{j \in J} x^2_{rjk+1} \leq \sum_{j \in J} x^2_{rjk} \quad \forall r \in R, k \in k_i : k < \mathcal{N} \tag{6.21}$$

Constraints (6.18) and (6.19) dictate the trip precedence of primary vehicles. Constraints (6.18) ensure that the departure time of a primary vehicle from a terminal for its $l+1$th trip is greater than its arrival time to the same terminal for its lth trip. Constraints (6.19) ensure that a primary vehicle does not perform its $l+1$th trip unless it has performed its lth trip. Constraints (6.20) and (6.21) dictate the trip precedence of secondary vehicles.

$$t^d_{rk} \geq t^1_{rl} - M(1 - u_{rkl}) \quad \forall r \in R, k \in K, l \in L \tag{6.22}$$

$$t^1_{rl} \geq t^a_{rk} - M(1 - u_{rkl}) \quad \forall r \in R, k \in K, l \in L \tag{6.23}$$

$$\sum_{j \in J^P} \sum_{i \in V^2} x^2_{jik} \leq M \sum_{r \in R} \sum_{l \in L} u_{rkl} \quad \forall k \in K \tag{6.24}$$

$$v_{il} + \sum_{j \in V^2} x^2_{jik} \leq 1 + \sum_{r \in R} u_{rkl} \quad \forall i \in J, k \in K, l \in L \tag{6.25}$$

$$u_{rkl} \leq \sum_{i \in V^1} x^1_{irl} \quad \forall r \in R, k \in K, l \in L \tag{6.26}$$

$$u_{rkl} \leq \sum_{j \in J^D} x^2_{rjk} \quad \forall r \in R, k \in K, l \in L \tag{6.27}$$

$$u_{rkl} \leq \sum_{j \in J^P} x^2_{jrk} \quad \forall r \in R, k \in K, l \in L \tag{6.28}$$

$$\sum_{j \in J^D} \sum_{i \in V^2} x^1_{jik} \leq M \sum_{r \in R} \sum_{l \in L} u_{rkl} \quad \forall k \in K; \tag{6.29}$$

Constraints (6.22), (6.23), (6.24), (6.25), (6.26), (6.27), (6.28), and (6.29) impose the synchronization of primary and secondary vehicles. Constraints (6.22) state that a secondary vehicle cannot depart from an RP with delivery demands before a primary vehicle loads it. Constraints (6.23) ensure that a primary vehicle cannot depart from an RP with pickup demands before a secondary vehicle loads it. Constraints (6.24) state that, if secondary vehicle k picks up from at least one customer, it must load at least one primary vehicle. Constraints (6.25) state that, if primary vehicle l and secondary vehicle k are used to serve node $i \in J$ (i.e., $v_{il} = 1$ and $\sum_{j \in V^2} x^2_{jik} = 1$), then l and k must meet at some RP (i.e., $\sum_{r \in R} u_{rkl} = 1$). Constraints (6.26), (6.27), and (6.28) imply that the reloading between primary vehicle l and secondary vehicle k at RP r cannot happen unless both visit RP r

in either the delivery or pickup wave. Constraints (6.29) state that, if a secondary vehicle k delivers to at least one customer, it must be loaded from at least one primary vehicle. Finally, constraints (6.30) define the domain of the variables.

$$
\begin{aligned}
&w_o \in \{0,1\} \quad \forall o \in O; \quad z_r \in \{0,1\} \quad \forall r \in R; \\
&u_{rkl} \in \{0,1\} \quad \forall r \in R, k \in K, l \in L; v_{il} \in \{0,1\} \quad \forall i \in J, l \in L; \\
&x^1_{ijl} \in \{0,1\} \quad \forall (i,j) \in A^1, l \in L; \quad x^2_{ijk} \in \{0,1\} \quad \forall (i,j) \in A^2, k \in K; \\
&t^1_{il} \geq 0 \quad \forall i \in V^1, l \in L; \quad t^{end}_{ol} \geq 0 \quad \forall o \in O, l \in L; \quad t^2_i \geq 0 \quad \forall i \in J; \quad t^d_{rk}, t^a_{rk} \geq 0 \quad \forall r \in R, k \in K.
\end{aligned}
\tag{6.30}
$$

Having presented the new 2E-LRP in Chapter 2 and proposed the decomposition-based heuristic as outlined in Chapter 3, Chapter 4 presented numerical experiments on the four sets of instances while Chapter 5 proposed three schemes to reduce the set of feasible solutions and Chapter 6 extended the new 2E-LRP incorporating vehicle capacity, multiple trips for vehicles and location decisions on terminals. Contrary to the first part of the thesis where we addressed different aspects of an actual problem through the optimization model, in the second part of the thesis, we do not aim to introduce a new routing problem but the scope is to illustrate how a simple vehicle routing problem could be used to enhance economic evaluation procedures of supporting policies for electric vehicles. In the following chapter, we provide a framework that combines an optimization model with economic analysis in order to evaluate the effect of different freight policies for supporting electric vehicles on an individual company's logistics decisions (i.e., vehicle purchase and routing plans) in response to the policies and determine the changes in social welfare.

Chapter 7

A framework to evaluate policy options for supporting electric vehicles in urban freight transport[1]

Urban freight transport that serves trading activity is fundamental to sustaining current lifestyles. The logistic costs of freight transport have a direct bearing on economic efficiency and social welfare. Heavy freight vehicles cause more severe environmental and health problems than passenger vehicles. Russo and Comi (2012) noted that urban freight vehicles account for about 6%-18% of total urban transport but for about 19% of energy use and for about 21% of CO_2 emissions. Urban freight vehicles are also responsible for a large part of local transport-based pollution (IEA, 2013) such as nitrogen oxides (NO_x), sulfur dioxide (SO_2), and particulate matter (PM). Cities clearly need to reduce pollution-intensive freight traffic by managing logistic processes more efficiently and switching to low emission vehicles. Electric vehicles (EVs) are being considered to replace internal combustion engine vehicles (ICEVs) in order to mitigate the pollution caused by urban freight transport owing

[1]This chapter is part of a paper in co-authorship with Shiyu Yan, at the Department of Business and Management Science, NHH, that has been accepted for publication in *Transportation Research Part D: Transport and Environment.*

to the former's zero tailpipe emissions, although introducing EVs to the market will increase emissions at the site of the power plants. A long-term shift to an economy that is compatible with climate stabilization will require a vehicle fleet that is predominantly powered by electric drives in the 2040-2050 timeframe (Mock and Yang, 2014).

The main challenges facing use of EVs in real-life urban freight transport are their high acquisition cost, long recharging time, low capacity, and limited driving range. These influence the vehicle purchase and routing decisions of logistics companies. Various national and local policies have been implemented to provide fiscal incentives for encouraging the purchase and use of EVs in freight transport (Taefi et al., 2016). Several examples of the measures[2] are given below.

- Purchase subsidy on EV: Direct subsidy is given to reduce the EV purchase price.
- Limited access (zone fee) to congestion/low-emission zone: For the purpose of generality, we define the term *limited zone* as representing a *low-emission zone* or *congestion zone* with restricted entry for high-emission or heavy vehicles (e.g., a fee charge or other deterrent) in order to reduce emissions or congestion.
- Vehicle taxes with exemptions for EVs: There are two main types of vehicle taxes. The vehicle registration tax is paid for the first registration. The annual circulation tax is paid to use the vehicle on the road. With an appropriate discount rate, these two taxes can be designed to work in the same way. EVs can be exempted from at least one of the vehicle taxes.

We consider an individual logistics company that provides delivery services for its customers. In response to these policies, the logistics company would adapt its vehicle fleet composition

[2]The measures are commonly used in European cities for promoting EVs. With a focus on vehicle specific measures, we choose purchase subsidy for EVs, free access to the limited zone (congestion/low-emission zone) for EVs and vehicle taxes with exemptions for EVs for evaluation purpose. In terms of providing free access for EVs and imposing limitations for ICEVs, the concept of "limited zone" can be further generalized as parking lots/bus lanes/low-noise zones/pedestrian zones/areas with toll.

and vehicle routing plan in order to minimize the total logistic costs. This can have an influence on changes in the external costs resulted from congestion, local air pollution and CO_2 emission, and the overall social welfare.

Despite growing research interest in urban freight transport, few studies have addressed the impacts of EV-supporting policies on logistics and society. Previous empirical economic studies on relevant policy evaluation have usually focused on upfront purchase cost and assumed fixed annual routing costs for vehicles. In this study, we illustrate how an optimization model (i.e., a vehicle routing problem) could be used to enhance economic evaluation procedure of EV-supporting policies. In contrast to the previous empirical economic research, the optimization model provides an opportunity to study how the policies can affect a logistics company's decisions on both vehicle purchase and routing. As we discuss in the literature review in Section 7.1, research is needed to explore the relationships between 1) policy measures, 2) individual company's actions in response to the measures, 3) the effect on operational (routing) costs, and 4) the resulting changes to environmental impacts and welfare. As a contribution to cover this gap, we establish a framework that combines an optimization model with economic analysis to evaluate the potential operational, financial, and environmental effects of using EVs in urban freight operations. The framework focuses on obtaining an individual company's expected response to policies and corresponding changes in externalities and welfare.

We develop different scenarios in which logistics companies are exposed to policy options that support EVs: The purchase subsidy for EVs, vehicle taxes with exemptions for EVs, and limited access (zone fee) to the limited zone with exemptions for EVs. We establish an optimization model to determine the optimal fleet for the logistics company that transports the given demands of a single product from multiple dispersed depots to a known set of customers located in or outside a congestion/low-emission zone using two types of vehicles: EVs and ICEVs. The two types of vehicles differ in driving range, capacity, acquisition cost, energy cost, and entrance fee to congestion/low-emission zones. The aim of the company's logistic problem is to decide the vehicle fleet composition and routing while minimizing the fixed usage costs, routing costs, and entrance fees of vehicles to the congestion/low-emission zone. We term the problem as the *zone-dependent vehicle routing problem with a mixed fleet*. Based on the results of solving the optimization model, changes in the externalities produced by EVs and ICEVs and in the total welfare are calculated, and the influence of EV-supporting policies is calculated.

We tested the proposed framework with numerical experiments. The data are generated for a transport network under different scenarios. We also performed a sensitivity analysis to determine the robustness of the results with different types of vehicles and transport networks. Based on the results from our numerical experiments, the purchase subsidy, zone fee, and vehicle taxes were found to increase the EV share in the vehicle fleet composition of the logistics company, decrease the distances traveled by ICEVs, and reduce externalities (i.e., congestion, local air pollution and CO_2 emission) and improve social welfare. In the numerical experiments, the zone fee had a larger impact on improving social welfare. This is because the zone fee significantly reduces the external cost by preventing emissions and congestion inside a zone with higher marginal external costs from a high population, dense pollution, and heavy traffic. However, in some cases in the sensitivity analysis, the zone fee may increase external costs by forcing ICEVs to travel around the zone to reach customers on the other side of the zone, which may lead to more emissions from fuel combustion or congestion. Finally, local factors at the company and city levels, such as the vehicle type and transport network, were found to also be important for designing policies that efficiently support EV for urban logistics.

The rest of this chapter is organized as follows. Section 7.1 reviews the related literature. Section 7.2 proposes a framework for evaluating urban freight policies. Section 7.3 presents the numerical experiments. Section 7.4 concludes the chapter.

7.1 Literature review

In this section, we review relevant research on both economic and logistics research for the use and evaluation of EV policies in the context of urban freight transport.

Traditionally, evaluation of transport policies in urban freight transport involves social and economic issues (Lagorio et al., 2016). Hosoya et al. (2003), Anderson et al. (2005), and Quak and De Koster (2006) performed general assessments of policies that affect urban freight transport. Hosoya et al. (2003) studied Tokyo and used a survey to evaluate a number of freight policies: bans on large trucks, road pricing, and the construction of logistic centers. Anderson et al. (2005) provided an ex ante assessment of regulation measures in UK cities, including time windows and charging. Quak and De Koster (2006) addressed regulations based on time windows. They reviewed practices in Dutch cities and assessed possible changes to current policy.

However, this is still an evolving field of research because of the greater sensitivity to environmental issues, new policy measures, and introduction of new technologies. In the case of promoting the purchase and use of EVs, several types of policies are involved (e.g., access to low-emission zones, exemptions from vehicle taxes, and purchase subsidy). Taefi et al. (2016) reviewed policy measures directed at emission-free urban road freight transport. They assessed and compared policies against other prospective options by multi-criteria analysis. In the previous economic research, evaluation of EV-supporting policies mainly focused on ex post analysis based on empirical data and econometric approaches, such as the consumer choice model (Lee et al., 2016; Greene et al., 2014), fixed effect model (Chandra et al., 2010; Gallagher and Muehlegger, 2011), and other ordinary least squares models (Sierzchula et al., 2014; Diamond, 2009; Jenn et al., 2013; Jiménez et al., 2016; Yan and Eskeland, 2016).

From the perspective of logistics, the literature on urban freight transport does not yet provide an ample discussion of specific policy measures to support EVs in urban freight transport. The main focus is on the use of EV in the context of *heterogeneous vehicle* *routing problem*. Survey papers on *heterogeneous vehicle routing problems* are provided by Hoff et al. (2010); Baldacci et al. (2008); Koç et al. (2016). The *heterogeneous vehicle routing problem* generally considers a limited or unlimited fleet of vehicles with different attributes (e.g., capacity, fixed cost, and driving range) in order to serve a set of customers with given demand. The objective is to decide the vehicle fleet composition and routes while minimizing the vehicle routing and usage costs. Juan et al. (2014) extended the heterogeneous vehicle routing problem to consider multiple driving ranges for vehicles. The multiple driving range variant implies that the total distance traveled by each type of vehicle is limited and is not necessarily the same for all vehicles. This problem arises in routing of EVs (Schneider et al., 2014; Goeke and Schneider, 2015) and hybrid electric vehicles for which the driving range is limited due to limited capacity of batteries. Sassi et al. (2014) introduced a new real-life heterogeneous vehicle routing problem where the mixed fleet consists of ICEVs and heterogeneous EVs with different battery capacities (i.e., driving range limit) and fixed costs. Partial recharging for EVs at available recharging stations during trips is allowed, as well as intermittent recharging at the depot. The main challenges with using EVs are their limited driving range and considerably long charging time. The limited driving range will likely remain the main obstacle to using EVs in the medium term as long as there is no global infrastructure for replacing batteries or direct power induction to EVs during their trip.[3]

Although the driving range limit of EVs make them less practical for use in real life, advantages like free or cheap access to a congestion zone provide an incentive to use them as an alternative fleet. The zone-dependency aspect of the problem that we discuss in this chapter, is similar to *site dependency* in the *site-dependent vehicle routing problem* introduced by Nag et al. (1988). In their problem, different types of vehicles could only visit their preassigned customers; that is, no vehicle traveled from one customer to another customer unless both customers were assigned to the same type of vehicle. The difference between the *site-dependent vehicle routing problem* and our problem is that, in the latter,

[3] http://www.isoe.de/english/projects/futurefleet.htm

the customers are not preassigned to each type of vehicle. There are two types of customers with regard to their geographic location: inside or outside congestion/low-emission zones. ICEVs are charged a zone fee when they cross the congestion/low-emission zone. Hence, customers of both types can be potentially visited by each type of vehicle.

In contrast to economic empirical research focusing on national or household data, optimization models, used in the logistic problems, provide a chance to study the economic impacts of EV policies on freight transport at a company level. The literature has scarcely addressed a research that explores the relationships between 1) policy measures, 2) likely individual company's actions in response to the measures, 3) effects on operational (routing) costs, and 4) changes to the environmental impact and welfare. The present study establishes a framework combining an optimization model with economic analysis for evaluating EV-supporting policies and investigating these relationships.

7.2 A framework for policy evaluation

To evaluate the impacts of different EV-supporting policy options on the logistic costs of the company and welfare, we propose a framework that combines an optimization model with economic analysis, as shown in Figure 7.1. First, we develop scenarios for comparison based on policies that support the purchase and use of EVs: The purchase subsidy for EV, limited access (zone fee) to congestion/low-emission zones with exemptions for EVs, and vehicle taxes with exemptions for EVs. Second, we evaluate policy implementations and adjustments for their effect on a company's decision on vehicle fleet composition and routing. Finally, we evaluate the influence of company's optimal decisions on the tax revenue of the government, customer and producer surpluses, and externalities such as emissions and congestion. Then, we calculate the total change in welfare in order to evaluate the impacts of policies on society.

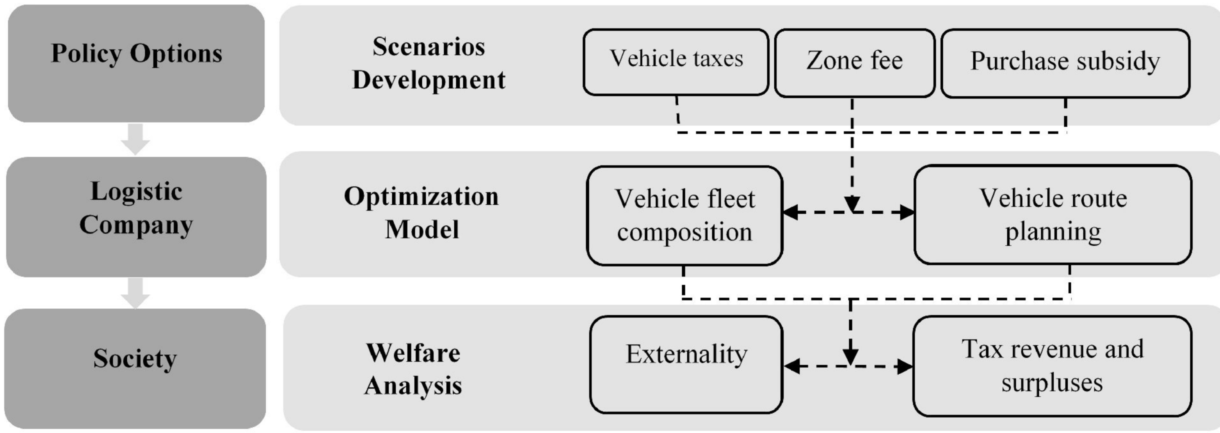


Figure 7.1: Framework for evaluating the impacts of policies on the logistic costs of a company and social welfare

7.2.1 Scenarios

We consider three policies owing to their comparable efficiencies and social feasibility for supporting EV adoption (Taefi et al., 2016): The purchase subsidy for EV, limited access (zone fee) to congestion/low-emission zones with exemptions for EVs, and vehicle taxes with exemptions for EVs. A baseline scenario and three primary scenarios are established, as presented below.

- Baseline: no purchase subsidy, no vehicle taxes, and no zone fee charged for both EVs and ICEVs.
- Scenario 1: implementation of purchase subsidy on vehicle prices for EVs.
- Scenario 2: implementation of a zone fee with exemptions for EVs.
- Scenario 3: implementation of vehicle taxes with exemptions for EVs.

7.2.2 Optimization model

In this section, we describe a company's logistic problem and provide an optimization model. We consider an individual logistics company[4] that provides delivery service for a single product within a single-echelon distribution system. The distribution system consists of two levels. The first level consists of depots, and the second level consists of customers. Each customer is visited once. Each customer is given a deterministic delivery demand, and the splitting of demands is not permitted. The depots are uncapacitated. Each vehicle visits the customers in a tour starting and ending at the same depot. Figure 7.2 illustrates the two levels. The black circles represent the customers. The triangles represent the depots. The mixed fleet of vehicles consists of EVs and ICEVs. The two types of vehicles differ regarding the driving range, cargo capacity, acquisition cost, energy cost, and zone fee to access the limited zone. We assume that both types of vehicles move at a constant speed that is the same for both inside and outside the limited zone. The EVs are fully charged at depots. We did not consider EV recharging during a daily delivery service because the EVs are being used by a logistics company for short-distance deliveries in an urban area.

The urban area in the problem is divided into two areas: outside and inside the limited zone. The area inside the dashed line circle in Figure 7.2 represents the boundary of the limited zone. The marginal external cost is higher for driving vehicles inside the limited zone than outside owing to the high-density population, heavy traffic, and urban landscape. The aim of the problem is to decide the vehicles routes and fleet size for EVs and ICEVs while minimizing the vehicle routing costs, purchasing costs, and entrance fee to the limited zone. We term the problem as the zone-dependent vehicle routing problem with a mixed fleet.

[4]We focus on a logistics company that provides delivery service for products such as milk or newspapers, where the vehicle routing plan is the same everyday.

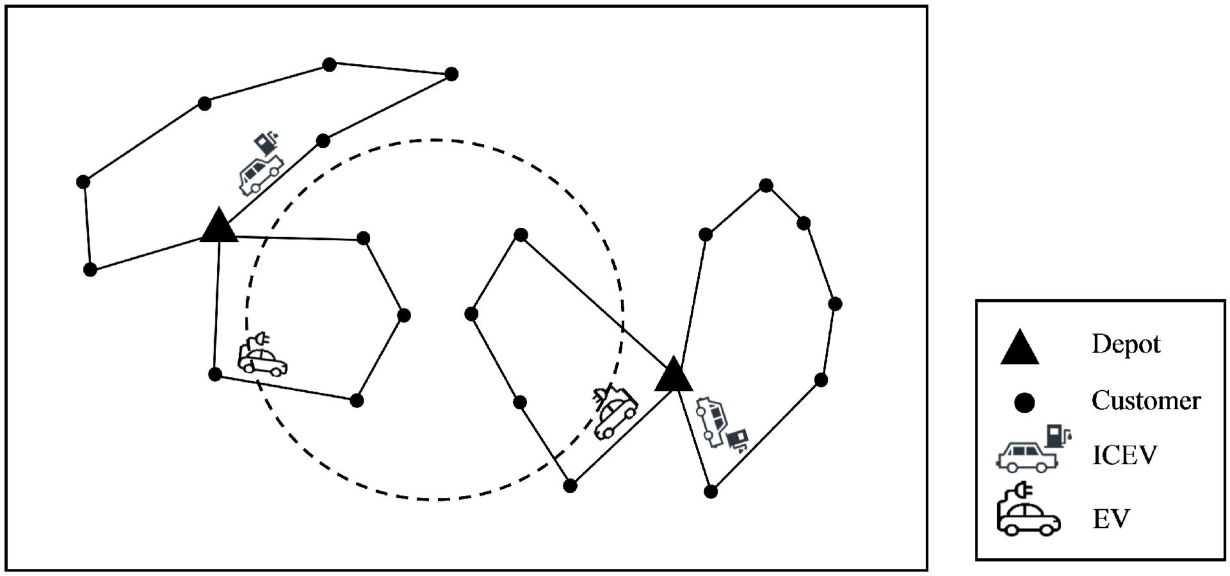


Figure 7.2: Illustration of the first and second levels

Below, we present an arc-based mixed-integer linear programming (MILP) formulation for the zone-dependent vehicle routing problem with a mixed fleet. The time frame of the optimization model is set to one day. The problem is defined on a directed graph $G(V, A)$, where V represents the set of nodes and A is the set of arcs. $V = D \cup J$, where D is the set of depots and J is the set of customers. V^O is the subset of nodes $i \in V$ located outside the limited zone. The set of arcs A includes arcs between node $i \in V$ and node $j \in V$, excluding the arcs between node i and j, $\forall i, j \in D$. It is defined as $A = \{(i,j)|i,j \in V \setminus \{(i,j)|i,j \in D\}\}$. d_{ij} is the traveling distance for traversing arc (i, j), $\forall (i,j) \in A$. $A^Z \subset A$ is the subset of arcs $(i, j) \in A$ that connect two nodes $i, j \in V^O$ without crossing the limited zone. α_{ij} is the proportion of arc $(i, j) \in A$ that is located inside the zone.

$\mathcal{D}_j$ is the given demand of customer $j \in J$. K_{EV} is the set of EVs. K_{ICEV} is the set of ICEVs. $\mathcal{Q}_k$ is the capacity of vehicle $k \in K_t, t \in \{EV, ICEV\}$. A fixed acquisition cost f_k including vehicle registration tax is assigned to vehicle $k \in K_t, t \in \{EV, ICEV\}$. A purchase subsidy S_k is assigned to vehicle $k \in K_t, t \in \{EV, ICEV\}$. A fixed annual circulation tax $\mathcal{C}_k$ is assigned to vehicle $k \in K_t, t \in \{EV, ICEV\}$. $\mathcal{P}_k$ is the energy price, and $\mathcal{T}_k$ is the energy tax per liter for ICEVs and per watt-hour for EVs for vehicle $k \in K_t, t \in \{EV, ICEV\}$. $\mathcal{E}_k$ is the energy efficiency (in Wh/km for EVs and L/km for ICEVs) for vehicle $k \in K_t, t \in \{EV, ICEV\}$. $\mathcal{F}_k$ is the entrance fee paid by vehicle $k \in K_{ICEV}$ if it crosses the limited zone at least once (i.e., if the trip for vehicle $k \in K_{ICEV}$ includes at least one arc $(i, j) \in A \setminus A^Z$). $\mathcal{F}_k$ is paid by the ICEV only for its first entrance to the limited zone. Each vehicle $k \in K_{EV}$ has a limited driving range R_k.

The decision variables are as follows. $x_{ijk} \in \{0, 1\}$ is the routing variable. It is equal to unity if arc (i, j) is traversed by vehicle $k, \forall k \in K, (i, j) \in A$ and zero otherwise. Binary variable $y_k \in \{0, 1\}$ is defined as equal to unity if the route performed by vehicle $k \in K$ consists of at least one arc crossing the zone and zero otherwise.

The sets, parameters, and decision variables are summarized in Table 7.1.

Table 7.1: Sets, parameters, and variables used in the MILP model for the zone-dependent vehicle routing problem with a mixed fleet

Sets and parameters	**Description**
D	set of depots
J	set of customers
$V = D \cup J$	set of all nodes
V^O	subset of nodes $i \in V$ located outside the limited zone
A	set of arcs
$A^Z \subset A$	subset of arcs $(i,j) \in A$ that connect two nodes $i,j \in V^O$ without crossing the limited zone
$\mathcal{D}_j$	demand of customer j, $\forall j \in J$
d_{ij}	traveling distance for traversing arc (i,j), $\forall (i,j) \in A$
α_{ij}	proportion of arc (i,j) located inside the zone, $\forall (i,j) \in A$
K_{EV}	set of EVs
K_{ICEV}	set of ICEVs
$K = K_{EV} \cup K_{ICEV}$	set of all vehicles
$\mathcal{Q}_k$	capacity of vehicle $k \in K_t, t \in \{EV, ICEV\}$
f_k	acquisition cost of vehicle including vehicle registration tax, $k \in K_t, t \in \{EV, ICEV\}$
S_k	subsidy on purchase price of vehicle, $k \in K_t, t \in \{EV, ICEV\}$
$\mathcal{C}_k$	annual circulation tax of vehicle $k \in K_t, t \in \{EV, ICEV\}$
$\mathcal{F}_k$	entrance fee paid by vehicle $k \in K_{ICEV}$ entering the limited zone
R_k	driving range limit for vehicle $k \in K_{EV}$
$\mathcal{P}_k$	energy price per liter for ICEV and per watt-hour for EV for vehicle $k \in K_t, t \in \{EV, ICEV\}$
$\mathcal{T}_k$	energy tax per liter for ICEV and per watt-hour for EV for vehicle $k \in K_t, t \in \{EV, ICEV\}$
$\mathcal{E}_k$	energy efficiency for vehicle $k \in K_t, t \in \{EV, ICEV\}$
M	a sufficiently large number
Variable	**Description**
$x_{ijk} \in \{0,1\}$	binary variable equal to 1 if arc (i,j) is traversed by vehicle k, $\forall k \in K, (i,j) \in A$, 0 otherwise
$y_k \in \{0,1\}$	binary variable equal to 1 if the route performed by vehicle $k \in K$ consists of at least one arc crossing the zone, 0 otherwise

$$\min \sum_{k\in K}\sum_{(i,j)\in A}(\mathcal{P}_k+\mathcal{T}_k)\mathcal{E}_k d_{ij}x_{ijk}+\sum_{k\in K}\sum_{i\in D}\sum_{j\in J}(f_k+\mathcal{C}_k-S_k)x_{ijk}+\sum_{k\in K_{ICEV}}\mathcal{F}_k y_k \tag{7.1}$$

The objective function (7.1) consists of three components: the routing costs, fixed costs of vehicles, and sum of entrance fees to the limited zone for ICEVs. The costs in the objective function are calculated on daily basis. The constraints can be classified as follows: routing constraints, vehicle capacity, vehicle range, and vehicle symmetry removal.

Constraints

$$\sum_{i\in D}\sum_{j\in J}x_{ijk}\le 1 \quad \forall k\in K \tag{7.2}$$

$$\sum_{i\in V}\sum_{k\in K}x_{ijk}=1 \quad \forall j\in J \tag{7.3}$$

$$\sum_{i\in V}x_{ijk}=\sum_{i\in V}x_{jik} \quad \forall j\in V, k\in K \tag{7.4}$$

$$\sum_{i\in \mathcal{S}}\sum_{j\in \mathcal{S}}x_{ijk}\le |\mathcal{S}|-1 \quad \forall \mathcal{S}\subseteq J, k\in K \tag{7.5}$$

Constraints (7.2), (7.3), (7.4), and (7.5) are routing constraints. Constraints (7.2) impose that no vehicle starts from more than one depot. Constraints (7.3) state that each customer is visited by exactly one vehicle. Constraints (7.4) state that, if a vehicle enters node $j\in V$, it must exit from it. Constraints (7.5) eliminate sub-tours.

$$\sum_{(i,j)\in A\setminus A^Z}x_{ijk}\le M y_k \quad \forall k\in K \tag{7.6}$$

Constraints (7.6) ensure that y_k is equal to unity if the route performed by vehicle $k\in K$

consists of at least one arc $(i,j) \in A \setminus A^Z$ (i.e., $\sum_{(i,j)\in A\setminus A^Z} x_{ijk} \geq 1$).

$$\sum_{i\in V}\sum_{j\in J} \mathcal{D}_j x_{ijk} \leq \mathcal{Q}_k \quad \forall k \in K \tag{7.7}$$

Constraints (7.7) ensure that the demand volumes of customers must respect the vehicle capacity.

$$\sum_{(i,j)\in A} d_{ij} x_{ijk} \leq R_k \quad \forall k \in K_{EV} \tag{7.8}$$

Constraints (7.8) limit the vehicle range and ensure that the total duration of a tour performed by an EV must respect its driving range limit.

$$\sum_{i\in D}\sum_{j\in V} x_{ijk} \leq \sum_{i\in D}\sum_{j\in V} x_{ijk-1} \quad \forall k \in K_t \neq K_t^1, t \in \{EV, ICEV\} \tag{7.9}$$

Constraints (7.9) avoid vehicle symmetry. These constraints are valid because the fleet of vehicles for each type is identical. Constraints (7.9) state that vehicle k can only be dispatched if vehicle $k-1$ has already been dispatched. K_t^1 is the first element of $K_t, t \in \{EV, ICEV\}$.

$$x_{ijk} \in \{0,1\} \quad \forall (i,j) \in A, k \in K; \quad y_k \in \{0,1\} \quad \forall k \in K \tag{7.10}$$

Finally, constraints (7.10) define the nature of the variables.

7.2.3 Economic analysis

Following the least cost principle, the optimal decisions of an individual logistics company regarding vehicle fleet composition and routes with a mixed fleet of EVs and ICEVs are determined in response to different EV-supporting policy options. The proposed optimization model provides rational decisions of an individual company regardless of unobserved factors, such as personal preferences of the decision makers. The optimal decisions of a company may change according to policy adjustments under different policy scenarios in Section 7.2.1. Together with changes in the vehicle fleet composition and routing plan, such decisions change the total cost of the company (i.e., surplus), tax revenue of the government, energy consumption, and thus the emissions of different pollutants. Such responsiveness changes the social welfare as given in the following expression:

$$\Delta W = \Delta S + \Delta R - \Delta EC \tag{7.11}$$

ΔW is the change in social welfare that is induced by policy changes and the company's responses. ΔS is the sum of changes in the customer surplus ΔCS and producer surplus ΔPS in terms of the delivery service.

$$\Delta S = \Delta CS + \Delta PS \tag{7.12}$$

The customer surplus is the total difference between the willingness to pay WP and service price for all customers P_c.

$$\Delta CS = \Delta WP - \Delta P_c \tag{7.13}$$

The producer surplus is the difference between the service price for the producer P_p and the total delivery cost TC (i.e., value of the objective function in the optimization model) for the logistics company.

$$\Delta PS = \Delta P_p - \Delta TC \tag{7.14}$$

In order to focus on the company side, we assumed that the price that the customer pays and price that the producer receives are the same: P_c=P_p. Any taxes imposed by the government are treated as an internal business cost for the company in the short run.

Therefore, the service price does not change. The customer's willingness to pay does not change either in the short run. Finally, we obtain the change in the total surplus as the company's total delivery cost.

$$\Delta S = -\Delta TC \tag{7.15}$$

ΔR is the change in government tax revenues, including changes in the vehicle purchase subsidy ΔPS, vehicle taxes ΔVT, fuel tax ΔFT, and zone fee for getting access to the limited zone ΔLEZ.

$$\Delta R = \Delta PS + \Delta VT + \Delta FT + \Delta LEZ \tag{7.16}$$

The proposed optimization model is based on a daily calculation. The purchase subsidy and vehicle taxes are converted to a daily cost with a discount rate of 0.05 and lifetime of 10×365 days. The zone fee and fuel tax are daily costs for using EVs and ICEVs.

$$\Delta PS = \Delta \sum_{k\in K}\sum_{i\in D}\sum_{j\in J} -S_k x_{ijk} \tag{7.17}$$

$$\Delta VT = \Delta \sum_{k\in K}\sum_{i\in D}\sum_{j\in J}(f_k + \mathcal{C}_k) x_{ijk} \tag{7.18}$$

$$\Delta FT = \Delta \sum_{k\in K}\sum_{(i,j)\in A} \mathcal{T}_k \mathcal{E}_k d_{ij} x_{ijk} \tag{7.19}$$

$$\Delta LEZ = \Delta \sum_{k\in K} \mathcal{F}_k y_k \tag{7.20}$$

ΔEC is the change in the total external cost of climate change, local air pollution and congestion. $e_k^j, \forall k \in K_t, t \in \{EV, ICEV\}, j \in \{I, O\}$ is the marginal external cost per liter of fuel for an ICEV or per watt-hour of electricity for an EV, where I stands for inside the limited zone and O stands for outside the limited zone. α_{ij} is the proportion of arc $(i,j) \in A$ located inside the zone. $\mathcal{E}_k$ is the energy efficiency for vehicle $k \in K_t, t \in \{EV, ICEV\}$.

ΔEC is calculated as follows.

$$\Delta EC = \Delta \sum_{k \in K} \sum_{(i,j) \in A} \alpha_{ij} e_k^I \mathcal{E}_k d_{ij} x_{ijk} + \Delta \sum_{k \in K} \sum_{(i,j) \in A} (1 - \alpha_{ij}) e_k^O \mathcal{E}_k d_{ij} x_{ijk} \tag{7.21}$$

The first component in Equation (7.21) represents the change in the external cost inside the limited zone, and the second component relates to the change in the external cost outside the limited zone.

The marginal external costs are calculated differently for EVs and ICEVs. The costs of three externalities are considered: climate change ${e_1}_k^j$, local air pollution ${e_2}_k^j$, and congestion ${e_3}_k^j$.

$$e_k^j = {e_1}_k^j + {e_2}_k^j + {e_3}_k^j \;\; \forall k \in K_t, t \in \{EV, ICEV\}, j \in \{I, O\} \tag{7.22}$$

- *Climate change*: The CO_2 emissions of driving (per liter) an ICEV come from the fuel combustion, while the CO_2 emissions of EV (per kWh) result from the electricity production depending on the energy source. The impact of CO_2 emissions from road vehicles on global warming is independent of the timing and location. Therefore, the marginal damage costs of CO_2 from inside and outside the zone are the same: ${e_1}_k^I = {e_1}_k^O, \forall k \in K_t, t \in \{EV, ICEV\}$.

- *Local air pollution*: Local emissions (NO_x, SO_2, PM, NMVOC, CO_2 for gasoline) from driving an ICEV (per liter) come from fuel combustion, while emissions (NH_3, NO_x, SO_2, $PM_{2.5}$, NMVOC, CO_2) from driving an EV (per kWh) result from electricity production. Local emissions give rise to air pollution and cause cardiovascular and respiratory diseases. Emissions are released from high stacks. Within-country externalities of power plants are less dependent on the local population density, whereas externalities of fuel combustion in cars are strongly site-specific. The emissions from ICEVs have higher damage cost inside the limited zone, which is usually highly populated, than outside the zone: ${e_2}_{ICEV}^I > {e_2}_{ICEV}^O$. Emissions from electricity production only affect the residents around the power plant, which is usually located outside of urban areas. Thus, for urban areas inside and outside the zone, the marginal costs of local pollution resulting from electricity production are the same: $e2^{I}_{EV} = e2^{O}_{EV}$.

- *Congestion*: External costs of congestion occur when users plan their mobility individually but the required resource (i.e., the infrastructure) is too scarce to fulfil the demand mobility (Jochem et al., 2016). For both EVs and ICEVs, the congestion cost per kilometer are the same, but the congestion cost inside the limited zone, which usually has heavy traffic, is higher than outside the zone: $e3^{I}_{k} > e3^{O}_{k}, \forall k \in K_t, t \in \{EV, ICEV\}$. To maintain unit consistency in the equations, the marginal congestion cost (per kilometer) can be converted to the marginal congestion cost (per liter for ICEVs and per kWh for EVs) according to the energy efficiency $\mathcal{E}_k$.

7.3 Numerical experiments

As an application of the proposed framework, we implemented numerical experiments using data generated for a transport network and the policy scenarios provided in Section 7.2.1 in order to analyze the impact of different policies on the optimal decisions of a logistics company. We also performed a sensitivity analysis to determine the robustness of the results with different types of vehicles and transport networks. The heterogonous vehicle routing problems are hard optimization problems. Because of the complexity of the problem, only small-size instances can be solved optimally by exact solvers, and for large-size instances obtained from real transport networks, a solution approach that can provide high-quality solutions would be required in order to fairly compare the results under different policies. Here, we do not provide a solution approach for the problem, but we aim to implement the proposed framework on a small transport network in order to have a fair comparison among the optimal solutions obtained by the optimization model under different scenarios. The computations for the MILP formulation (i.e., equations (7.1)-(7.10)) were coded in AMPL by using the solver Gurobi 6.5 on a computer with 24 CPU cores and 35 GB of RAM. All of the instances were solved optimally within a time limit of 12 hours.

7.3.1 Problem instances

In this section, we provide the problem instances. All instances were generated for a transport network consisting of 15 customers that are scattered on a square plane with a single depot. The instances differed regarding the purchase subsidy, vehicle taxes, and zone fee for the different scenarios provided in Section 7.2.1 (i.e., each instance corresponds to each scenario with the same transport network but with different values of parameters S_k, f_k, $\mathcal{C}_k$, and $\mathcal{F}_k$ in the objective function of the optimization model). Figure 7.3 shows an example of a feasible solution for the transport network. The black circles represent the customers. The triangle represents the depot. The area inside the dashed line circle in Figure 7.3 represents the limited zone. The customers inside the limited zone are distributed uniformly. The dotted lines represent the routes performed by EVs and the solid lines represent the routes performed by ICEVs. The customer demands were generated from a uniform distribution between 15% and 25% of the ICEV capacity: $d_j \sim \mathcal{U}(0.15 * \mathcal{Q}_{ICEV}, 0.25 * \mathcal{Q}_{ICEV})$. In order to replicate the experiments, the distance matrix and demands are available upon request.

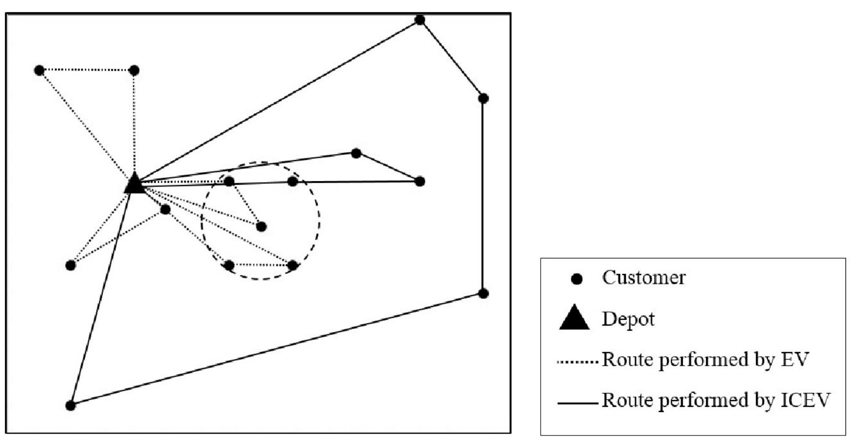


Figure 7.3: Feasible solution for the transport network

The selected vehicles for urban freight transport were *Renault Kangoo Maxi ZE* for EVs and *Renault Trafic Energy dci 95* for diesel vehicles. Table 7.2 provides the vehicle characteristics that are collected from the official website of the car manufacturer. Header *Price* corresponds to the purchase price of the vehicle. Header *Playload* represents the maximum load weight (in kg) that each vehicle can carry. Header *Tailpipe* CO_2 corresponds to the amount of CO_2 (g/km) emitted by each vehicle. Header *Energy efficiency* represents the amount of energy consumed per kilometer by each type of vehicle (Wh/km for EV and L/km for diesel vehicles).[5]

Table 7.2: Vehicle characteristics

Type	**EV**	**ICEV**
Model	Kangoo Maxi ZE	Trafic Energy dci 95
Price	22650 £	25750 £
Playload	650 kg	1040 kg
Tailpipe CO_2	0 g/km	164 g/km
Energy efficiency	150 Wh/km	0.064 L/km

We converted taxes/costs into a daily basis with an annual discount rate of 5%. Three types of policies were set at three pounds per vehicle per day[6] for the convenience of comparison. For further analysis on the primary scenarios in Section 7.2.1, we generated additional sub-scenarios regarding the related amount of taxation. The amount of taxation (i.e., the vehicle purchase subsidy, vehicle taxes, and zone fee) was changed from one to ten pounds in Scenarios 1, 2, and 3. We compared all scenarios to the baseline for welfare changes.

In this study, we chose the UK as an example to set the parameters in the optimization model and economic analysis. The data from IEA (2017) was used in order to obtain the

[5] In sensitivity analysis, we also use a smaller diesel vehicle (*Kangoo Maxi dci 90*) with same car model and a larger diesel vehicle (*Master Energy dci 110*).

[6] These are reasonable amounts according to the fiscal incentives offered in European countries like the UK and France.

prices and taxes of electricity and diesel for the UK in 2014. The marginal external costs per unit of electricity are calculated by Yan (2017) based on the energy mix of electricity generation (IEA, 2016), emission factors (Buekers et al., 2014) and social costs of pollutants (Markandya et al., 2010) in UK. The marginal external costs per unit of diesel are calculated based on emission factors and social costs of pollutants by Parry et al. (2014). The congestion cost was taken from Maibach et al. (2008). We regard the terms *inside the limited zone* and *outside the limited zone* as *urban* and *suburban*, respectively, that are defined for calculating different external costs of congestion in Maibach et al. (2008). The marginal cost of emissions or congestion inside the limited zone was set as 50 % higher than that outside the zone. The details of the data are presented in the Table 7.3.

Table 7.3: Data for variables

Variable	**Data**
Electricity price	0.1556 £/kWh
Electricity tax	0.0074 £/kWh
Diesel price	1.3350 £/L
Diesel tax	0.8020 £/L
Marginal external cost of CO_2 emission (electricity generation)	0.0084 €/kWh
Marginal external cost of CO_2 emission (diesel combustion)	0.2024 €/L
Marginal external cost of local air pollution (electricity generation)	0.0045 €/kWh
Marginal external cost of local air pollution (diesel combustion)	0.2177 €/L
Marginal external cost of congestion for diesel and electric vehicles	0.0100 €/km

7.3.2 Computational results

We tested the proposed framework by using the data provided in Section 7.3.1 under the policy scenarios provided in Section 7.2.1. Table 7.4 provides the results on a daily basis obtained by solving the optimization model under different scenarios. Header *Number* represents the optimal number of vehicles for each type obtained by solving the optimization model. The numbers in parentheses refer to the number of ICEVs entering the limited zone. Columns *Distance (in)* and *Distance (out)* represent the total distance (in kilometers) traveled by each type of vehicle inside the limited zone (i.e., $\sum_{k \in K_t} \sum_{(i,j) \in A} \alpha_{ij} d_{ij} x_{ijk} \ \forall t \in \{EV, ICEV\}$) and outside (i.e., $\sum_{k \in K} \sum_{(i,j) \in A} (1 - \alpha_{ij}) d_{ij} x_{ijk} \ \forall t \in \{EV, ICEV\}$), respectively. Header *Total cost* represents the sum of the routing costs, fixed usage cost of vehicles, and entrance fee to the limited zone (i.e., the optimal value for the objective function of the optimization model). Headers ΔR, ΔEC, and ΔS represent the changes in tax revenues, external costs, and producer surplus, respectively. ΔW is the change in total welfare for different scenarios.

When the incentive of three pounds per day (net present value) was provided, the purchase subsidy on EVs and zone fee on ICEVs increased the share of EVs in the vehicle fleet composition. With the purchase subsidy and zone fee, two EVs were purchased in order to replace one diesel car. This means that the operational cost (i.e., routing cost and zone entrance fee) saving of replacing two EVs by one diesel vehicle exceeded the extra purchasing cost of two EVs. The vehicle taxes on ICEVs made no difference to the company's logistic decisions.

With the purchase subsidy (Scenario 1) and zone fee (Scenario 2), the total distance (i.e., either inside or outside the limited zone) covered by all EVs increased almost twofold, while the average distance per EV decreased. For the diesel vehicles, the opposite changes were observed. EVs are limited by their driving range, so ICEVs have to visit customers out of EVs' driving ranges. In particular, without the zone fee, all diesel vehicles crossed the limited zone in order to travel the shortest delivery distance. With the zone fee for ICEVs and fee exemptions for EVs (Scenario 2), only one out of two diesel vehicles entered the limited zone. In order to avoid paying the zone fee, the diesel vehicles needed to travel around the zone to reach the customers on the other side of the zone, which increased the total traveling distance. Still, the zone fee did not prevent all diesel vehicles from entering the limited zone. For some diesel vehicles, paying the zone fee to go through the zone led to a lower total cost than traveling around the zone to reach customers on the other side.

The purchase subsidy and zone fee reduced the use of ICEVs both inside and outside the zone. Notably, they reduced the inside-zone distance traveled by ICEVs by more than 50 % compared to the baseline. The external costs of emissions and congestion were decreased by more than 10%. Because taxes and subsidies are transferred within the society, the change in welfare largely depends on changes in the external cost. As one can see from the results in Table 7.4, the zone fee produced the largest improvement in welfare.

The vehicle taxes were not observed to have any impact on the company's decisions. To directly compare policies, the effects of different amounts of taxation on the resultant welfare were compared.[7] In Figure 7.4, the horizontal axis represents the amount of tax (net present value) for all three policies from one to ten pounds per day. With a daily subsidy/tax rate of two or more than two pounds, the zone fee and purchase subsidy led to increase EV share and the total social welfare was improved. With a daily subsidy/tax rate of four pounds, these two policies were stable, and no further change was induced, while the vehicle taxes started to impact company's logistic decisions. Above four pounds, further strengthening of EV policies failed to promote the use of more EVs or improve the welfare. This was due to the technical performances of the vehicles rather than the incentives provided by policies. Overall, the zone fee improved the welfare, while vehicle taxes and purchase subsidy had the same level of welfare improvement.

Table 7.4: Impacts of different EV-supporting policy options on company's decisions and social welfare

Scenario	**Type**	**Number**	**Distance (in)**	**Distance (out)**	**Total cost**	ΔS	ΔR	ΔEC	ΔW
Baseline	EV	2	135.43	346.05	195.23				
	ICEV	3(3)	275.47	1131.83					
Scenario 1 (purchase subsidy)	EV	4	231.25	606.65	186.50	8.73	-20.76	-14.26	2.23
	ICEV	2(2)	122.94	1106.06					
Scenario 2 (zone fee)	EV	4	231.25	606.65	201.72	-6.49	-5.63	-17.94	5.83
	ICEV	2(1)	104.28	1127.26					
Scenario 3 (vehicle taxes)	EV	2	135.43	346.05	204.23	-9.00	9.00	0.00	0.00
	ICEV	3(3)	275.47	1131.83					

[7]details are provided in Tables 7.5–7.7 in the appendix

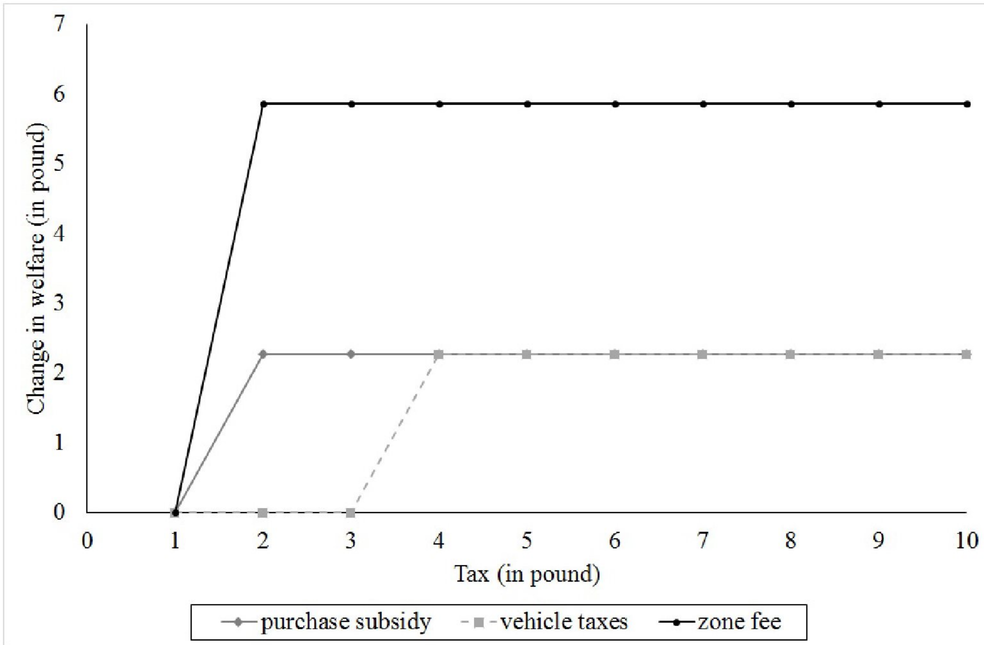


Figure 7.4: Welfare changes corresponding to changes in the daily tax rate

7.3.3 Sensitivity analysis

The results of the sensitivity analysis are presented here. We focused on the fact that a logistics company might have different types of vehicles or operates in different cities. We used the scenarios in Section 7.2.1 to determine the results of changes in EV technology [8], the transport network[9], substitution between vehicles by comparison to a smaller diesel vehicle, and changes in customer demand[10]. All results are provided in Tables 7.8–7.12 in the appendix.

For each individual case in the sensitivity analysis, the total social welfare hardly improved after the purchase subsidy, zone fee, and vehicle taxes were implemented. For the within-scenario comparison to the main results (i.e., the results provided in Table 7.4), the current policies designed for promoting the use of EVs were less effective according to the

[8] The driving range was increased from 258 to 300 km, or the capacity was increased by 25%.
[9] Distances between customers were reduced by 50%.
[10] The customer demand was increased by 20%.

sensitivity analysis. As one can see from the results in Tables 7.8–7.10, technological improvements reduced the relative disadvantage of EV (i.e., limited driving range) in the cases of extended range, enlarged capacity, and smaller diesel vehicles. In these cases, the EV share in the vehicle fleet composition increased compared to the main results. As presented in Tables 7.11–7.12, local factors (e.g., short distances between customers) in favor of EV worked the same way as technological improvements.

In a few cases with the zone fee, the social welfare decreased while the vehicle fleet composition did not change. The zone fee increased the total travel distance for diesel vehicles, which led to a higher external cost and lower welfare.

7.4 Conclusions

EVs are often considered as a critical solution to climate stabilization. For an individual logistics company, costs and technical disadvantages limit the purchase and use of EVs. EV-supporting policies provide strong incentives for EVs in urban freight transport, which is responsible for a significant amount of CO_2 and local pollutant emissions. Only a small body of literature has focused on how EV policies affect logistics companies and therefore society. To throw light on the relevant issues, we examined common vehicle specific EV-supporting policies: the purchase subsidy for EVs, vehicle taxes with exemptions for EVs, and limited access (zone fee) to a low-emission/congestion zone with exemptions for EVs. We developed a framework that combines an optimization model with economic analysis to evaluate the effects of EV-supporting policies on an individual company's optimal decisions regarding vehicle fleet composition and routes, external costs of emissions and congestions, and social welfare.

We carried out numerical experiments using data generated for a small transport network under different policy scenarios. Based on the results from the numerical experiments, the purchase subsidy on EVs, zone fee on ICEVs, and vehicle taxes on ICEVs increased the EV share in the vehicle fleet of the logistics company and decreased the distances traveled by ICEVs, which reduced externalities and improved social welfare. In the considered scenarios, the zone fee was more effective at improving social welfare. This is because the zone fee significantly reduces the external cost by preventing emissions and congestion inside the limited zone. However, in some cases of the sensitivity analysis, the zone fee increased external costs by forcing ICEVs to travel around the zone to reach customers on the other side, which may lead to more emissions from fuel combustion or congestion. The vehicle taxes and subsidy had the same influences on the company and society, although they performed differently at low tax/subsidy rates. Lastly, the sensitivity analysis showed that local factors at the company and city levels, such as the vehicle type and transport network, are also important for designing efficient EV-supporting policies for urban logistics.

7.5 Appendix: details of results obtained from tax changes and sensitivity analysis

Tax changes

Table 7.5: Impacts of different EV-supporting policy options with different purchase subsidy

Scenario	Subsidy	Type	Number	Distance (in)	Distance (out)	Total cost	ΔR	ΔEC	ΔS	ΔW
Scenario1.10	10	EV	4	231.30	606.70	158.50	-48.72	-14.26	36.73	2.27
		ICEV	2(2)	122.90	1106.10					
Scenario1.9	9	EV	4	231.30	606.70	162.50	-44.72	-14.26	32.73	2.27
		ICEV	2(2)	122.90	1106.10					
Scenario1.8	8	EV	4	231.30	606.70	166.50	-40.72	-14.26	28.73	2.27
		ICEV	2(2)	122.90	1106.10					
Scenario1.7	7	EV	4	231.30	606.70	170.50	-36.72	-14.26	24.73	2.27
		ICEV	2(2)	122.90	1106.10					
Scenario1.6	6	EV	4	231.30	606.70	174.50	-32.72	-14.26	20.73	2.27
		ICEV	2(2)	122.90	1106.10					
Scenario1.5	5	EV	4	231.30	606.70	178.50	-28.72	-14.26	16.73	2.27
		ICEV	2(2)	122.90	1106.10					
Scenario1.4	4	EV	4	231.30	606.70	182.50	-24.72	-14.26	12.73	2.27
		ICEV	2(2)	122.90	1106.10					
Scenario1.3	3	EV	4	231.30	606.70	186.50	-20.72	-14.26	8.73	2.27
		ICEV	2(2)	122.90	1106.10					
Scenario1.2	2	EV	4	231.30	606.70	190.50	-16.72	-14.26	4.73	2.27
		ICEV	2(2)	122.90	1106.10					
Scenario1.1	1	EV	2	135.40	346.10	193.23	-2.00	0.00	2.00	0.00
		ICEV	3(3)	275.50	1131.80					

Table 7.6: Impacts of different EV-supporting policy options with different zone fees

Scenario	Fee	Type	Number	Distance (in)	Distance (out)	Total cost	ΔR	ΔEC	ΔS	ΔW
Scenario 2.10	10	EV	4	231.25	606.65	208.72	1.41	-17.94	-13.49	5.86
		ICEV	2(1)	104.28	1127.26					
Scenario 2.9	9	EV	4	231.25	606.65	207.72	0.41	-17.94	-12.49	5.86
		ICEV	2(1)	104.28	1127.26					
Scenario 2.8	8	EV	4	231.25	606.65	206.72	-0.59	-17.94	-11.49	5.86
		ICEV	2(1)	104.28	1127.26					
Scenario 2.7	7	EV	4	231.25	606.65	205.72	-1.59	-17.94	-10.49	5.86
		ICEV	2(1)	104.28	1127.26					
Scenario 2.6	6	EV	4	231.25	606.65	204.72	-2.59	-17.94	-9.49	5.86
		ICEV	2(1)	104.28	1127.26					
Scenario 2.5	5	EV	4	231.25	606.65	203.72	-3.59	-17.94	-8.49	5.86
		ICEV	2(1)	104.28	1127.26					
Scenario 2.4	4	EV	4	231.25	606.65	202.72	-4.59	-17.94	-7.49	5.86
		ICEV	2(1)	104.28	1127.26					
Scenario 2.3	3	EV	4	231.25	606.65	201.72	-5.59	-17.94	-6.49	5.86
		ICEV	2(1)	104.28	1127.26					
Scenario 2.2	2	EV	4	231.25	606.65	200.72	-6.59	-17.94	-5.49	5.86
		ICEV	2(1)	104.28	1127.26					
Scenario 2.1	1	EV	2	135.43	346.05	198.23	3.00	0.00	-3.00	0.00
		ICEV	3(3)	275.47	1131.83					

Table 7.7: Impacts of different EV-supporting policy options with different vehicle taxes

Scenario	**Tax**	**Type**	**Number**	**Distance (in)**	**Distance (out)**	**Total cost**	ΔR	ΔEC	ΔS	ΔW
Scenario 3.10	10	EV	4	231.25	606.65	218.50	11.28	-14.26	-23.27	2.27
		ICEV	2(2)	122.94	1106.06					
Scenario 3.9	9	EV	4	231.25	606.65	216.50	9.28	-14.26	-21.27	2.27
		ICEV	2(2)	122.94	1106.06					
Scenario 3.8	8	EV	4	231.25	606.65	214.50	7.28	-14.26	-19.27	2.27
		ICEV	2(2)	122.94	1106.06					
Scenario 3.7	7	EV	4	231.25	606.65	212.50	5.28	-14.26	-17.27	2.27
		ICEV	2(2)	122.94	1106.06					
Scenario 3.6	6	EV	4	231.25	606.65	210.50	3.28	-14.26	-15.27	2.27
		ICEV	2(2)	122.94	1106.06					
Scenario 3.5	5	EV	4	231.25	606.65	208.50	1.28	-14.26	-13.27	2.27
		ICEV	2(2)	122.94	1106.06					
Scenario 3.4	4	EV	4	231.25	606.65	206.50	-0.72	-14.26	-11.27	2.27
		ICEV	2(2)	122.94	1106.06					
Scenario 3.3	3	EV	2	135.43	346.05	204.23	9.00	0.00	-9.00	0.00
		ICEV	3(3)	275.47	1131.83					
Scenario 3.2	2	EV	2	135.43	346.05	201.23	6.00	0.00	-6.00	0.00
		ICEV	3(3)	275.47	1131.83					
Scenario 3.1	1	EV	2	135.43	346.05	198.23	3.00	0.00	-3.00	0.00
		ICEV	3(3)	275.47	1131.83					

Sensitivity analysis

Table 7.8: Impacts of different EV-supporting policy options for EVs with an extended driving range

Scenario	Type	Number	Distance (in)	Distance (out)	Total cost	ΔS	ΔR	ΔEC	ΔW
Baseline	EV	4	328.48	623.04	184.74				
	ICEV	2(1)	70.23	966.61					
Scenario 1 (subsidy)	EV	4	328.48	623.04	172.74	12.00	-12.00	0.00	0.00
	ICEV	2(1)	70.23	966.61					
Scenario 2 (zone fee)	EV	4	328.48	623.04	187.74	-3.00	3.00	0.00	0.00
	ICEV	2(1)	70.23	966.61					
Scenario 3 (vehicle taxes)	EV	4	328.48	623.04	190.74	-6.00	6.00	0.00	0.00
	ICEV	2(1)	70.23	966.61					

Table 7.9: Impacts of different EV-supporting policy options for EVs with a larger carrying capacity

Scenario	Type	Number	Distance (in)	Distance (out)	Total cost	ΔS	ΔR	ΔEC	ΔW
Baseline	EV	3	142.94	515.00	182.51				
	ICEV	2(2)	143.94	1085.06					
Scenario 1 (subsidy)	EV	3	142.94	515.00	173.51	9.00	-9.00	0.00	0.00
	ICEV	2(2)	143.94	1085.06					
Scenario 2 (zone fee)	EV	3	180.30	554.08	187.51	-5.00	3.22	0.10	-1.88
	ICEV	2(1)	104.28	1127.26					
Scenario 3 (vehicle taxes)	EV	3	142.94	515.00	188.51	-6.00	6.00	0.00	0.00
	ICEV	2(2)	143.94	1085.06					

Table 7.10: Impacts of different EV-supporting policy options with a smaller diesel vehicle

Scenario	Type	Number	Distance (in)	Distance (out)	Total cost	ΔS	ΔR	ΔEC	ΔW
Baseline	EV	3	192.91	541.25	163.26				
	ICEV	3(3)	195.01	1241.43					
Scenario 1 (subsidy)	EV	3	192.91	541.25	154.26	9.00	-9.00	0.00	0.00
	ICEV	3(3)	195.01	1241.43					
Scenario 2 (zone fee)	EV	3	276.25	429.13	170.76	-7.50	7.82	9.13	-8.81
	ICEV	3(2)	157.51	1315.03					
Scenario 3 (vehicle taxes)	EV	3	192.91	541.25	167.74	-4.48	4.48	0.00	0.00
	ICEV	3(3)	195.01	1241.43					

Table 7.11: Impacts of different EV-supporting policy options for a smaller city

Scenario	Type	Number	Distance (in)	Distance (out)	Total cost	ΔS	ΔR	ΔEC	ΔW
Baseline	EV	6	196.19	924.57	118.32				
	ICEV	1(1)	47.78	45.82					
Scenario 1 (subsidy)	EV	6	196.19	924.57	100.32	18.00	-18.00	0.00	0.00
	ICEV	1(1)	47.78	45.82					
Scenario 2 (zone fee)	EV	6	196.19	924.57	121.32	-3.00	3.00	0.00	0.00
	ICEV	1(1)	47.78	45.82					
Scenario 3 (vehicle taxes)	EV	6	196.19	924.57	121.32	-3.00	3.00	0.00	0.00
	ICEV	1(1)	47.78	45.82					

Table 7.12: Impacts of different EV-supporting policy options for a city with larger demands

Scenario	Type	Number	Distance (in)	Distance (out)	Total cost	ΔS	ΔR	ΔEC	ΔW
Baseline	EV	3	231.25	434.13	208.61				
	ICEV	3(2)	174.51	1201.07					
Scenario 1 (subsidy)	EV	3	231.25	434.13	199.61	9.00	-9.00	0.00	0.00
	ICEV	3(2)	174.51	1201.07					
Scenario 2 (zone fee)	EV	3	231.25	434.13	214.61	-6.00	6.00	0.00	0.00
	ICEV	3(2)	174.51	1201.07					
Scenario 3 (vehicle taxes)	EV	3	231.25	434.13	217.61	-9.00	9.00	0.00	0.00
	ICEV	3(2)	174.51	1201.07					

Chapter 8

Conclusions and future work

In the first part of the thesis, we introduced a new location-routing problem, and discussed both modeling and solution approaches. Motivated by the actual problem of a national postal service company, we introduced and defined a new problem that incorporates synchronization and delivery and pickup activities in a two-echelon location-routing problem (2E-LRP). Due to the complexity of the problem, only very small instances could be solved using exact approaches. We proposed a decomposition-based heuristic and provided the computational results with this method for four sets of instances. These sets included 112 instances: 96 *small-* and *medium-size* instances and 16 *large-size* instances. The decomposition-based heuristic was able to find the best known solutions in 26 of the 112 instances, including 11 small- and medium-size instances and 15 large-size instances. For the small- and medium-size instances, the average gaps to the best-known solution (GBKs) with the decomposition-based heuristic and CPLEX were 4.23 and 0.34, respectively, and the computational effort of the decomposition-based heuristic was almost one-fourth the time spent by CPLEX. In order to check the effect of the first phase of the decomposition-based heuristic on the solution quality, we modified the proposed method according to the common approach used in the literature for choosing facility configurations. We compared the results of the original and modified methods, and the former provided better-quality solutions for a given number of iterations. It could be worthwhile to test the first phase of the proposed method on other solution approaches in the LRP literature. It is also worth adapting the state of the art heuristics for 2E-LRP (e.g., the adaptive large neighborhood search by Contardo et al. (2012)) for the new 2E-LRP that we introduced in this thesis.

In addition to the solution approach, we proposed three data-driven schemes that we used in combination with mixed-integer linear programming (MILP). The aim of the schemes is to remove routes that are unlikely to be part of high-quality solutions so that promising solutions can be obtained in considerably less time. The computational results on the four sets of instances revealed that, with the first scheme (i.e., removing long arcs connecting pairs of far apart nodes), the solution quality either stayed the same or improved. When all three schemes were used in combination, feasible solutions were found for some of the larger instances that were unsolvable without schemes or with only the first scheme. In our numerical experiments, we observed that, with the increase in size of instances, the solution quality obtained by the schemes was better than without the schemes. Let's consider the first scheme. For large-size instances, in the optimal solution, we expect that far away customers are connected to each other through the customers located between them. Therefore, we expect a better performance by the first scheme because more long arcs are expected to be removed from the set of feasible solutions. However, due to the limitations of the exact solver, we were not able to observe further improvement in solution quality by the schemes for larger-size instances. As an opportunity for future research, it could be worthwhile to test the proposed schemes in combination with other heuristics or exact approaches provided in the LRP literature.

We generalized the problem by considering the vehicle capacity, multiple trips by vehicles, and decisions on terminal locations. In the new 2E-LRP that we introduced in this thesis, traveling times were assumed to be deterministic, but in reality they depend on different factors such as congestion and weather. In addition, for parcel services, the presence of customers is often not known from day to day because not all customers receive packages every day. In such uncertain situations, the use of deterministic and static methods might lead to suboptimal solutions. Future research needs to address the incorporation of the stochastic presence of customers and time-dependency of travels in the actual problem of Posten Norge.

The scope of the second part of the thesis was to illustrate how a simple vehicle routing problem could be used to enhance economic evaluation procedures of supporting policies for electric vehicles. We proposed a framework that combines an optimization model with economic analysis in order to evaluate the effects of EV-supporting policies on the logistic costs of a company and the environmental benefits/social welfare. Based on three EV-supporting policy options: The purchase subsidy, vehicle taxes with exemptions for EVs, and zone fee exemptions for EVs, we determined optimal decisions of a company regarding vehicle fleet composition and routes, and we evaluated the policies according to externality and welfare changes. We carried out numerical experiments using data generated for a small transport network under different policy scenarios. Based on the results from the numerical experiments, the purchase subsidy on EVs, zone fee on ICEVs, and vehicle taxes on ICEVs increased the EV share in the vehicle fleet of company and decreased the distances traveled by ICEVs, which reduced externalities and improved social welfare. Among EV-supporting policies, the zone fee was more effective at improving social welfare because it significantly reduces the external cost by preventing emissions and congestion inside the limited zone. However, in some cases of the sensitivity analysis, the zone fee increased external costs by forcing ICEVs to travel around the zone. The results from the sensitivity analysis showed that local factors at the company and city levels, such as the vehicle type and transport network, are also important for designing efficient EV-supporting policies for urban logistics.

The proposed framework should be seen as a preliminary attempt to evaluate individual company's actions in response to policies for EVs and effectiveness of the policies through the combination of an optimization model and economic analysis, which provide an evaluation of EV policies from a different perspective and also lays an important basis for further explorations. As opportunities for future research, more comprehensive models can be established to deal with realistic issues such as real-time deliveries and idling. Deliveries during off-hours with less traffic will consume less fuel or emit less pollution per kilometer, while idling due to deliveries during rush-hours will lead to more fuel consumption (and emissions) than moving traffic. Moreover, transport networks my turn more complicated in practice. For instance, urban geographic features and regional driving requirements have important impacts on driving speeds and therefore, real-world fuel consumption and CO_2 emission can be different from the one labelled by car companies. In order to consider the gaps between the labelled values and real values of fuel consumption and emission rates, scientific evidences for specific vehicles are needed for precise calculations. A more realistic issue that we did not consider in our study is alternative roads between customers. Especially, in this study, the cost per unit of distance will consist of both fuel cost and entrance fee to the zone. Therefore, the shortest roads between two customers do not necessarily mean roads with the lowest cost. To study cases of alternative roads, visualizing urban road grids though geographic information systems may be necessary. At last, due to the complexity of the optimization problem, an efficient solution approach for large-scale transport networks would improve the validity of our proposed framework. To do this, one could adapt state-of-the-art heuristics used in the literature of heterogenous vehicle routing problems (e.g., Subramanian et al. (2012); Penna et al. (2013)).

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