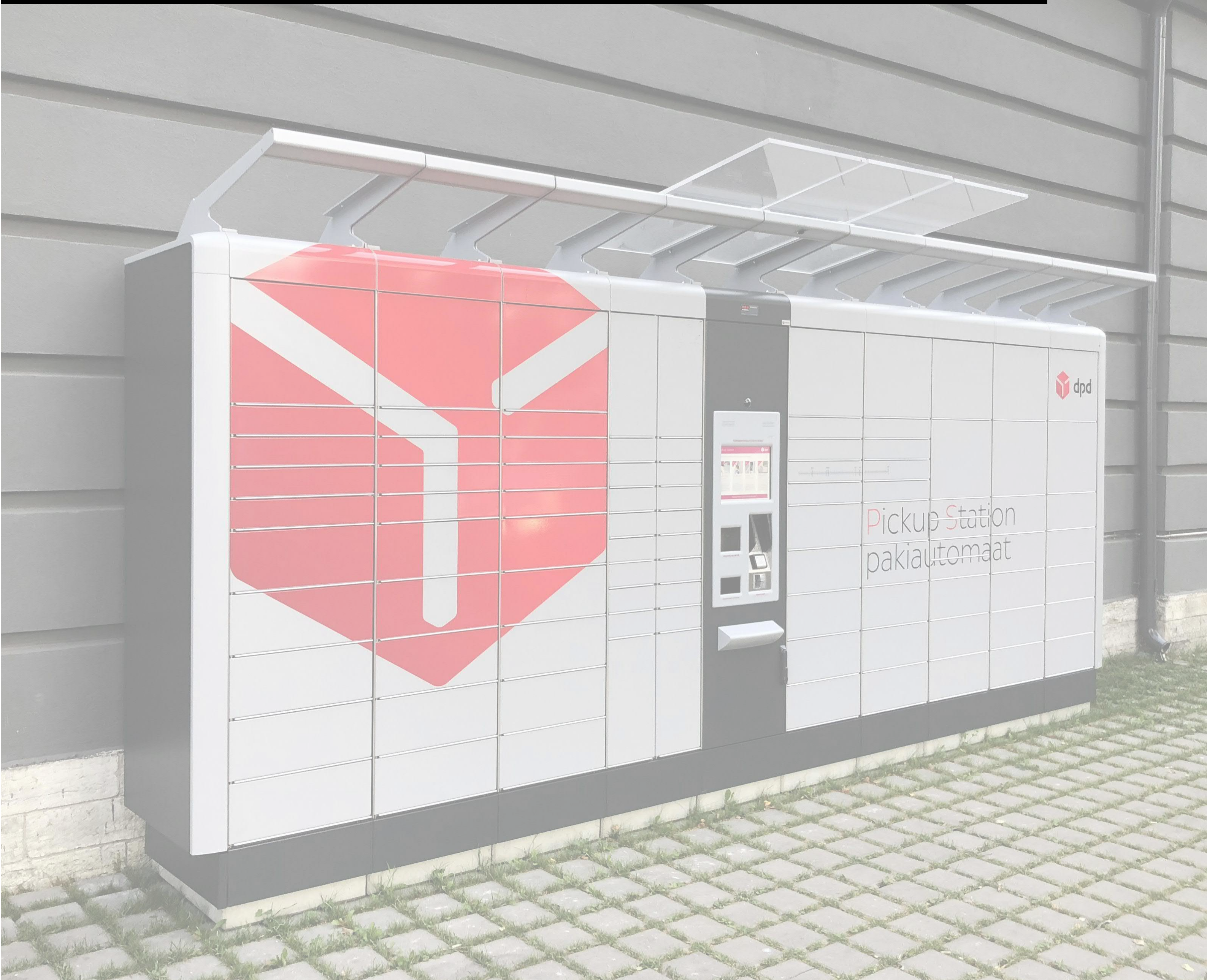
Implementation of Receiver Preferences in a Parcel Locker Network for Last Mile Deliveries

A. Genius Coca



TNO innovation for life

TU Delft

Implementation of Receiver Preferences in a Parcel Locker Network for Last Mile Deliveries

by

A. Genius Coca

to obtain the degree of Master of Science in

Transport, Infrastructure and Logistics

at the Delft University of Technology
to be defended publicly on Tuesday May 12th, 2020.

Student number:	4749200	
Thesis committee:	Prof. dr. ir. L.A. Tavasszy,	TU Delft, chairman
	Dr. M.Y. Maknoon,	TU Delft
	Dr. B. Atasoy,	TU Delft
	MSc. E. van Kempen,	TNO

Preface

This research is the result of the graduation project for the Master in Transport, Infrastructure and Logistics at the Delft University of Technology and it has been developed in collaboration with TNO (Netherlands Organisation for Applied Scientific Research).

I would like to thank my thesis committee: Lóri Tavasszy, Yousef Maknoon, Bilge Atasoy and Elisah van Kempen, who have guided me throughout the whole process of defining, developing and writing my research. I would like to specially thank Yousef for challenging me during all the discussions we had, which I enjoyed and were crucial to see that I was going in the good direction. I would also like to thank Bilge for the brief but really helpful discussions we had and Lóri, for his guidance towards a relevant and concise work, always reminding me the scientific but also practical perspective of what I was doing. Last, but not least, I would like to thank Elisah for always trying to help and for her support with my ideas at TNO from the beginning. It was a great opportunity to work at TNO, which gave me a really good perspective of how research in logistics can easily be developed together with companies.

Finally, I would like to give the biggest thank you to my family, for their unconditional support throughout all my studies and also to Robert, without whom by my side I would not have reached this far. Of course, counting with the support of my friends here in Delft was also really important during this period. Thank you for always being there.

A. Genius Coca
Delft, May 2020

Abstract

E-commerce is significantly growing amongst nowadays society and a lot of parcels have to be moved from a depot to the locations specified by the end-users. Couriers need to serve a bigger demand and it is often the case that receivers are not at the location when the parcels are delivered, which has an impact on the efficiency of the delivery routing process.

The use of parcel lockers is seen as a good option for improving the problem of failed deliveries. However, implementing a parcel locker network has an impact on both couriers and receivers, which still prevents couriers from directly adopting this technology. The aim of this research is to develop a new tool that helps couriers analyse the impact of using a parcel locker network taking also into account receiver preferences to pick up parcels from lockers.

This research presents an optimization model combined with a choice behaviour model in order to determine the trade-offs between delivering to parcel lockers or to the end-users, in terms of service level and total transportation costs. Specifically, this trade-offs are evaluated with a Pareto Frontier.

In order to solve this model for large instances, an Adaptive Large Neighbourhood Search algorithm has been adapted with operators and criteria specific for the problem presented. Computational experiments were carried out in a set of the Solomon instances and show that the problem can be solved efficiently with the proposed algorithm. Moreover, the algorithm was also applied in a small delivery area in Rotterdam, showing the sensitivity of the model to the preferences of the receivers in the area and directing the next steps to further research this aspect.

Contents

1
Introduction

E-commerce is significantly growing amongst nowadays society and a lot of parcels have to be moved from a depot to the locations specified by the receivers. This means that the business to consumer (B2C) couriers need more vehicles and longer travelling distances to serve a bigger demand.

Moreover, it is often the case that the receiver is not at the location when the parcels are delivered and this has an impact on the efficiency of the delivery routing process. If this is known in advance, the B2C courier could save some traveling distance and time trying to meet that receiver.

There are different ways in which this issue can be tackled, for example, telling the receiver in advance the delivery time period or asking the receiver beforehand during what time is possible to find him/her at the location. However, there is always some probability of the receiver not being at the location at the given period of time. For this reason, some research (Pan, Giannikas, Han, Grover-Silva, & Qiao, 2017; Voccia, Campbell, & Thomas, 2013; Yang, Strauss, Currie, & Eglese, 2016) is already being done trying to take into account these probabilities when defining the delivery routes.

Another line of research is focused on the Physical Internet concept (Montreuil, Meller, & Ballot, 2012) and the use of parcel lockers (Deutsch & Golany, 2018; Morganti, Seidel, Blanquart, Dablanc, & Lenz, 2014). Using these parcel lockers is considered to be positive because the B2C couriers can serve multiple receivers at a single point, which reduces travelling costs and at the same time eliminates the problem of failed deliveries. On the receiver side, having to pick up the parcel from the locker means a little extra effort which is compensated with the flexibility of doing it whenever it is more convenient for them.

Using these parcel lockers can make it easier to allow for a Self-Organising Logistics System (SOLS) (Pan, Trentesaux, & Sallez, 2017) to occur, as these lockers would represent points where different type of agents can enter or leave the system to move parcels with a set of simple rules, without the need of interaction. For example, using parcel lockers makes it easier to have a system where crowd-sourcing can take place, as occasional couriers could easily pick-up parcels from one locker and move it to another locker or even to the end-receiver (Raviv & Tenzer, 2018).

Taking all the aforementioned into account and focusing on the transition to Self-Organizing Logistics(SOL), the aim of this research is to develop a new tool that helps couriers see the impact of using a parcel locker network taking into account preferences of receivers to pick up parcels from lockers.

1.1. Context

A new system is defined to allow for SOL in the last mile deliveries and overcome the challenges mentioned in the paragraphs above. This system is based on a parcel locker network, where different agents (couriers or people) take care of moving the parcels through the network. Moreover, in order to reduce kilometers driven and have a more sustainable last mile delivery, receivers are expected to pick up the parcels from the lockers. However, the option of home delivery is still considered as a possibility. For this reason, different levels of vehicles are defined:

1. Vehicles that move the parcels from the depot to the lockers.
2. Vehicles that move the parcels between lockers.
3. Vehicles that move the parcels from the lockers to the end-receivers.

Couriers are always in charge of the first level of vehicles, whereas in the other levels, multiple agents can enter the system. For example, crowd-shipping can help to move parcels of receivers who would like to change their delivery destination once the parcel is already at the locker, or bringing the parcel from the locker to the end-receiver. Also, self-driving autonomous delivery robots can be part of the third level of vehicles. A sketch of this system is presented in Figure 1.1.

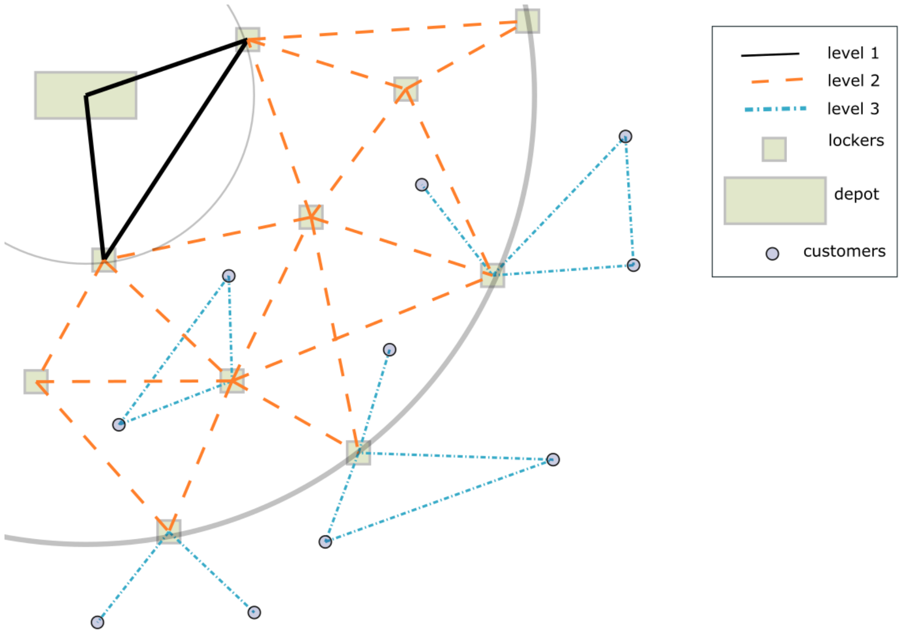


Figure 1.1: *Sketch of the system defined, where the different levels of the vehicles are represented.*

Another important thing to take into account in this new system is the capacity of the locker infrastructure. For this reason, the PI-boxes defined by Faugère and Montreuil (2017) are going to be considered for this research. Within the context of PI, Faugère and Montreuil (2017) present a modular grid-wall to which PI-boxes of different sizes can be attached. These PI-boxes can be described as small containers of different sizes with the parcels inside. Their capacity modularity is seen as a better option than having rigid lockers.

As this new system is not yet existent, and it is common to define transition steps towards a big change, this research assumes that the courier performs part of the 3 levels, delivering parcels to lockers but also to homes.

Using lockers allows for an aggregation of the demand, which is expected to reduce the total travel costs. However, not all receivers are willing to go to any locker and therefore, the utility of the receiver picking up a parcel in a specific locker is an important factor to take into account. For this reason, the main challenge of this problem is basically incorporating these utilities in the decision making process.

Specifically, this research aims to find the trade-offs between delivering to parcel lockers or at homes, in terms of service level offered, which is defined as the average of the probabilities of each receiver to go to the parcel locker where its parcel is being delivered.

Hence, the problem is reduced to a B2C courier which has to distribute parcels from a depot to a set of parcel lockers and homes. This courier owns a depot with an homogeneous fleet available to cover the daily demand and there is an existing network of parcel lockers with limited capacity (as the PI-boxes will take some time to be implemented) which can be rented by the courier. Therefore, every day, decisions about the tactical planning activities have to be made, as the specific number of vehicles and the lockers to rent have to be determined together with the delivery routes and all these taking into account the preferences of the receivers for certain lockers.

1.2. Research & Societal Relevance

The novelty of this research lies into defining a new system for the last mile deliveries within the context of physical internet and self-organising logistics. Both these concepts are still under study and some steps have to be done in order to see what are the implications of applying such systems and what would be the transition from the current model to the new concept of logistics. This research investigates a possible step towards allowing parcel deliveries to occur in an open network where different agents can work in order to achieve a common goal, which is moving the parcels to the end-receiver.

Specifically, this research wants to solve a routing problem to deliver parcels from a depot to parcel lockers with the aim of maximizing the utilities of the receivers going to the lockers. The objective of this type of problems is different in the existing literature, where the main goal is to minimize the total travel costs.

The societal relevance of this research is related to having a more sustainable and efficient last mile delivery. If it can be shown that using a different system can help to reduce the kilometers driven and the number of delivery vehicles, not only couriers will benefit by reducing their operational costs but society will benefit from having less congested cities, with less pollution and therefore reducing the impact of humanity in the climate change, while allowing for e-commerce to take place.

1.3. Research Questions

The main research question is formulated as follows:

What is the impact of implementing a network of parcel lockers for the last mile delivery on couriers' and receivers' costs?

Some sub-research questions are defined below to help to answer the main research question:

1. *How to take receiver preferences into account when modelling the routing in a parcel locker network?*

   A new conceptual and mathematical model will be defined to combine a vehicle routing problem (VRP) with a choice behaviour model.

2. *How to represent the effect of providing a specific service level on total transportation costs?*

   Since multiple solutions are possible at different combinations of service level and total transportation costs for a given network, a function will be used to represent the best solutions.

3. *How to solve the proposed optimization model efficiently for large instances?*

   In general, VRP for large instances are too complex to be exactly solved in a short time period. An heuristic algorithm will be proposed to reduce the computation time required.

4. *What is the trade-off between accuracy and computation efficiency of the solution method?*

   A number of synthetic data sets will be used to compare the heuristic algorithm with exact methods in terms of computational time and gap with the lower bound solutions.

5. *What is the effect of the number and capacity of lockers, the renting cost and the type of receivers on the total transportation costs and service level?*

   Scenarios have to be build in which the number, capacity and renting cost of the lockers are varied. Also, other scenarios will be build where the choice behaviour model is adapted to represent different types of receivers. The trends observed will help to see the effects of these parameters in the total transportation costs and the service level.

2

Literature review

This section introduces the concepts of Physical Internet and Self-Organising Logistics with the aim to remark the relation between the two. Later on, both concepts are key to explain the reasons for using parcel lockers in the last mile delivery and a literature review on parcel lockers is presented at the end.

2.1. Physical Internet

The current global transportation network allows society to get products from all over the world within a short time. However, this is not always done in the most efficient and sustainable way. For this reason, new concepts like the Physical Internet (PI) are emerging in order to redefine the way goods are transported from one place to another.

PI is a new concept that aims to define a new global logistics system based on the way digital internet works. Montreuil (2011) is generally understood to be the first to talk formally about this concept, explaining that the PI idea or concept initially appeared as a way to face the Global Logistics Sustainability challenge. This challenge consists essentially in finding a way to transport, store, supply and use physical objects in a sustainable way in all of its senses: economically, socially and environmentally. Montreuil (2011) reports thirteen symptoms that characterise the unsustainability of the logistics around the world, which are presented in Table 2.1 .

	Unsustainability symptoms	Economical	Environmental	Societal
1	We are shipping air and packaging	●	●	
2	Empty travel is the norm rather than the exception	●	●	
3	Truckers have become the modern cowboys	●		●
4	Products mostly sit idle, stored where unneeded, yet so often unavailable fast where needed	●		●
5	Production and storage facilities are poorly used	●	●	
6	So many products are never sold, never used	●	●	●
7	Products do not reach those who need them the most	●		●
8	Products unnecessarily move, crisscrossing the world	●	●	
9	Fast & reliable intermodal transport is still a dream or a joke	●	●	●
10	Getting products in and out of cities is a nightmare	●	●	●
11	Networks are neither secure nor robust	●		●
12	Smart automation & technology are hard to justify	●		●
13	Innovation is strangled	●	●	●

Table 2.1: *Unsustainability symptoms (Montreuil, 2011).*

Montreuil (2011) describes the basic characteristics of the PI on the basis of the symptoms in Table 2.1. For example, to improve the reliability (and speed) of intermodal transport symptom nr.9 he proposes to "encapsulate merchandise in world-standard smart modular containers" and "universal interconnectivity" as basic characteristics of PI. Similarly, a more robust and secure network symptom nr.11 would be solved with “distributed multi-segment intermodal transport” and an “open global supply web”.

Later on, Montreuil et al. (2012) use a web as analogy for the PI: a space where actors and networks are interconnected in an open and global way. They define the PI as “an open global logistics system founded on physical, digital and operational interconnectivity through encapsulation, interfaces and protocols”. In this way, logistic chains are accessible from any place worldwide, allowing any actor to use any network.

The main idea is that each parcel that has to be transported will carry enough information to identify the product and to route it to the proper destination. In this way, when parcels move from one network to another, the new agent or system moving it will have all the necessary information. This allows for a higher robustness of the system, as the parcel can move adapting to different disruptions occurring in real time. Of course, to make these interchanges within networks possible, a standardization of the process is required. For this reason, Montreuil (2011) also describes the concept of PI-containers, which are built up from smaller unitary PI-containers of different sizes.

PI is still quite a new concept and is still under development by various experts. In fact, Faugère and Montreuil (2017) try to conceptualise this concept within the last mile deliveries, which can be related to symptom nr.10 in Table 2.1 (“Getting things in and out of a city is a nightmare”). They assume that parcels are not delivered directly to the end-customers but to a sort of lockers, PI-lockers. Specifically, they define a grid-wall (see Figure 2.1) where the previously mentioned unitary PI-containers with the parcels inside can be attached.

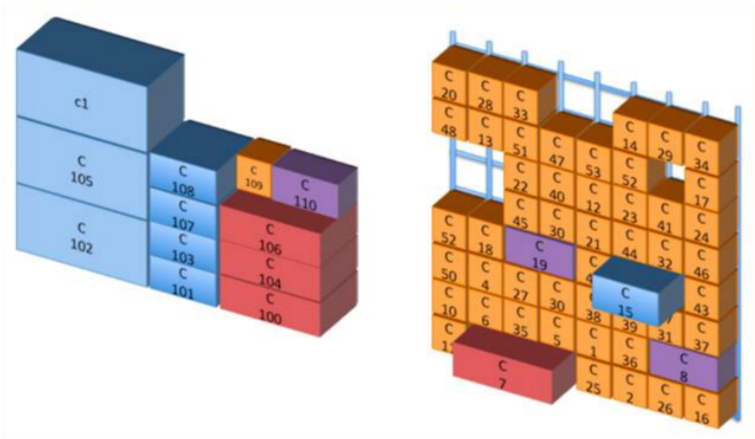


Figure 2.1: *Illustration of the grid-wall and PI-containers attached (Faugère & Montreuil, 2017).*

The following section introduces the concept of SOLS in relation with PI. For example, the open network of the PI can be directly linked to the concept of Self-Organizing Logistics.

2.2. Self Organising Logistics

Even though only limited literature about SOLS is available, it is not difficult to relate its main characteristics to PI. In particular, it can be linked with solutions to some of the last unsustainable symptoms in Table 2.1.

Pan, Trentesaux, and Sallez (2017) define SOLS as an open, intelligent and holonic logistics system that aims to harmonise and lead individuals within the system towards a system-wide common goal, without significant human intervention from outside. In the same direction, Bartholdi, Eisenstein, and Lim (2009) compare the SOLS with the way ants and bees behave, each of them doing a small task in order to achieve a common goal.

Pan, Trentesaux, and Sallez (2017) try to give a deeper insight on the functionalities of such a system and further describe its main characteristics:

- openness,
- intelligence, and
- decentralised control.

Openness refers to having a system without rigid boundaries that allows agents to enter, interact or leave the system when they want. For this to happen, connectivity between the agents and the environment needs to be possible. Besides, adaptation is crucial for a good coordination between them as the system also needs to be able to cope with disruptions. For example, in the case of deliveries, being able to reconfigure and fulfill new requests. All this is common within the PI, which in fact is presented as an open global network.

Intelligence enhances the ability of the agents to make decisions and interact with other agents or the environment. Agents should be able to collect, store and process information in order to make a decision and later execute it by acting autonomously. This intelligence can also be related to PI, as each parcel is supposed to store information, which is transmitted to the agents that are going to move them and interact with other agents in order to be more efficient. However, in the case of the PI, the agents do not have to act autonomously per se.

Decentralised control is based on a holonic multi-agent system, where a set of rules and protocols are defined in order to allow an effective communication to achieve a common goal. This is the main difference that SOLS has with PI, where decisions can also be taken with a centralised or hierarchical system control.

Taking into account the affinity of SOLS with PI, any step that helps defining SOLS also helps to define PI. For example, Quak, Kempen, and Hopman (2018) aim to get more insights in the development of such a SOLS. Their aim is to apply some of the previous SOLS ideas into practice. Specifically, in the way parcels are moved within last-mile deliveries in distribution centers and later on delivered to the end customers. The results of this project will help to see the possible effects towards SOLS and PI.

2.3. Parcel Lockers

Following on the previous two sections, the use of parcel lockers in the last mile delivery can make it easier to allow for a SOLS to occur. These parcel lockers, would represent points where different type of agents can enter or leave the system to move parcels with a set of simple rules, without the need of interaction. Moreover, a modular system of parcel lockers, could easily be related to the grid-wall of unitary PI-container described before.

In this section, the description of a parcel locker is presented together with the main insights given in the current literature, which includes studies regarding the willingness of the end-user to use them but also studies which define delivery networks including them.

As defined by Deutsch and Golany (2018), a parcel locker is a group of electronic lockers attached to each other that can be easily opened with a code. The idea is to place them in locations accessible during the most hours a day, such as train stations or supermarkets, so that the consumers have total freedom to pick their parcels at any moment of the day.

Many companies have already implemented the use of parcel lockers for the last mile delivery in various countries. Iwan, Kijewska, and Lemke (2016) state that *InPost* has installed more than 3000 parcel lockers in different countries. In similar terms, Morganti et al. (2014) remark that *DHL* has also implemented in Germany 2500 parcel lockers, which allows them to state that 90% of the German population is within 10 minutes of a parcel locker. Deutsch and Golany (2018) also mention the use of parcel lockers from *Amazon* and the *Canada Post*. In the Netherlands, van Duin, Wiegmans, Arem, and van Amstel (2019) present a pilot project of *PostNL* in Amsterdam.

On the one hand, the main advantage of delivering the parcels to these parcel lockers is that they allow couriers to reduce the number of failed deliveries, as the customers do not have to be present at the moment of delivery. At the same time they can consolidate the demand into a single point, which reduces the travel distance needed and therefore the routing costs. Moreover, parcel lockers are usually placed in locations opened 24h a day, giving consumers more flexibility. Not to forget, they also help to diminish congestion in cities and make the last mile delivery more environmentally friendly (Deutsch & Golany, 2018; Iwan et al., 2016; Yuen, Wang, Ng, & Wong, 2018).

On the other hand, the main consequence of parcel lockers is that consumers are the ones covering part of the last mile delivery. Therefore, their willingness to go to the locker is an important factor to take into account. For this reason, there is many research trying to find out more about the opinion of the consumers about this innovative solution to improve the last mile delivery.

Nguyen, de Leeuw, and Dullaert (2018) determine factors that are important for identifying the behaviour of online consumers. Vakulenko, Hellström, and Hjort (2018) studied the value of parcel lockers for consumers in Sweden, they mention that consumer value is created when a service of delivery or pick-up takes place and they conclude that future interactions with the last mile delivery services are affected by the meaning of previous services. Iwan et al. (2016) did a survey about the use of parcel lockers and concluded that their location has an important effect on their efficiency. Their survey gives an overview of parcel locker users in Poland.

In line with Iwan et al. (2016), Lachapelle, Burke, Brotherton, and Leung (2018) get some insights on the locations of parcel lockers in Australia. They identify clusters within the current locations and state that the majority of them are located on commercial streets and shopping centres. Deutsch and Golany (2018) focus on the design of a parcel-network, which in the end, is also related to determine the best location of the lockers. However, their research is from a quantitative perspective. They develop a mathematical model to determine how many parcel lockers to open, where to locate them in order to maximise the profit of the operating courier.

Following on the quantitative research on lockers, Veenstra, Roodbergen, Coelho, and Zhu (2018) define a location-routing problem for delivering health care medication in the Netherlands. They determine which lockers to open and the routes to visit the lockers and the routes that visit the patients, minimizing the routing and opening costs.

2.4. Contribution to literature

In line with Veenstra et al. (2018), this research wants to solve a routing problem to deliver parcels from a depot to parcel lockers or homes with the aim of reducing the impact on costs for the courier and the receivers. Therefore, this research contributes to the current literature by taking into account the preferences of the receivers when deciding the routes. The objective of this type of problems is different in the existing literature, where the main goal is to minimize the total travel costs for the couriers (Deutsch & Golany, 2018; Veenstra et al., 2018).

Specifically, this research aims to combine a vehicle routing problem with a choice behaviour model, to deliver parcels from a depot to parcel lockers or homes, minimizing the total transportation costs and maximizing the utilities of receivers going to parcel lockers.

Besides, given the nature of the VRPt's, solving them with an exact method usually requires a high computational time which leads to the necessity of using heuristics, as shown by many references presented in Lahyani, Khemakhem, and Semet (2015). This research uses the Adaptive Large Neighbourhood Search (ALNS) heuristics (Pisinger & Ropke, 2007) for solving the optimization model and contributes with the design of repair and destroy operators specifics for this problem, which are different from the ones existing in literature.

Lastly, this research aims at developing an algorithm able to solve the problem for large instances efficiently and able to be implemented in real networks, helping couriers take tactical decisions about the specific lockers to rent and receivers to visit together with the delivery routes.

3

Conceptual Model

3.1. Problem Description

The model from Veenstra et al. (2018) is used as a reference for developing the model presented in this study. There are two main differences for this research: vehicle routes can visit both, parcel lockers and end-consumers; and the optimization model is combined with a choice behaviour model, in order to account for the preferences of the receivers to the different parcel lockers available.

The problem consists of a B2C courier which has to distribute a set of parcel requests (n ∈ R) from a depot to a set of parcel lockers (l ∈ L) or to several home locations. Specifically, the depot has an homogeneous fleet of vehicles (k ∈ K) with capacity Q_V available to cover the daily demand. The parcel requests are assumed to be known in advance .

There is an existing network of lockers with a limited capacity Q_L which can be rented by the B2C courier, who has to determine every day which lockers to use. Therefore, every day, decisions about the tactical planning activities have to be done, as the specific lockers to rent have to be determined together with the delivery routes.

The renting costs of the lockers are directly related to the amount and size of the parcels delivered to the lockers every day. For simplicity, a fixed cost per request is assumed.

As not all receivers are willing to go to all the lockers, the utility of a receiver picking up a parcel in a specific locker is an important factor to take into account. Preferences of receivers are described in terms of probabilities to go to a certain locker. These probabilities, as described later on, are a function of the utilities.

Following this, the service level of a courier can be understood as the degree to which the courier adjusts to the preferences of the receivers. In mathematical terms, the service level ($SL = \sum_{i \in R} P_{ij}/n$) offered by the courier is defined as the average of the probability of each receiver to go to the locker where its parcel is being delivered.

Therefore, in order to give a better service level, the aim of the courier will be to deliver the parcel to the locker giving the maximum utility to the receiver or to deliver the parcel at their home. This reasoning is in line with the utility maximization theory (McFadden, 2001).

The probability P_{ij} of a receiver i to go to one of the lockers j will be determined using a discrete choice model, the Multinomial Logit (MNL), which has already been used in literature in the context of parcel lockers by Collins (2015); Lyu and Teo (2019); Oliveira, Morganti, Dablanc, and Oliveira (2017), where they tried to model the preferences of the people to go to the parcel lockers. P_{ij} is defined by the MNL model by $P_{ij} = e^{U_{ij}}/(\sum_{j \in L} e^{U_{ij}} + e^{U_H})$. Where U_{ij} is the utility of receiver i to go to locker j and U_H is the utility of home delivery.

The utility functions from Lyu and Teo (2019) are going to be used for the MNL model. Lyu and Teo (2019) estimated the parameters for two different utility U_{ij} functions depending on whether the receiver is located in a residential area or in a commercial area. The attributes included in them are travel distance d_{ij} and type of locker $type_j$ ($type_j = 1$ if locker j is located nearby a shopping center and a train/subway/tram station). They defined the attraction A_{ij} of a locker j to receiver i as the exponential of the utility function. The utility functions presented below were estimated with data of an area in Singapore and the lockers were located in distances smaller than 1 km. They also estimated the attraction A_H values of not going to any locker (home delivery) for both type of receivers.

$$Residential\ area:\ U_{ij} = log(A_{ij}) = -4.59\ d_{ij}^{1/3} + 1.5\ type_j, \quad A_H = 7.06$$

$$Comercial\ area:\ U_{ij} = log(A_{ij}) = -4.47\ d_{ij}^{1/3} + 0.52\ type_j, \quad A_H = 17.79$$

Each parcel request has a consideration set of lockers for the receiver $L_i \subseteq L$. This set of lockers specific for each receiver is used to limit the choices available to the receivers, as it is not expected that they want to go to lockers which are located further away. Therefore, each consideration set of lockers is going to be limited to the lockers that give at least a minimum attraction value of A_{min}.

There is a service time s associated to the time spend to put a parcel in a locker, which has to be taken into account when determining the total routing time and cannot exceed a specific amount of hours T_{max} (driver working hours).

There are two main objectives in this problem, 1) minimize the total transportation costs (TTC) of the courier while 2) maximizing the utilities of each receiver. In most cases these are conflicting objectives because delivering the parcels to a locker where only a few people is willing to go comes with an additional cost for the courier. Therefore, in order to balance the two objectives, obtaining a Pareto frontier (Sun & Lang, 2015) is proposed.

The problem will first be solved with each of the objective functions independently. The results for the second objective function in both cases are used to define the upper and lower boundaries of the Pareto frontier. Then, the problem is solved with only the first objective function and adding the second objective as a constraint limited by an ε value. This ε is a value between the two boundaries previously found. In order to obtain the Pareto Frontier, the difference between the two boundaries is divided by a number of intervals in order to obtain multiple ε values with which to solve the problem.

3.2. Graphical Example

In this section, a small example created with the Solomon instances R101 is presented. The transportation network consists of a depot and 5 parcel lockers available to cover a demand of 10 receivers. Therefore, the problem is represented with a graph of 16 nodes in total, where the blue node is the depot, the light green nodes are the parcel lockers and the dark green nodes are the receivers.

Figure 3.1 shows the solution of the problem solved for the first objective function. As can be seen in the figure, the vehicle routes only visit lockers. This is expected to happen because the objective is to minimise the total transportation costs. Contrarily, in figure 3.3, only receivers are visited, which happens as a result of solving the problem with the second objective function.

Figure 3.2 illustrates another solution, where the trade-offs between the previous two cases can be observed. In this case, the problem is solved for first objective function and having the second objective as a constraint delimited by an ε. As a result, some receivers are assigned to lockers but others have home delivery.

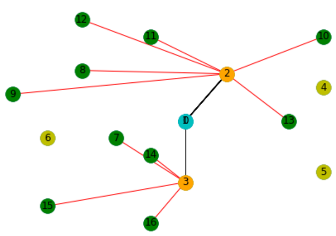


Figure 3.1: *Solution obtained minimising the TTC.*

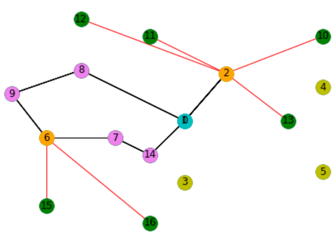


Figure 3.2: *Solution obtained minimising the TTC with an ε constraint.*

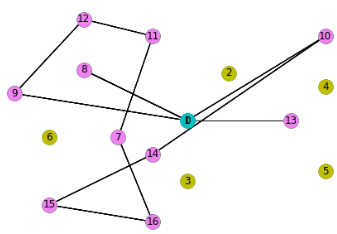


Figure 3.3: *Solution obtained maximizing the utilities of the receivers.*

3.3. Mathematical Model

This problem is defined under a directed graph $\mathcal{G}(N, A)$ where $N = R \cup L \cup O$ is the set of nodes and $A = A(R) \cup A(O) \cup A(L)$ is the set of arcs. $A(R) = \{(i, j) | i \in R \cup L \wedge j \in R \cup L\}$; $A(O) = \{(i, j) | i \in \{0\} \wedge j \in R \cup L \vee i \in R \cup L \wedge j \in \{1\}\}$; $A(L) = \{(i, j) | i \in R \wedge j \in L_i\}$. The sets R and L correspond to all the receivers and lockers locations and set $O = \{0, 1\}$ includes two nodes that correspond to the depot (departure, arrival). Each arc $(i, j) \in A$ has associated some cost, which is travel distance d_{ij}.

Sets	
O	Set of depot nodes. $\{0, 1\}$
L	Set of potential lockers. $\{2, ..., l+1\}$ $l \in \mathbb{N}$
R	Set of receivers. $\{l+2, ..., l+n+2\}$ $l \in \mathbb{N}, n \in \mathbb{N}$
L_i	Consideration set of lockers for receiver i. $\{j \in L | A_{ij} \leq A_{min} \subseteq L\}$ $i \in R$
K	Set of vehicles. $\{1, ..., k\}$ $k \in \mathbb{N}$
Parameters	
Q_V	Capacity of the vehicles
Q_L	Capacity of the lockers
C_{km}	Cost of driving 1 km
C_{rent}	Cost of renting a locker
T_{max}	Maximum route duration
A_{min}	Minimum attraction considered for the subset Li
s	Service time per parcel
d_{ij}	Distance of moving from node i to j
v	Velocity of the vehicles
A_{ij}	Attraction of locker j to receiver i
A_H	Null attraction or Home delivery attraction
M	Large constant
Decision Variables	
y_j	Binary variable equal to 1 if locker j is rented.
w_i	Binary variable equal to 1 if receiver i has home delivery.
z_{ij}	Binary variable equal to 1 if receiver i is assigned to locker j.
g_i^k	Binary variable equal to 1 if parcel from request i is delivered by vehicle k.
r_j^k	Binary variable equal to 1 if node j is visited by vehicle k.
x_{ij}^k	Binary variable equal to 1 if vehicle k moves from i to j.
t_j^k	Accumulated time of vehicle k having served node j.

There are two objective functions, Function 3.1 minimizes the total transportation costs, which includes the travelling distance costs and the rent of the lockers and Function 3.2 maximizes the attraction of the receivers, which comes from a locker delivery or a home delivery.

$$minimize \sum_{(i,j)\in A} C_{km}\, d_{ij}\, x_{ij}^k + \sum_{i\in R}\sum_{j\in L_i} C_{rent}\, z_{ij} \tag{3.1}$$

$$maximize \sum_{i\in R}\sum_{j\in L_i} A_{ij}\, z_{ij} + \sum_{i\in R} A_H\, w_i \tag{3.2}$$

Subject to:

$$z_{ij} \leq y_j \qquad \forall i \in R, j \in L_i \tag{3.3}$$

$$y_j \leq \sum_{(i,j)\in A(L)} z_{ij} \qquad \forall j \in L \tag{3.4}$$

$$\sum_{j\in L_i} z_{ij} + w_i = 1 \qquad \forall i \in R \tag{3.5}$$

Constraints (3.3) and (3.4) make sure that the receivers are only assigned to lockers that are rented and lockers can only be rented if there is at least one receiver assigned to it. Constraint (3.5) ensures that each receiver is either assigned to one locker or has home delivery.

$$\sum_{j\in R\cup L} x_{0j}^k - \sum_{j\in R\cup L} x_{j,1}^k = 0 \qquad \forall k\in K \tag{3.6}$$

$$\sum_{j\in R\cup L\cup\{1\}} x_{ij}^k - \sum_{j\in R\cup L\cup\{0\}} x_{ji}^k = 0 \qquad \forall k\in K, i\in R\cup L \tag{3.7}$$

$$\sum_{j\in R\cup L} x_{0j}^k \le 1 \qquad \forall k\in K \tag{3.8}$$

$$t_j^k \ge t_i^k + \frac{d_{ij}}{v} + s\sum_{n\in C} g_n^k - M(1-x_{ij}^k) \qquad \forall i\in R\cup L\cup\{0\}, j\in R\cup L, k\in K \tag{3.9}$$

$$t_1^k \ge t_i^k + \frac{d_{ij}}{v} - M(1-x_{ij}^k) \qquad \forall i\in R\cup L, k\in K \tag{3.10}$$

$$t_1^k \le T_{max} \qquad \forall k\in K \tag{3.11}$$

$$t_0^k = 0 \qquad \forall k\in K \tag{3.12}$$

The flow conservation constraints are included in constraints (3.6 - 3.8). The consistency of the time variables is ensured by constraints (3.9 - 3.12), which at the same time eliminate possible subtours. Constraint (3.11) makes sure that the route duration does not exceed the working time T_{max}.

$$\sum_{i\in R\cup L\cup\{0\}} x_{ij}^k = r_j^k \qquad \forall j\in R\cup L, k\in K \tag{3.13}$$

$$r_j^k \le y_j \qquad \forall j\in L, k\in K \tag{3.14}$$

$$y_j \le \sum_{k\in K} r_j^k \qquad \forall j\in L \tag{3.15}$$

$$\sum_{k\in K}\sum_{j\in R\cup L\cup\{1\}} x_{ij}^k = w_i \qquad \forall j\in R \tag{3.16}$$

$$g_i^k \ge z_{ij} + r_j^k - 1 \qquad \forall k\in K, i\in R, j\in L_i \tag{3.17}$$

$$g_i^k \ge w_i + r_i^k - 1 \qquad \forall k\in K, i\in R, j\in L_i \tag{3.18}$$

$$\sum_{k\in K} g_i^k = 1 \qquad \forall i\in R \tag{3.19}$$

Constraints (3.13 - 3.19) are the linking constraints. Specifically, constraints (3.14) and (3.15) enforce that vehicles only visit lockers that are rented and constraint (3.16) ensures that receivers with home delivery are visited by a vehicle. Constraint (3.19) forbids that a parcel for a receiver is carried for more than one vehicle.

$$\sum_{i\in R} g_i^k \le Q_V \qquad \forall k\in K \tag{3.20}$$

$$\sum_{i\in R|j\in Li} z_{ij} \le Q_L \qquad \forall j\in L \tag{3.21}$$

$$y_j \in \{0,1\} \qquad \forall j\in L \tag{3.22}$$

$$w_i \in \{0,1\} \qquad \forall i\in R \tag{3.23}$$

$$z_{ij} \in \{0,1\} \qquad \forall i\in R, \forall j\in L_i \tag{3.24}$$

$$g_i^k \in \{0,1\} \qquad \forall i\in R\cup L, \forall k\in K \tag{3.25}$$

$$r_j^k \in \{0,1\} \qquad \forall j\in R\cup L, \forall k\in K \tag{3.26}$$

$$t_j^k \ge 0 \qquad \forall j\in N, \forall k\in K \tag{3.27}$$

$$x_{ij}^k \in \{0,1\} \qquad \forall i\in N\backslash\{1\}, \forall j\in N\backslash\{0\}, \forall k\in K \tag{3.28}$$

Finally, constraints (3.20) and (3.21) enforce the vehicle and lockers capacity restrictions, respectively and constraints (3.22 - 3.28) define the nature and range of the decision variables.

4 Multi-objective Adaptive Large Neighborhood Search

The Mathematical Model presented in Section 3.3 is not possible to be solved for large instances within a short time period. Therefore, an Adaptive Large Neighborhood Search (ALNS) heuristic is proposed as a solution method.

4.1. Adaptive Large Neighbourhood Search

The ALNS described by Pisinger and Ropke (2007) is an adaptation of the Large Neighborhood Search (LNS), where multiple destroy and repair heuristics are used in the same search. Hence, the main components of the ALNS are: destroy operators, repair operators and an adaptive mechanism, which controls the usage of the operators according to their performance in the previous iterations. These components are presented and further described in the sections below.

The solution method starts by giving an initial solution x^i, to which the ALNS algorithm is applied. This means that part of the solution is destroyed and repaired. Later, the acceptance criteria is used to evaluate whether the new solution is accepted and a weight is assigned to the destroy/repair operators used, to control how they perform. This is an iterative process that searches for better solutions and finishes after N iterations.

The ALNS heuristics is presented in Algorithm 4.1, where the current solution x^c given to the destroy operator always has to be feasible. O^-, O^+ define the set of destroy (-) and repair (+) operators and $f(x)$ represents the value of the objective function given solution x. Specifically, $f(x) = t(x) + r(x) + M\ u(x)$ is the sum of the total routing costs $t(x)$, the total renting costs $r(x)$ and a penalization M that applies when the total utilities $u(x)$ are lower than an ε (introduced in Section 3.1).

Because there are two objectives functions(minimise total transportation $f(x)$ costs and maximise total attractions $f_2(x)$), the ALNS works with a pool of best solutions instead of only one best. This is because the purpose is to find the Pareto Frontier.

Algorithm 4.1 Adaptive Large Neighborhood Search (ALNS)

```
Input: x^i, O^-, O^+, N, λ, (ω_1, ω_2, ω_3, ω_4), T_0, T_end, α
pool^b, x^c ← x^i
ρ^-, ρ^+ ← (1,..,1)
for i = 1,2,...,N do
    O^-, O^+ ← Select a destroy and repair operators
    x ← O^+(O^-(x^c)) Apply first O^- and later O^+ to x^c
    pool^b, x^c, Ψ ← Apply A&W criteria (pool^b, x, x^c, (ω_1, ω_2, ω_3, ω_4), T_{i-1}, T_end, α)
    ρ^- ρ^+ ← Update(ρ^-, ρ^+, λ, Ψ)
end for
Output: pool^b
```

4.2. Adaptive Control

4.2.1. Acceptance Criterion

Among the different acceptance criteria used within literature, Simulated Annealing (SA) is the one mostly applied when using ALNS. As described by Hillier, Price, and Austin (2010), the temporary solution x is accepted if $f(x) \leq f(x^c)$ and otherwise, it is accepted with probability $P = e^{(f(x^c)-(f(x))/T}$. The temperature ($T > 0$) is updated at each iteration i using a cooling rate α $\{T_i = \alpha\ T_{i-1} \mid 0 \leq \alpha \leq 1\}$. An initial and end temperature must be given to the algorithm as well.

Algorithm 4.2 Simulated Annealing (SA)

```
input: x, x^c, T_{i-1}, T_{end}, α
T_i ← α max(T_{i-1}, T_{end})
z ← Accepted with P(x, x^c, T_i)
if z ≠ Accepted then
    z ← Rejected
end if
output: z
```

4.2.2. Adaptive selection and weight adjustments

Hillier et al. (2010) state that at each iteration, the repair and destroy operators are selected using a roulette wheel. It consists on assigning a probability to each operator, which is updated at each iteration according to its previous performance. The probability of selecting operator j from the set of operators Ω is:

$$P_j = \frac{\rho_j}{\sum_{k \in |\Omega|} \rho_k} \tag{4.1}$$

where ρ_j is the vector of weights assigned to operator j.

As Hillier et al. (2010) describe, these weights are adjusted at each iteration based on the current performance (with a score Ψ) and on the previous performance of the operator. They also use a $\lambda \in [0,1]$ that controls the sensitivity of the weights and it is called decay parameter.

Specifically, the weight ρ_j^i of operator j in iteration i is updated with the following equation:

$$\rho_j^i = \lambda \rho_j^{i-1} + (1-\lambda)\Psi \tag{4.2}$$

where Ψ =

ω_1 if the new solution is a new global best
ω_2 if the new solution is better than the current one
ω_3 if the new solution is accepted
ω_4 if the new solution is rejected
$\omega_1 \geq \omega_2 \geq \omega_3 \geq \omega_4 \geq 0$ are given parameters.

The Acceptance and Weight (A&W) criteria followed are presented in Algorithm 4.3.

4.3. Initial Solution

The initial solution given in order to start applying the ALNS algorithm is usually obtained by applying one of the repair operators already defined for the algorithm. The aim is to start with a solution that can be obtained fast but also that it is a high quality solution so that less iterations are needed. In this case, the *Greedy receiver insertion in lockers* (one of the repair operators presented in Section 4.4.2) is considered to be the best option to obtain the initial solution, as it gives a good solution quality within less time than other repair operators defined that obtain higher quality solutions.

4.4. Destroy & Repair operators

As already mentioned at the end of Section 2, some of the following repair and destroy operators have been designed specifically for solving the mathematical model presented in Section 3.3.

Algorithm 4.3 A&W criteria

input: $pool^b, x, x^c, (\omega_1, \omega_2, \omega_3, \omega_4), T_{i-1}, T_{end}, \alpha$
if $f(x) > f(x^c) \& f_2(x) < f_2(x^c)$ **then**
  $z \leftarrow SA(x, x^c, T_{i-1}, T_{end}, \alpha)$
  if z = Accepted **then**
    $x^c, \Psi \leftarrow x, \omega_3 \ \ (ACCEPTED)$
  else
    $x^c, \Psi \leftarrow x^c, \omega_4 \ \ (REJECTED)$
  end if
end if
for $x^b \in pool^b$ **do**
  if $f(x) >= f(x^b) \& f_2(x) <= f_2(x^b)$ **then**
    $S \leftarrow add(1)$
  end if
end for
if $S >= 1$ **then**
  $x^c, \Psi \leftarrow x, \omega_2 \ \ (BETTER)$
else
  $x^c, \Psi \leftarrow x, \omega_1 \ \ (BEST)$
  $pool^b \leftarrow add(x)$
end if
Output: $pool^b, x^c, \Psi$

4.4.1. Destroy operators

Receiver random removal: This operator randomly removes a number of receivers from the given solution. The number is determined by the product of the number of receivers and the degree of destruction. These receivers could be part of the route or inside a locker.

Receiver worst cost removal: This operator removes the receiver with the highest cost of having it in one of the given solution routes. Having a receiver in a locker is given a zero cost value.

Receiver worst utility removal: This operator removes the receiver with the lowest utility of having it in one of the lockers or visiting it.

Receiver related removal: This operator randomly chooses a receiver and removes all the receivers within a given distance. This distance is determined by the product of the maximum distance between the nodes and the degree of destruction.

Routes random removal: This operator randomly removes a number of routes from the given solution. The number is determined by the product of the number of routes and the degree of destruction.

Routes worst cost removal: This operator removes the route with the highest cost in the given solution.

Routes worst utility removal: This operator removes the route with the lowest utilities in the given solution.

Routes cheapest cost removal: This operator removes the route with the lowest cost in the given solution.

Routes cheapest utility removal: This operator removes the route with the highest utilities in the given solution.

Locker random removal: This operator randomly removes a number of lockers from the given solution. The number is determined by the product of the number of lockers and the degree of destruction.

Locker worst cost removal: This operator removes the locker with the highest cost in the given solution.

Locker worst utility removal: This operator removes the locker with the lowest utilities in the given solution.

Locker random removal plus route: This operator randomly chooses a locker and removes the entire route visiting it.

For all these operators, if when removing a receiver a locker is emptied, this locker is taken out of the route. If a route is removed and there were lockers in it, this ones are emptied. If a locker is removed, this one is emptied.

4.4.2. Repair operators

Greedy receiver insertion in routes This operator inserts the receivers that are not in the given destroyed solution by taking a receiver from the list, checking the cost of locating it in the less costly position at each of the available routes and then choosing the route with the lowest insertion cost. Once the best route is determined, the operator inserts the receiver in this route and repeats the procedure until all receivers have been placed.

Best receiver insertion in routes This operator inserts the receivers that are not in the given destroyed solution by checking the cost of locating each receiver in the less costly position at each of the available routes and then choosing the receiver and the route with the lowest insertion cost. Later, the operator inserts the receiver in the route and repeats the procedure until all receivers have been placed.

Regret receiver insertion in routes This operator inserts the receivers that are not in the given destroyed solution by checking the regret of inserting each receiver. The regret of a receiver is defined as the difference between the costs of locating the receiver in the two cheapest routes. Later, The operator inserts the receiver with the highest regret in the route and repeats the procedure until all receivers have been placed.

Greedy receiver insertion in maximum utility lockers This operator inserts the receivers that are not in the given destroyed solution by taking a receiver from the list, checking the utility of locating it in each of the available lockers and then choosing the locker giving the maximum utility. Once the best locker is determined, the operator adds the receiver to this locker and repeats the procedure until all receivers have been placed.

Greedy receiver insertion in cheapest lockers This operator inserts the receivers that are not in the given destroyed solution by taking a receiver from the list, checking the cost of locating it in each of the available lockers and then choosing the cheapest locker. Once the best locker is determined, the operator adds the receiver to this locker and repeats the procedure until all receivers have been placed.

Best receiver insertion in maximum utility lockers This operator inserts the receivers that are not in the given destroyed solution by checking the utility of locating each receiver in each of the available lockers and then choosing the receiver and the locker that give the maximum utility. Later, the operator adds the receiver in the chosen locker and repeats the procedure until all receivers have been placed.

Regret receiver insertion in maximum utility lockers This operator inserts the receivers that are not in the given destroyed solution by checking the regret of inserting each receiver. In this case, the regret of a receiver is defined as the difference between the utilities of locating the receiver in the two lockers with the highest utilities. Later, the operator adds the receiver in the chosen locker and repeats the procedure until all receivers have been placed.

Regret receiver insertion in cheapest lockers This operator inserts the receivers that are not in the given destroyed solution by checking the regret of inserting each receiver. In this case, the regret of a receiver is defined as the difference between the costs of locating the receiver in the two cheapest lockers. Later, the operator adds the receiver in the chosen locker and repeats the procedure until all receivers have been placed.

For all the operators that insert receivers in lockers, the following applies. If there is any locker that is filled with receivers and is not part of any route, then this locker is added to one of the available routes, taking into account the amount of receivers inside it. If there are no available routes for that, all lockers are deleted from the routes and are inserted following the greedy insertion method. Moreover, a check is done at the end, in case the parcels could be rearranged to lockers with higher utilities, keeping the number of receivers in each locker.

5 Experimental Setup

In this section a computational experiment is presented to check the computational efficiency of the ALNS implementation explained in the previous section, which has been implemented in Python. Particularly, the mathematical model defined in Section 3.3 has also been implemented in Python using the optimization solver Gurobi (for 20 receivers) and Cplex (for 40 and 80 receivers).

In the following sections, the synthetic data and the parameters with the ALNS are presented followed by an analysis on the computational performance and on the results given the different spacial distributions of the data used.

5.1. Data description (synthetic data)

The performance of the exact method and the ALNS is evaluated on a set of the Solomon instances (Solomon, 1987), which have 100 requests. They are divided into different types depending on the distribution of the nodes. Experiments have been performed with random instances (R) and with a mix of random and clustered instances (RC) to verify the ALNS method. Specifically, the characteristics of the instances considered, are summarised in Table 5.1.

Table 5.1: *Characteristics of instances*

Characteristic	Values
Distribution type	R; RC
Number of requests (r)	20; 40; 80
Number of lockers	0.25 r
Number of vehicles	0.2 r
Vehicle capacity	0.4 r
Locker capacity	0.3 r; 0.2 r

For all instances, a fictional driving cost of 0.5 €/km is assumed together with a driving speed of 30 km/h. The maximum duration of a route is limited to 8h in line with the drivers' working hours. The service time is assumed to be 2 min per parcel and the renting costs 0.005 €/parcel. The attraction function for residential areas presented in Section 3.1 is used, assuming that all receivers are nearby a supermarket or a bus station. Moreover, only parcel lockers that give at least an attraction of 0.1 to the receivers are taken into account.

5.2. Parameters of ALNS

The parameters used for running the ALNS with the previously presented instances are shown in Table 5.2. In the following sections, the effect of the number of iterations and epsilons are analysed as well as the effects of the cooling rate and the initial temperature in the SA.

Table 5.2: *Parameters used in ALNS.*

Parameter	Description	Value
λ	decay parameter	0.95
N	number of iterations	5000
e	number of epsilons	6
M	Penalty value for violating the Utility constraint	1000
$\omega_1, \omega_2, \omega_3, \omega_4$	Score weights	(4, 3, 2, 0.5)
α	cooling rate	0.9998

5.2.1. Number of iterations & epsilons

As explained in Section 3.1 epsilon values are used to add one of the objective functions as a constraint and solve the mathematical model with an exact method. When running the ALNS for different epsilons, the algorithm will only search solutions with an attraction higher than the epsilon given. For each of the epsilons, a Pareto Frontier is obtained and later all of them are combined into a single one. Therefore, as can be seen in Figure 5.1, the right-upper part of the Pareto Frontier is run for a larger number of iterations.

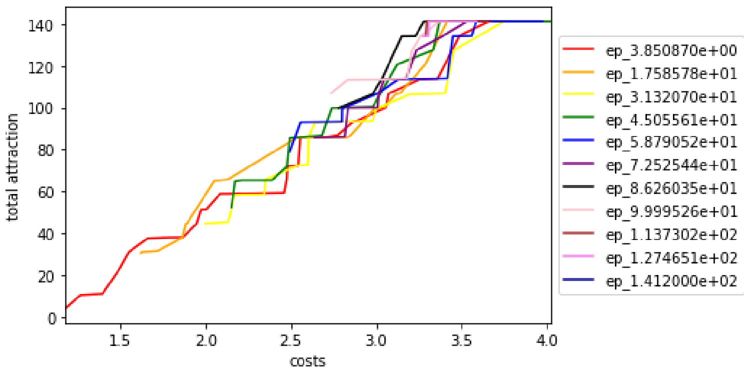


Figure 5.1: *Pareto frontiers obtained for each epsilon in one run for instance R101_20req_8Ql*

In Figure 5.2 the same case has been run with different number of iterations and the Pareto Frontiers are compared to the exact method. The different curves represent the relative difference of each case with the exact method (which is represented by the horizontal axis at 0). It can be observed that all curves are closer to the 0 axis for higher attractions. One reason that explains this is that the repair operators that insert receivers in lockers (associated with lower cost solutions) are less accurate than the ones that insert receivers in routes (associated with higher attractions and higher costs). Therefore, it is not only enhanced for the number of iterations run due to using the epsilons but also due to the specific operators used.

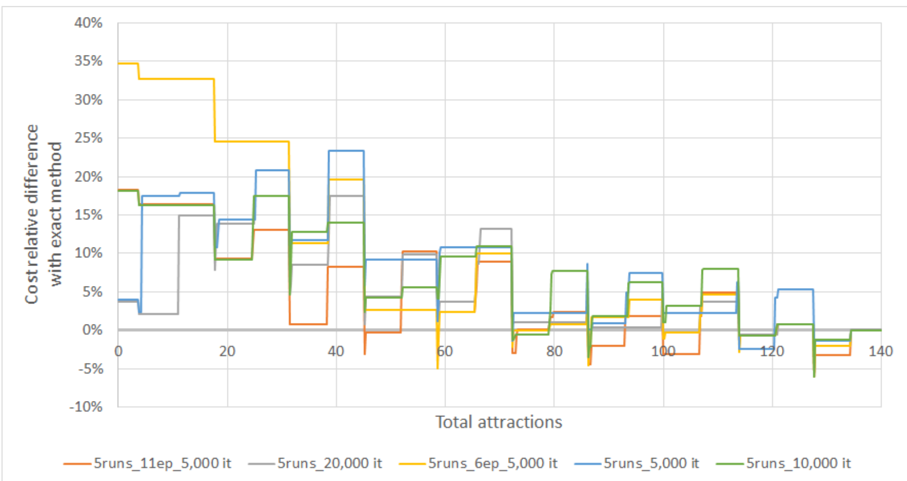


Figure 5.2: *Cost relative differences with the exact method Pareto Frontier from running instance R101_20rec_8Ql with different iterations.*

Moreover, the running time for the higher epsilons is shorter (23 seconds) than for the lowest epsilons (133 seconds). This is due to the repair operators used. In order to obtain solutions that give higher attraction values, the ALNS enhances the use of repair operators that insert receivers in routes rather than lockers and those ones have lower running times. Therefore, using the epsilons can be useful in order to reduce the running time.

For each cost value, the difference between the minimum and the maximum attraction obtained from 5 runs is computed. Then the mean of all the differences is obtained and that is the value presented in Table 5.3. From this, it is shown that the running time with the epsilons is shorter and that the more iterations, the lowest is the deviation with different runs.

Therefore, the number of epsilons used can be reduced and it does not need to be the same as in the exact method. However, it is still beneficial to use a reduced number of epsilons because they help to reduce the running time. Finally, it is decided to run each of the cases with 6 epsilons and 5000 iterations.

Table 5.3: *Statistics from running instance R101_20rec_8Ql with different iterations.*

	1,000it	**5,000it**	**10,000it**	**20,000it**	**11 ep x 1000it (11,000it)**	**6 ep x 5000it (35,000it)**	**11 ep x 5000it (55,000it)**
Average run time [sec]	111	329	954	2254	692	1161	2150
ATTRACTIONS							
Mean differences	19.98	11.52	11.19	9.52	12.67	10.06	10.51
st.dv.	9.08	7.66	7.20	6.04	7.57	6.58	7.16
Percentage from maximum	14.1%	8.2%	7.9%	6.7%	9.0%	7.1%	7.4%
COSTS							
Mean differences	0.27	0.17	0.15	0.16	0.17	0.15	0.14
st.dv.	0.12	0.08	0.08	0.06	0.08	0.06	0.08
Percentage from maximum	7.4%	5.1%	4.5%	4.7%	4.9%	4.6%	4.3%

5.2.2. Initial temperature & Cooling rate

In order to understand how the acceptance criterion (simulated annealing) behaves, the following Figures 5.3, 5.4 and 5.5 are presented. The different lines in the legend represent the difference between the candidate solution and the current solution.

When comparing Figure 5.3 with 5.4, it can be observed that the distance between the lines is bigger when having a higher starting temperature. This shifted the lines in Figure 5.3 down, reducing the probability of accepting a worst solution. This can be clearly observed looking at line 4: with 2000 iterations has a probability of acceptance of 0.47 while in Figure 5.4 it is 0.62.

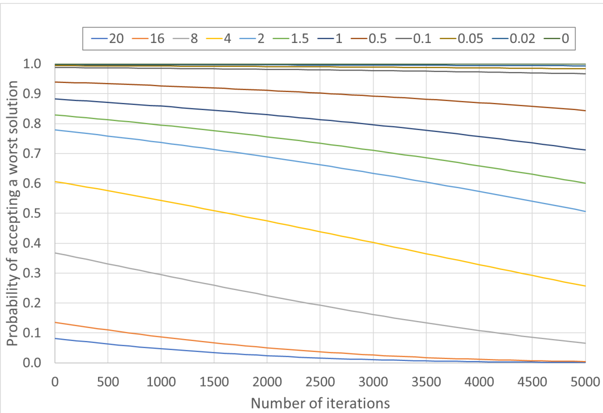


Figure 5.3: *Behaviour of the acceptance criterion with $\alpha = 0.9998$ and $T_i = 8$.*

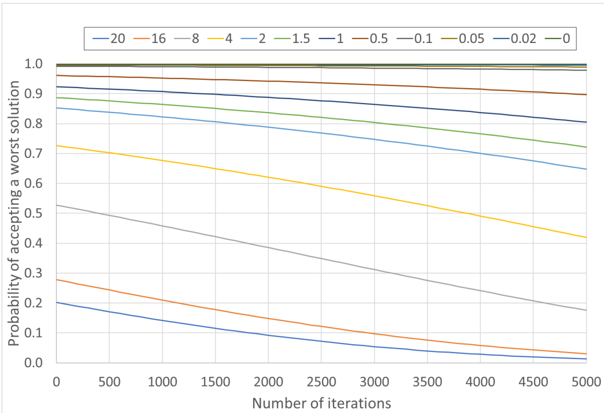


Figure 5.4: *Behaviour of the acceptance criterion with $\alpha = 0.9998$ and $T_i = 12.5$.*

Another important parameter that affects the acceptance criterion is the cooling rate. As can be observed when comparing Figures 5.4 and 5.5, the slope of the curves in Figure 5.5 is steeper than in Figure 5.5. This means that when the cooling rate is lower, the probability of accepting a worst solution is reduced faster with

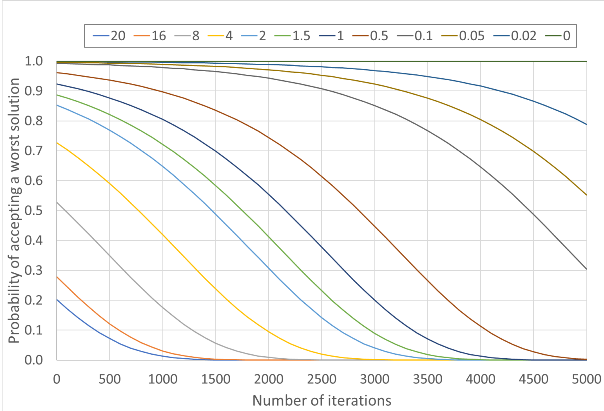


Figure 5.5: *Behaviour of acceptance criterion with* $\alpha = 0.999$ *and* $T_i = 12.5$.

the number of iterations. The aim of using a cooling rate is to allow more or less the ALNS to search solutions in various neighbourhoods in the first iterations.

For this research, the initial temperature is set in such a way that the probability of accepting a two times worst solution than the initial solution is 50%, which gives the value of 12.5 for instances with 20 receivers. And the cooling rate of 0.9998 was preferred over 0.999, as this last one quickly penalises solutions with smaller differences that could lead to better neighbourhoods. For solving the given model with two objective functions, it it important to allow enough movement in the solution space for improving the two and both chosen parameters seem to work good with the instances presented in the following sections.

5.3. Computational Performance

In this section the software implementation of the exact method and the ALNS algorithm are compared.

Because solving the model with the exact method requires a considerable amount of computational time, a time limit was used. Specifically, 1 hour per epsilon with the instances of 20 receivers (using Gurobi). For instances with 40 and 80 receivers, the Cplex runs were performed with different strategies, to achieve the best lower bound (LB) with a time limit of 12h per epsilon and to achieve the best solution with a time limit of 3 hours per epsilon. This was done in order to get better results combining the two.

However, it is important to keep in mind that the exact method was stopped with a time limit and the gaps with the LB are rather high in general.

Table 5.4 presents an average of the differences between the gaps of the ALNS minus the gaps of the exact method, which gives the general improvements achieved with the ALNS for each Pareto Frontier. The positive improvements mean that the ALNS performs better than the exact method and the negative improvements mean the that the ALNS performed indeed worse.

Table 5.4: *ALNS average run time and improvement achieved with respect to the exact method for R and RC instances.*

Instances	**R results**		**RC results**	
	Run Time	**Improvement**	**Run Time**	**Improvement**
20rec_8Ql	3.4%	-9.8%	2.6%	-4.0%
20rec_6Ql	3.4%	-10.8%	6.4%	-4.8%
40rec_16Ql	1.5%	-50.5%	7.8%	-74.2%
40rec_12Ql	3.6%	-46.9%	18.8%	-79.7%
80rec_32Ql	19.5%	144.4%	13.4%	143.2%
80rec_24Ql	8.5%	82.1%	21.7%	48.2%

Therefore, for the 20 receivers instances, within a 2.4%-6.4% of the Gurobi running time, the ALNS is able to find a solution that is only 4.0%-10.8% worst than the exact model. For the 40 receiver instances, the ALNS run time varies more, from 1.5% -18.8% and the results from the ALNS are further away from the solutions of the exact method. For the 80 receiver instances, the ALNS is able to find a solution for all the epsilons within 8.5%-21.7% of the exact running time, while the exact method was not able to find solutions for all the epsilons given the computation time limit. Moreover, on average the ALNS improves significantly the solutions from the exact method.

Appendix A contains the results of running the instances presented in Section 5.1 in a series of tables. It should be noted that all gaps are calculated with respect to the best LB.

Figures 5.6 to 5.8 present the results in the form of Pareto Frontiers for a number of representative cases only, as there are no significant differences between the results for the same number of receivers but different locker capacities.

Figure 5.6 shows the Pareto Frontiers for one of the 20 receiver instances, where the ALNS is really close to the exact solutions. However, Figure 5.7 confirms what was observed in the previous tables, that the ALNS solutions are at a further distance from the exact method solutions. Figure 5.8 shows that the exact method is not able to find good solutions within the given time limit whereas the ALNS can find better solutions than the exact method.

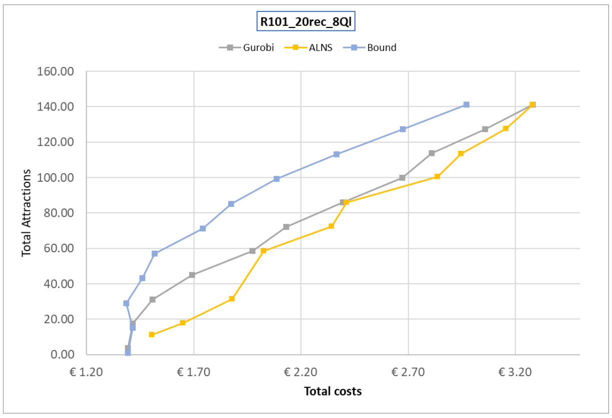


Figure 5.6: *Pareto Frontiers obtained for instance R101_20rec_8Ql.*

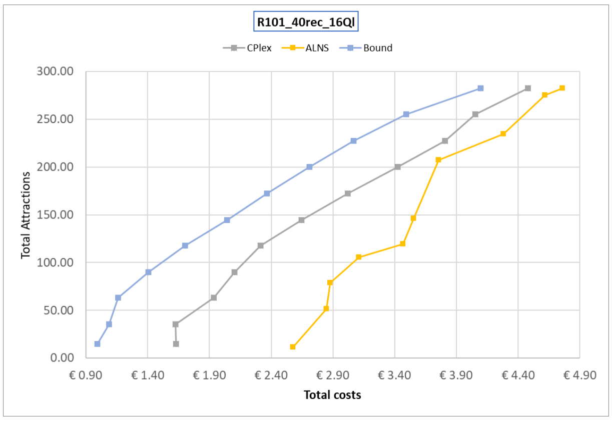


Figure 5.7: *Pareto Frontiers obtained for instance R101_40rec_16Ql.*

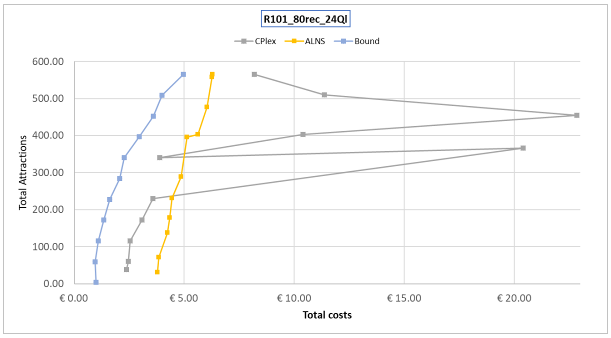


Figure 5.8: *Pareto Frontiers obtained for instance R101_80rec_24Ql.*

Figures 5.6, 5.7 also show that the exact model finds smoother Pareto Frontiers, meaning that probably the ALNS operators are not able to find all possible solutions.

To conclude, the ALNS can be used for solving the mathematical problem presented previously in Section 3.3. The ALNS algorithm is not able to find better solutions than the exact method for the smaller instances - at least for the selected running times - whereas it is able to find some better solutions for the bigger instances. Therefore, for instances equal or bigger than 80 receivers, the ALNS improves the performance of the exact method with a significant reduction of the running time, given the time limitation of 12h per epsilon in the exact method.

5.4. The impact of spatial distribution on delivery performance

In this section some general observations regarding differences between the R (uniformly distributed) and RC (mixed of uniformly distributed and clusters) are pointed out.

First, R instances costs are lower than the RC instances. Figures 5.9 and 5.10 show that the difference of cost between R and RC instances is due to the spatial distribution, as for RC there are more receivers located further away from the center than in R.

Figure 5.11 shows that the RC Pareto Frontiers are steeper than the ones from R. This means that adding home deliveries is cheaper for the courier delivering to RC distribution networks.

In general, the lockers are used at low capacity and the number of lockers used does not seem to differ much regarding the different distributions as well(e.g. in Figure 5.12). Therefore, these parameters are not affected for having different receiver distributions.

Finally, when the lockers are located in the clusters, receivers have to travel shorter distances to pick up their parcels, whereas in the R instances they have to travel longer distances.

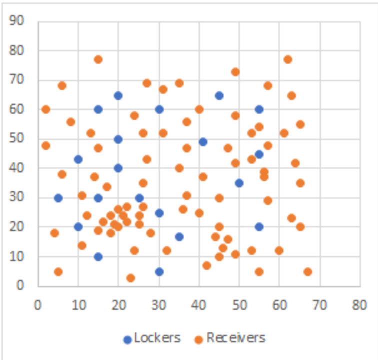


Figure 5.9: *Spatial distribution of R instances with 80 receivers.*

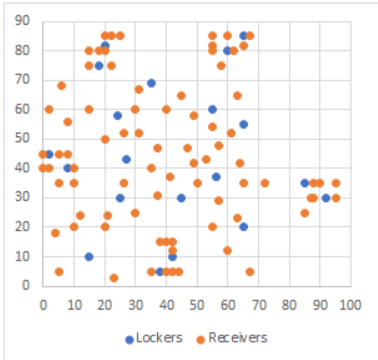


Figure 5.10: *Spatial distribution of RC instances with 80 receivers.*

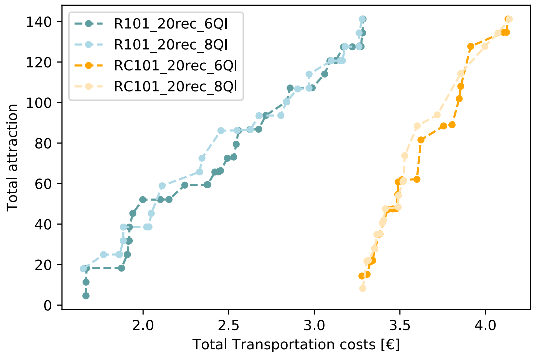


Figure 5.11: *Pareto Frontiers obtained for instances with 20 receivers.*

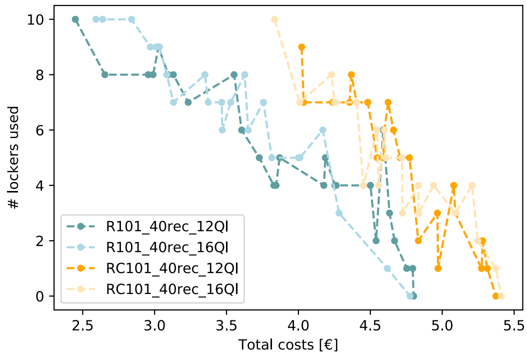


Figure 5.12: *Number of lockers used for each of the 40 receivers instances vs Total Transportation costs.*

6

Case study - DPD Netherlands

6.1. Implementation

In this section, the previous ALNS metaheuristics algorithm is applied to a case study. Specifically, data from the company DPD has been provided from year 2018. Some delivery companies have parcel lockers already in the Netherlands, however that is not the case of DPD. For this reason, they are planning to locate some parcel lockers in the city of Rotterdam and this is the reason of locating the case study in the Rotterdam area. DPD has 9 depots in the Netherlands and the closest one is the Rotterdam depot. The average number of requests being handled at this depot is 20.000 per day.

This amount of requests is too big for the current implementation of the ALNS algorithm presented. Therefore, a smaller area is chosen for the case study. An average day (18th September 2018) has been chosen and the number of requests has been limited to 80 parcels. The area shown in Figure 6.1 in the city center of Rotterdam represents the case study. In this case, the depot is not located inside the area where the requests are located but around 5.5 km North from the study area.

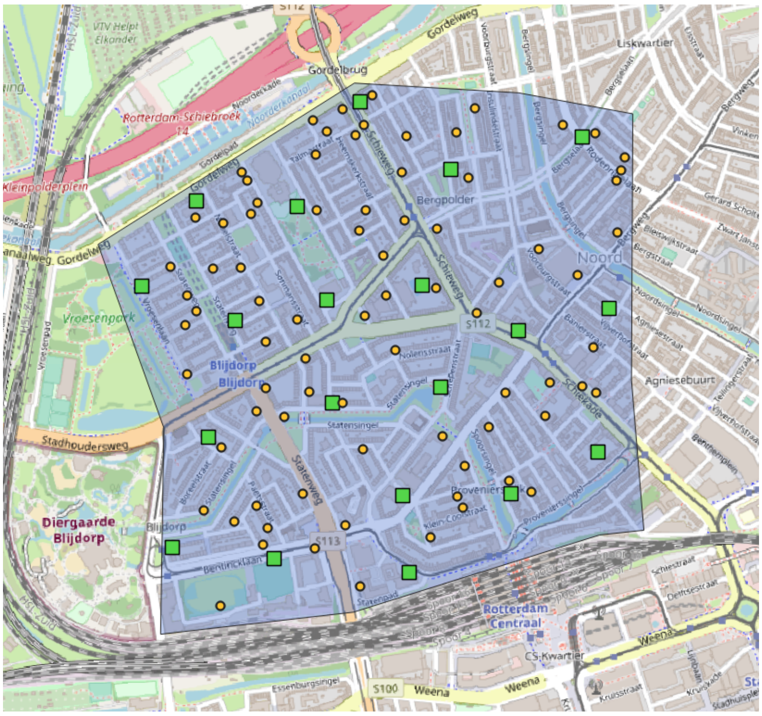


Figure 6.1: *Map with the location requests on day 18-09-2018 in the North site of Rotterdam Central. In squares there is a random location for the parcel lockers.*

First, a Base Scenario with a selected set of parameters is discussed. A total of 20 lockers with a capacity of 10 parcels are randomly located in the area, so that the algorithm has enough freedom to use more or less lockers, more or less full. The attraction function for residential areas presented in Section 3.1 is used, assuming that all receivers are nearby a supermarket or a bus station. Given the dimensions of the study area, a fleet of 6 vehicles with a capacity of 20 parcels each, was considered.

Lastly, the ALNS has been slightly modified, as for the case study, the renting cost is per locker instead of per parcel (inside the locker). A rent cost of 0.02 €/locker is used. This value was chosen because the Pareto Frontier is sensitive to the rent. For cases where the rent is high in comparison with the distances between receivers, the cheapest result with the highest service level would always be delivering all the parcels at home.

Different scenarios are created to see the effect on the whole system of the renting costs of the lockers, the number of lockers and their capacity and a change in preferences of end-users. For each of these scenarios, two different cases are created as shown in Table 6.1. For all scenarios, lockers are located randomly but uniformly spread in the study area in order to simulate the potential locations for the lockers.

Table 6.1: *Scenarios considered for the case study.*

Parameter to Change	Base Scenario	Variations
Rent [€/locker]	0.02	0.05; 0.0
Number of lockers [lockers]	20	15; 10
Locker capacity [parcels/locker]	20	15; 20
Home delivery [home attraction]	7.06	0.8; 0.3
Distance factor [distance parameter]	-4.59	-1.5; -0.5

For all scenarios, a fictional driving cost of 0.6 €/km is assumed together with a driving speed of 30 km/h inside the study area (between receivers and/or lockers) and 80 km/h between the depot and the study area. The maximum duration of a route is limited to 8h in line with the drivers' working hours. The service time is assumed to be 2 min per parcel. Moreover, only parcel lockers that give at least an attraction of 0.1 to the receivers are taken into account (as explained in Section 3.1).

For the scenarios where the distance parameter is different, the attraction functions have a different curve. This is shown in Figure 6.2, where the base scenario (distance parameter = -4.59) is represented in blue. For the base case, the end-user would still prefer to receive the parcel at home rather than at a parcel locker located at "0m", as the home attraction (7.06) is still much higher than the maximum attraction obtained when going to a locker(2.8). Therefore, home attraction has an important effect and that is why another scenario has been added, giving a lower home attraction to the end-user. For the base scenario curve and a home attraction of 0.3, the end-user will prefer going to a parcel locker at 100m from home (attraction of 0.5) rather than having home delivery.

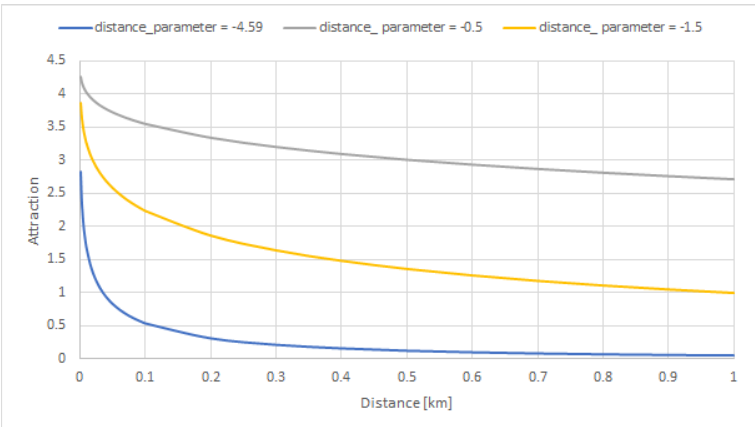


Figure 6.2: *Three attraction curves with different distance parameters (base scenario in blue).*

6.2. Results & Discussion

After running the different scenarios with the ALNS heuristics, some post-processing is required in order to obtain the probabilities and the service level (SL) described in Section 3.1. The final results for each scenario can be found in Appendix B and include the following performance indicators for each of the points of the corresponding Pareto Frontiers: total transportation costs (TTC), total attraction, service level, transportation distance, locker rent, lockers in use, lockers capacity usage, number of home deliveries and number of receivers travelling a specific distance to the locker.

It is to be remarked that the cloud of current solutions (as defined in Section 4.2) obtained for the case study scenarios are different than the ones obtained with the Solomon instances. Figure 6.3 presents the cloud of current (blue) and best (red) solutions obtained for a Solomon Instance. Figure 6.4 shows the cloud of solutions for the Base Scenario, which in this case is split in two clusters of points. The distance between the two clusters can be explained by the fact that the depot of DPD is not located inside the delivery area – which was the case for the Solomon instances. When the algorithm adds a new route (vehicle) to the solution, the additional travelling costs of driving from and to the depot corresponds with the space between the two clusters in Figure 6.4.

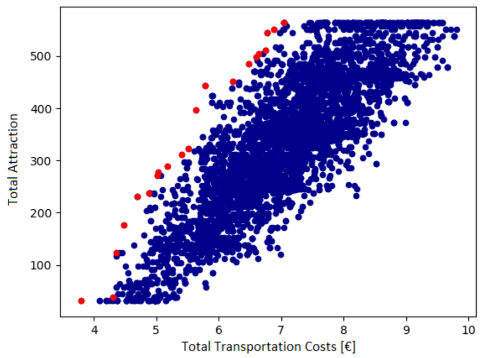


Figure 6.3: *Plot of all current solutions(in blue) and best solutions (in red) for an instance.*

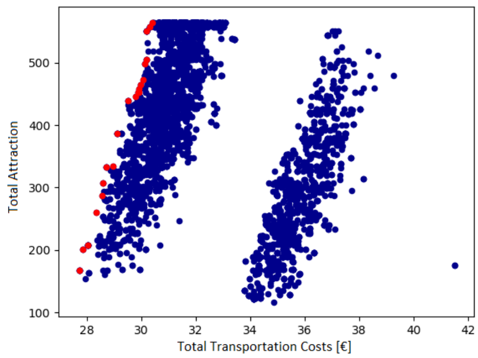


Figure 6.4: *Plot of all current solutions(in blue) and best solutions (in red) for the scenario of 10 lockers.*

6.2.1. Base Scenario

The SL curve of the base scenario is presented in Figure 6.5. The SL increases with the cost spent for the courier to deliver the parcels. Specifically, there are three steep steps in the Pareto Frontier (A-B; D-E; F-G) where the courier can increase around 20% of the SL with a very small increase in costs. These steps in the SL curve are directly related to an increase of the home deliveries, which can be observed with the shape of the orange line in Figure 6.6.

Another observation can be made regarding the flat curve between points B and C in the SL curve. This is caused by an increase of approximately 1km in the routing distances. Under this circumstances, the courier needs to spend an important amount of money to continue increasing the SL.

Figure 6.6 presents the distribution of distances that the receivers have to move in order to pick up their parcel. For the base scenario, the majority of parcels are put in lockers at a distance of 0.1-0.2km for the lower total transportation costs. For higher total transportation costs (and higher SL), the amount of home deliveries increases predominating over locker usage.

Figure 6.7 presents the number of lockers used and the occupancy rate of these lockers. A network with higher TTC is characterised for having more home deliveries and using less lockers. Having more home deliveries requires longer routes which are responsible of increasing the costs.

Nonetheless, looking at points C and D from Figure 6.7, with a small difference in costs, point C has 7 lockers opened at a high average capacity usage and point D has 11 lockers opened with a low average capacity usage. However, they have almost the same TTC and SL values. The differences can also be observed from the solution routes obtained at points C and D, shown in Figures 6.8 and 6.9.

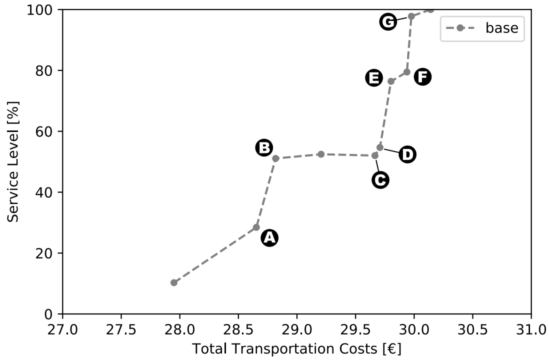


Figure 6.5: *Service level vs Total Transportation Costs from the Pareto Frontiers of the base scenario.*

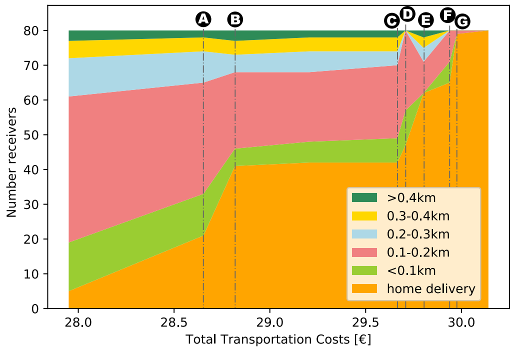


Figure 6.6: *Receiver distribution by distance to locker for the Base scenario.*

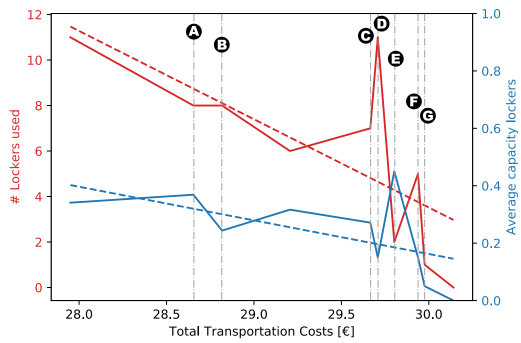


Figure 6.7: *Number of lockers used and average capacity usage trends for the base scenario.*

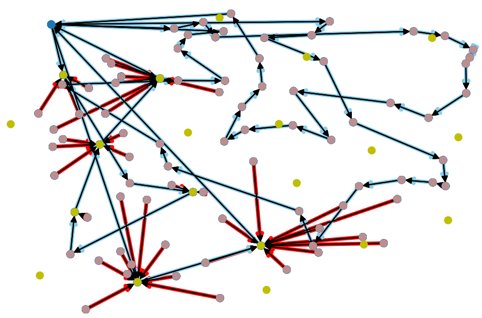


Figure 6.8: *Courier routes(blue) and receivers to lockers(red) for point C from Figure 6.7.*

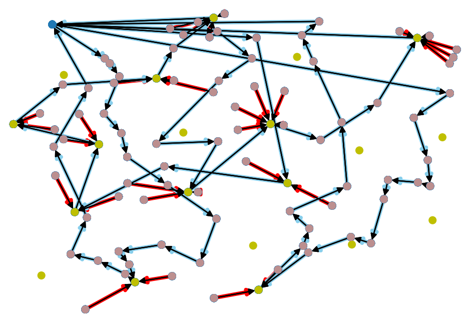


Figure 6.9: *Courier routes(blue) and receivers to lockers(red) for point D from Figure 6.7.*

This behaviour highlights the complexity of this problem: the large amount of possible solutions lead to the possibility of having solutions very similar in terms of transportation costs and total attractions, coming from significantly different route layouts.

Finally, if the courier wants to give a specific service level at a lower cost, this can be achieved by reducing the routing distance, which in the end is achieved by using more lockers. On the other hand if the courier wants to maintain the costs but give a higher service level, they have to increase the number of home deliveries and reduce the number of lockers.

6.2.2. Effect of locker rent cost

Given the limited size of the study area, the rent of each locker is a parameter that can have a significant effect on the total transportation costs. If renting costs were too high, using the lockers would always be avoided as a solution because the travelling distances between the receivers are relatively small in this network. The purpose of this research is to see the effects of using lockers and therefore, it was decided to use relatively low renting costs in the Base Scenario (0.02 €/locker).

To analyse the effect of the renting costs, two other scenarios were run with a rent of 0 €/locker and 0.05 €/locker. Figure 6.10 shows the SL curves comparing the three scenarios. It shows that the 0.05 € scenario has a similar curve than the base scenario. Besides, looking at Figures 6.12 and 6.13, the number of home deliveries can be directly related to the SL curves as well.

For a 0 € rent, less lockers are used than the base case and they are almost at a constant capacity usage of 30-50% for the cost range, as can be seen in Figure 6.11. Moreover, the number of receivers having to travel longer distances to the lockers is higher for the 0 € scenario, which reduces the SL of the receivers that do not have home deliveries even more. However, as the number of home deliveries is higher in this scenario, the SL curve is shifted to the left.

Finally, working with lower renting costs is beneficial for the courier, who will be able to provide a specific SL at a lower cost, as the routing distance will decrease with the use of more lockers.

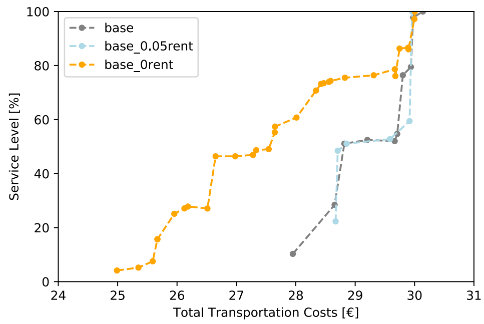


Figure 6.10: *SL curves for the base scenario (0.02 €) and two other scenarios of 0 € and 0.05 €.*

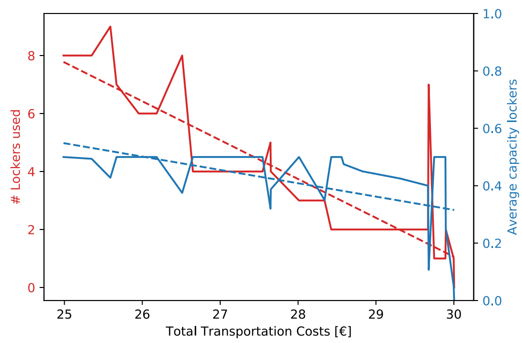


Figure 6.11: *Number of lockers used and their average capacity for the 0 € rent scenario.*

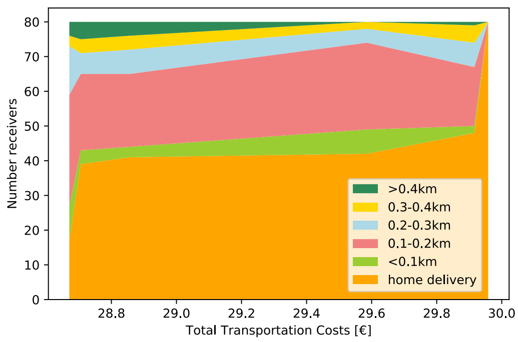


Figure 6.12: *Receiver distribution by distance to locker for 0.05 €/locker.*

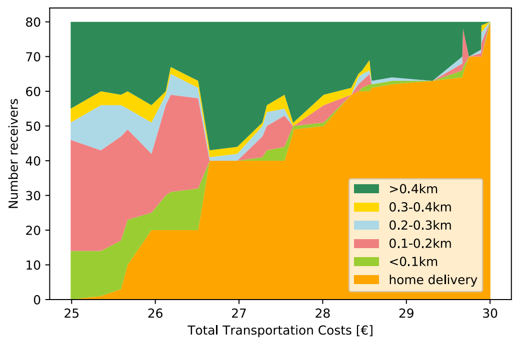


Figure 6.13: *Receiver distribution by distance to locker for 0 €/locker.*

6.2.3. Effect of number of lockers

Apart from the Base scenario with 20 lockers, two other scenarios have been run with 15 and 10 lockers. Looking at Figure 6.14, the SL curves of the base scenario and the 15 lockers are very similar. Differently, the 10 lockers SL curve is slightly shifted to the left, having lower costs for a given SL compared to the other two. Figure 6.15 shows that in general for this scenario with 10 lockers, these are used at higher capacities (around 70% full) than the base case.

Looking at Figures 6.16 and 6.17, having less lockers enhances home deliveries to the receivers located further away from the lockers.

To sum up, having a lower number of lockers reduces the total transportation costs of the network given the same SL. Moreover, more importance should be given to the location of this lockers rather than the amount of them.

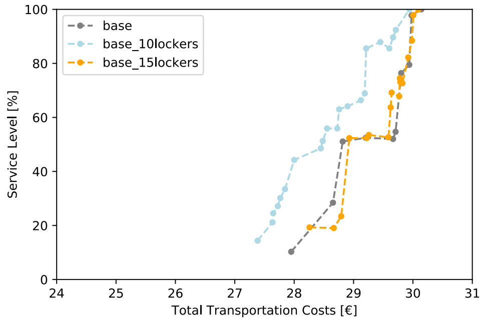


Figure 6.14: *SL curves for the base scenario (20 lockers) and two other scenarios of 15 and 10 lockers.*

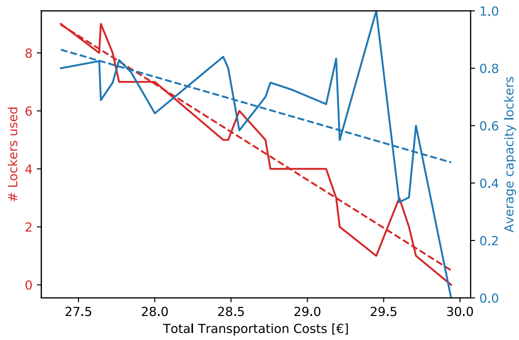


Figure 6.15: *Number of lockers used and their average capacity for the 10 lockers scenario.*

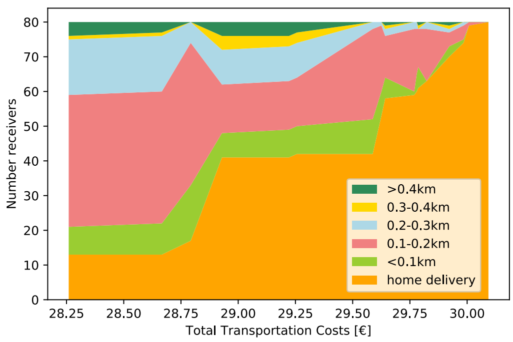


Figure 6.16: *Receiver distribution by distance to locker for 15 lockers.*

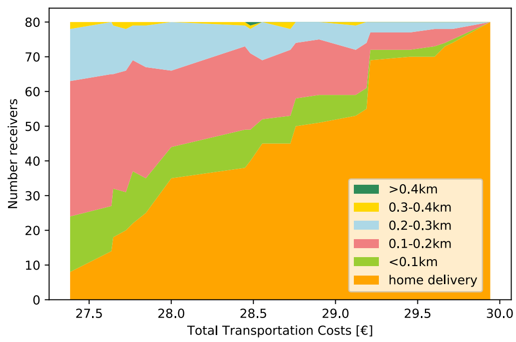


Figure 6.17: *Receiver distribution by distance to locker for 10 lockers.*

6.2.4. Effect of locker capacity

To analyse the effect of the locker capacity, two other scenarios were run with lower capacities, 15 parcels/locker and 20 parcels/locker. Looking at Figure 6.19, when increasing the capacity to 20 parcels, the minimum cost is achieved by using almost all lockers at a 20% capacity only. In this case, the majority of the receivers are located at less than 200 m from the lockers where they have to go as shown in 6.21.

With a lower capacity of 15 parcels, more home deliveries occur and receivers are sent to further away lockers because less lockers are used, which leads to a slightly move to the left of the SL curve in Figure 6.18. This shows that the home deliveries compensate the fact of sending receivers further away in this network.

When reducing even more the capacity, 10 parcels for the base case, more lockers are used again with an increase in the average capacity usage, as seen in Figure 6.7.

Therefore, it can be assumed that the Pareto Frontier is quite robust regarding this parameter as the SL curves from the scenarios where the capacity of the lockers is changed are both steep and similar.

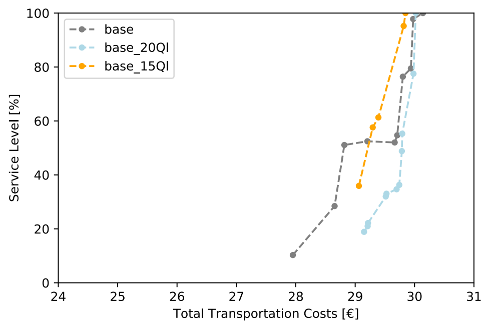


Figure 6.18: *SL curves for the base scenario (10 parcels/locker) and two other scenarios of 15 and 20 parcels/locker.*

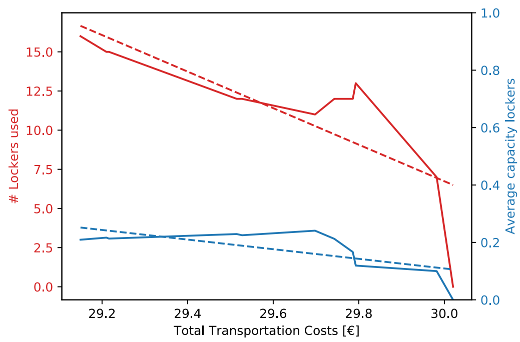


Figure 6.19: *Number of lockers used and their average capacity for the 20 parcels/locker scenario.*

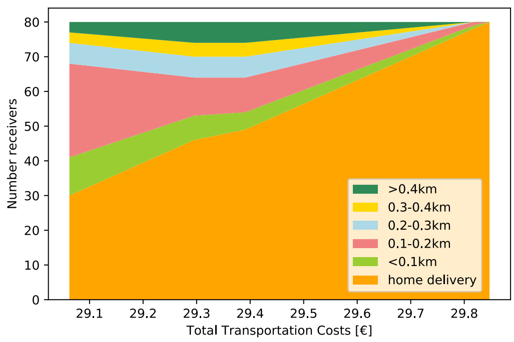


Figure 6.20: *Receiver distribution by distance to locker for 15 parcels/locker.*

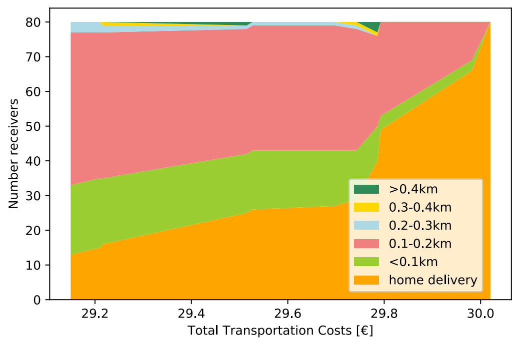


Figure 6.21: *Receiver distribution by distance to locker for 20 parcels/locker.*

6.2.5. Effect of home delivery attraction

When calculating the probabilities of a receiver to go to a specific locker, the probability function (Section 3.1) takes into account the attraction of all the lockers that are opened, as well as the attraction of home delivery. For this reason, the probabilities obtained tend to be low when there are many lockers opened or when the home attraction is high compared to the locker attractions, as they are competing options from which the receiver could choose from. For the same reason, when all the parcels are delivered at home, the receivers have no other option to choose from as there are no lockers opened. Therefore, the probability of them choosing the home delivery option is 1.

Due to this behaviour, an adjustment of the service level was needed (see Figure 6.22 and 6.23) to show the effect of the attraction function variations. This adjusted SL is the average of the attraction of each receiver with respect to the possible attraction range. Particularly, this is required for two scenarios: when varying the home delivery attraction and the distance parameter (next subsection).

To see the effect of the home delivery attraction, two cases were tested: reducing this parameter from 7.06 in the base scenario to 0.8 and 0.3. For the locker attraction to be higher than 0.8 home attraction, the locker needs to be located at less than 50 m from the receiver according to the attraction function presented in Section 6.2. As in the given network the majority of the lockers are located at longer distances, the 0.8 home delivery attraction still is the best option for the receivers. For this reason, the SL curve is partially similar to the base scenario in Figure 6.23 and it is directly related to the number of home deliveries observed in Figure 6.24. However, the adjusted SL shows that it is possible to provide a higher SL than the base scenario given the same cost.

On the other hand, to get an attraction higher than 0.3 going to a locker, the receiver only needs to be closer than 200m from the locker, which is easier to happen in the network of the case study. In this scenario, the lockers can compete with the home delivery and that is why the SL curve is different. Contrarily to the other two cases, where the maximum SL is provided when delivering all the parcels at homes, in this scenario, the maximum SL is provided delivering all the parcels to lockers located at less than 200m from the receivers. This can be observed in Figure 6.25 and it is achieved by using all the 20 lockers available at a 20% of the capacity (see Table B.8 in Appendix).

From this, the courier can see the importance of knowing the type of receivers present in their network. For example, if the receivers are willing to make the extra effort of going to a locker further away over receiving the parcel at home – which can be associated with sustainability consciousness or convenience of the parcel locker system – the courier will be able to provide a high SL while reducing the kilometers driven to serve the same network. Couriers can improve the SL by enhancing the positive effects of parcel lockers mentioned in Section 2.3.

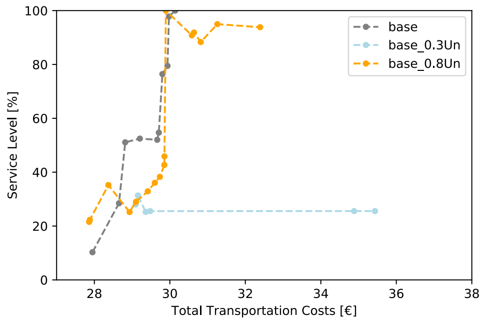


Figure 6.22: *SL curves for the base scenario (7.06 Home attraction) and two other scenarios of 0.3 and 0.8 Home attraction.*

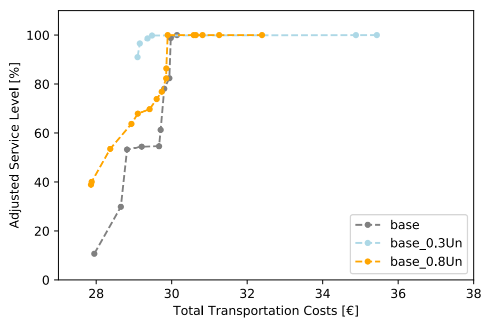


Figure 6.23: *Adjusted SL for the base scenario (7.06 Home attraction) and two other scenarios of 0.3 and 0.8 Home attraction.*

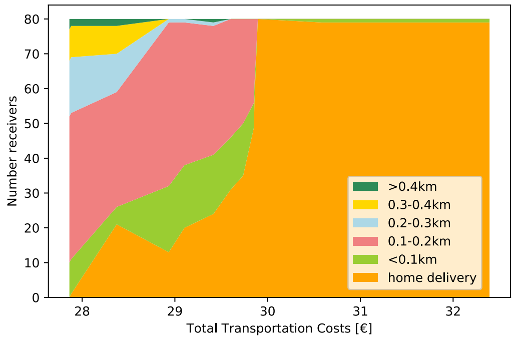


Figure 6.24: *Receiver distribution by distance to locker for 0.8 Home attraction.*

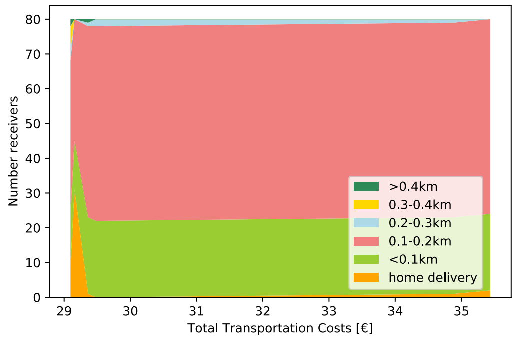


Figure 6.25: *Receiver distribution by distance to locker for 0.3 Home attraction.*

6.2.6. Effect of distance parameter in attraction

As explained in the previous subsection, an adjustment of the service level was needed in order to show better the effect of the distance parameter of the attraction function. Particularly, two cases were tested, reducing this parameter from -4.59 in the base scenario to -1.5 and -0.5.

When reducing the distance parameters, the adjusted SL curves become less steep than the base scenario as can be seen in Figure 6.27. This implies that the courier needs to invest a little more in order to see a significant improvement on the SL. However, this figure also shows that even though any change is applied to the network, the courier is able to provide a higher SL with the same cost if the receivers are less sensitive to the distance (-0.5 utility). Just to provide a 50% SL in the -0.5 utility case, the courier reduces the travelling distance 5km and the total transportation costs 3 € from the base scenario.

More parcels will be delivered to lockers that are further away from the receivers, allowing to reduce the routing distances, but still getting a similar service level. The fact that the parcels are located to lockers that are further away is shown with Figures 6.28 and 6.29, where the dark green area has significantly increased from the previous cases. Still, home delivery is preferred because the difference in attraction is high (maximum locker attraction 2.8 vs home attraction 7.06).

Seeing the significant effect this parameter has on the SL provided, it is shown the importance for the courier to study what type of receivers does their network have. For example, if there is more elderly people, they will be more sensitive to the distance and therefore, in order to offer a specific SL, more money will need to be invested.

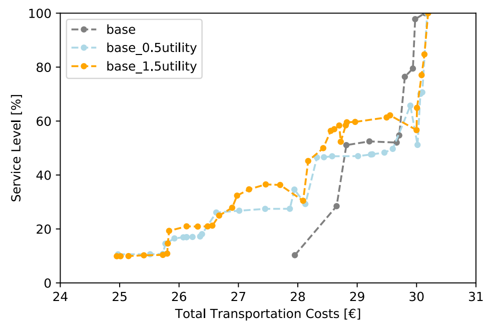


Figure 6.26: *SL curves for the base scenario (-4.59 dist. param.) and two other scenarios of -1.5 and -0.5 dist.param. .*

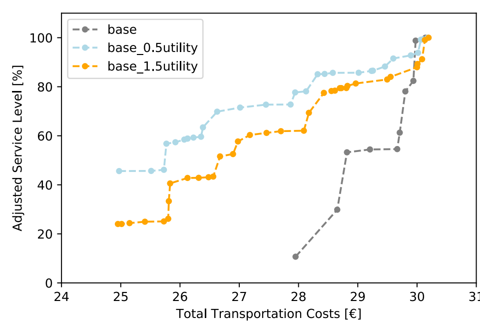


Figure 6.27: *Adjusted SL for the base scenario (-4.59 dist. param.) and two other scenarios of -1.5 and -0.5 dist.param. .*

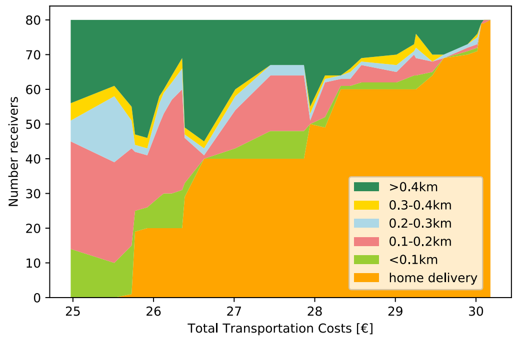


Figure 6.28: *Receiver distribution by distance to locker for -0.5 distance parameter.*

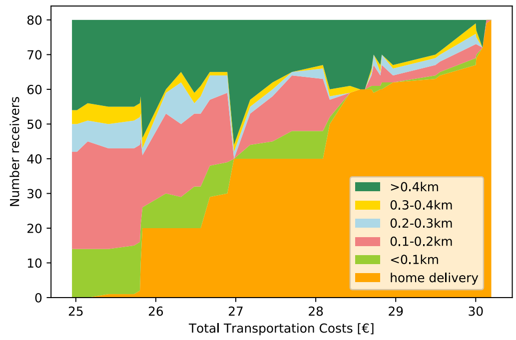


Figure 6.29: *Receiver distribution by distance to locker for -1.5 distance parameter.*

6.3. Key findings

Some remarks for the couriers are highlighted in this section, based on the analysis of the results presented in the previous paragraphs. First of all, it is important to keep in mind that similar SL and TTC can be obtained for significantly different routes, making this a complex system to analyse. When looking at the shape of the Pareto Frontiers, a steep slope means that the SL can be easily improved with a small impact on the total costs. On the other hand, a flat section in the Pareto Frontier means that a significant amount of money is required to further increase the SL. When looking at the relevance of the parameters analysed, the percentage of home deliveries is one of the main drivers for increasing the SL when home delivery attraction is high. The capacity of lockers does not have a big impact on the results, while low renting costs help to provide a specific SL at lower TTC. In general, using less lockers at a higher capacity helps to reduce costs.

It is crucial for the couriers to study what type of receivers belong to their delivery network before deciding on the implementation of parcel lockers. For example, if receivers are more sustainable, the resulting parcel locker network will enhance the use of more lockers, reducing the general distance from the receivers to the lockers. Also, if receivers are less sensitive to the distance to the lockers, the resulting parcel locker network will reduce the number of lockers used, increasing the distance to the lockers from the receivers side.

7

Conclusions and Further Research

In this section the conclusions of this research are presented. Firstly, the sub-research questions are answered followed by the main research question. Furthermore, the limitations of the given research are discussed and some further research is proposed.

7.1. Conclusions

The use of parcel lockers is regarded in literature as a good option for improving the problem of missing the receiver in home deliveries and enabling a transition towards self-organizing logistics. However, implementing a parcel locker network has an impact on both couriers and receivers, which still prevents couriers from directly adopting this technology.

This research proposes a model that provides a nuanced view on the relations between receiver attractions, service levels, lockers and total transportation costs. Moreover, it provides a tool for couriers to simulate different options before implementing such a network system with parcel lockers.

This research has been structured with one main research question and a number of sub-research questions. All of them are answered below:

1. *How to take receiver preferences into account when modelling the routing in a parcel locker network?*

   On the one hand, the vehicle routing problem in this network can be solved with an optimization model. On the other hand, receiver preferences can be considered with a choice behaviour model. To combine both, this research has described a mathematical model that contains two objective functions: one that minimizes the total transportation costs (i.e. the vehicle routing problem) and a second one that incorporates the choice behaviour model by maximizing the total attractions of the receivers to go pick up the parcel in a specific locker.

2. *How to represent the effect of providing a specific service level on total transportation costs?*

   Service level reflects the level to which all receiver preferences are fulfilled when deciding on a specific routing. As described in Section 3.1, maximizing service level while minimizing routing costs is usually contradictory and, therefore, it is not possible to find a single solution for a given network. This research uses Pareto Frontiers as an effective way to represent the cost impact of providing any given service level.

3. *How to solve the proposed optimization model efficiently for large instances?*

   Solving the given mathematical model for small instances is possible with an exact method. However, that is not the case for large instances (15 nodes or more) in a short computational time. For this reason, heuristics need to be used and an Adaptive Large Neighbourhood Search algorithm is implemented in this research. The ALNS destroy and repair operators have been specifically designed for this particular model.

4. *What is the trade-off between accuracy and computation efficiency of the solution method?*

   When applied to the Solomon instances, the ALNS algorithm is able to improve the solutions of the exact method with just 10-20% of the computational time, demonstrating that this algorithm can be effectively applied for solving the mathematical model. However, the Pareto Frontiers from the exact method are smoother and present lower gaps with the lower bounds, which shows that ALNS compromises the accuracy of the solutions at a cost of reducing the computational time.

   Nonetheless, it is important to note that while the exact method can only provide one point of the Pareto Frontier per run, the implementation of the ALNS heuristics developed in this research is able to find a pool of best solutions that represent the whole Pareto Frontier in a single run. To define more points of the Pareto Frontier, the exact method requires more runs and therefore higher running times. On the other hand, increasing the iterations of the ALNS algorithm directly improves the whole Pareto Frontier.

5. *What is the effect of the number and capacity of lockers, the renting cost and the type of receivers on the total transportation costs and service level?*

   The ALNS algorithm has been applied in a parcel delivery network of a small urban area in Rotterdam and changes where made in the parameters under study. The most critical parameter for the system is the type of receivers: If receivers are more sustainable, the resulting parcel locker network will enhance the use of more lockers, resulting in a reduction of the average distance from the receivers to the lockers. If receivers are less sensitive to the distance to the lockers, the resulting parcel locker network will reduce the number of lockers used, increasing the distance to the lockers from the receivers side.

   When looking at the other parameters, with relatively smaller effects on the results, using less lockers (with higher occupancy rate) proved to help reducing costs in order to provide the same SL. The same occurs when working with lower renting costs. On the other hand, varying the capacity of the lockers did not show a significant impact on the results.

What is the impact of implementing a network of parcel lockers for the last mile delivery on couriers' and receivers' costs?

A network of parcel lockers for the last mile delivery has been modeled for a case study in a small urban area in Rotterdam. The impact of using parcel lockers on both couriers and receivers is evaluated from the Pareto Frontier obtained from implementing an ALNS algorithm to this case study.

As a result, implementing a network of parcel lockers has a positive impact on the courier's costs as it helps to reduce their total transportation costs and by reducing the amount of home deliveries it also reduces the success-rate problem introduced at the beginning of this research. On the other hand, the impact for the receiver implies a reduction of the service level, depending on their preferences and the available lockers in the system.

It is important to highlight that changes in the network characteristics have a complex effect on the possible solutions, reflected in changes in the shape of the Pareto Frontier. Numerical models are essential to study this behaviour in a specific network, allowing decision makers evaluate the impact on couriers' and receivers' costs of implementing such a network. Therefore, this research contributed by providing a tool for logistics practitioners, such as DPD, to simulate different operations before implementation.

7.2. Key Contributions

This research has helped with several contributions to science but also to logistics practitioners. These are listed below:

- A new problem has been described, incorporating receivers' choice behaviour into a vehicle routing problem.
- This problem has been formulated in a Mathematical Model that can be solved numerically.
- A new ALNS algorithm implementation has been designed to suit this specific problem description and formulation.
- This algorithm is able to solve the problem for large instances efficiently.

- This algorithm can be implemented directly in real networks and extended to incorporate additional constraints.
- This algorithm can be used by couriers for taking tactical decisions about where to locate parcel lockers but also to determine the receivers to whom deliver at home.
- It is crucial for the couriers to study what type of receivers belong to their delivery network before deciding on the implementation of parcel lockers.

7.3. Limitations & further research

This research presents an initial effort to model a complex network system, setting the basis for further research. The assumptions made during this study can be linked to limitations of the model. These are presented below followed by suggestions for further improvements.

The network characteristics were simplified when defining the delivery structure. For example, the size of the parcels and time windows have not been introduced. Also, lockers can only be visited by one vehicle. These are aspects that could be added to the model in order to make the problem more realistic. Besides, the problem was solved with different network distributions, however it would also be interesting to see the effect of the lockers distribution as well.

The preferences of the receivers to go to different lockers are modelled with attraction functions from a case study located in Singapore, as this type of data is very scarce in literature. Taking into account the sensitivity of the model to these functions, it is recommended to do a survey to the receivers of the study area, to better estimate their choices and allow the courier to take adequate decisions from the obtained Pareto Frontiers. This would have an impact on both the attraction of home delivery and the considered set of lockers for each receiver. Additionally, in some cases (as explained in Section 6.2.5) the service level definition proposed initially does not reflect the actual effect of the attraction. In these cases the adjusted SL seems to work better.

There are a series of computational improvements to remark regarding the implementation of the ALNS:

- Firstly, the repair operators that insert receivers to lockers instead of routes have longer running times and also find solutions further away from the exact method. Therefore, efforts could be invested in improving these operators, which will help reducing the total running time of the ALNS algorithm.
- Secondly, the candidate weight criteria in the ALNS evaluates at each iteration the candidate solution with each of the best solutions inside the pool. Once a best solution is found, this one is simply added to the pool. At the end, the pool is checked and the Pareto Frontier is obtained. Updating the pool of bests inside the algorithm instead of post processing it, would increase the computational efficiency of the algorithm as well.
- Thirdly, the use of the epsilons in the ALNS results in running more iterations for the upper side of the Pareto Frontiers, Therefore, it would be interesting to not only use the epsilons as lower boundaries but also as upper boundaries, so that the same number of iterations is run in each part of the Pareto Frontier.
- Lastly, the resulting pool of bests from an epsilon could be used as the initial solution given to the next epsilon.

Moreover, it should be mentioned that the exact method was stopped with a time limitation of 12h and not with a minimum gap with the lower bound. Letting the model run for a longer time period will provide more accurate solutions to compare with the ALNS algorithm results and verify the accuracy of these last one as well.

Finally, the probability of a receiver to be at home could be taken into account explicitly to assess the impact of the hit-rate problem described in the introduction of this research. A new policy of assigning receivers with low probability of being at home to lockers could then be further investigated. The model can also be adapted to consider declared preferences of some receivers–when the courier knows in advance their real preference. The model can also be extended by adding a third level of vehicles from parcel lockers to homes (as described in Section 1.1). This could be implemented in the same model or defining a multi-echelon problem.

Bibliography

Bartholdi, J. J., Eisenstein, D. D., & Lim, Y. F. (2009). Self-organizing logistics systems. In (Vol. 13, pp. 1461–1468).

Collins, A. (2015). Travel behaviour in the context of parcel pickups. *ITLS*.

Deutsch, Y., & Golany, B. (2018). A parcel locker network as a solution to the logistics last mile problem. *International Journal of Production Research*, *56*(1-2), 251–261.

Faugère, L., & Montreuil, B. (2017). Hyperconnected Pickup and; Delivery Locker Networks. *In Proceedings of the 4th International Physical Internet Conference*, *6*(July), 1–14.

Hillier, F. S., Price, C. C., & Austin, S. F. (2010). *Handbook of Metaheursitics* (Vol. 173; M. Gendreau, Ed.). Springer.

Iwan, S., Kijewska, K., & Lemke, J. (2016). Analysis of Parcel Lockers' Efficiency as the Last Mile Delivery Solution - The Results of the Research in Poland. *Transportation Research Procedia*, *12*(June 2015), 644–655.

Lachapelle, U., Burke, M., Brotherton, A., & Leung, A. (2018). Parcel locker systems in a car dominant city: Location, characterisation and potential impacts on city planning and consumer travel access. *Journal of Transport Geography*, *71*(July), 1–14.

Lahyani, R., Khemakhem, M., & Semet, F. (2015). Rich vehicle routing problems: From a taxonomy to a definition. *European Journal of Operational Research*, *241*(1), 1–14.

Lyu, G., & Teo, C.-p. (2019). Last Mile Innovation : The Case of the Locker Alliance Network. *SSRN*, 1–51.

McFadden, D. (2001). Disaggregate Behavioral Travel Demands RUM Side A 30-Year Retrospective. *Travel behaviour research : the leading edge*, *2000*(July), 17–64.

Montreuil, B. (2011). Towards a Physical Internet: Meeting the Global Logistics Sustainability Grand Challenge. *Logistics Research*.

Montreuil, B., Meller, R. D., & Ballot, E. (2012). *Physical Internet foundations* (Vol. 472) (No. 6). IFAC.

Morganti, E., Seidel, S., Blanquart, C., Dablanc, L., & Lenz, B. (2014). The Impact of E-commerce on Final Deliveries: Alternative Parcel Delivery Services in France and Germany. *Transportation Research Procedia*, *4*(0), 178–190.

Nguyen, D. H., de Leeuw, S., & Dullaert, W. E. (2018). Consumer Behaviour and Order Fulfilment in Online Retailing: A Systematic Review. *International Journal of Management Reviews*, *20*(2), 255–276.

Oliveira, L. K. d., Morganti, E., Dablanc, L., & Oliveira, R. L. M. d. (2017). Analysis of the potential demand of automated delivery stations for e-commerce deliveries in Belo Horizonte, Brazil. *Research in Transportation Economics*, *65*, 34–43.

Pan, S., Giannikas, V., Han, Y., Grover-Silva, E., & Qiao, B. (2017). Using customer-related data to enhance e-grocery home delivery. *Industrial Management and Data Systems*, *117*(9), 1917–1933.

Pan, S., Trentesaux, D., & Sallez, Y. (2017). Specifying Self-organising Logistics System: openness, intelligence, and decentralised control. *Springer, Cham.*

Pisinger, D., & Ropke, S. (2007). A general heuristic for vehicle routing problems. *Computers and Operations Research*, *34*(8), 2403–2435.

Quak, H., Kempen, E. V., & Hopman, M. (2018). Moving towards practical implementation of self-organizing logistics making small steps in realizing the PI vision by raising awareness. (June), 1–14.

Raviv, T., & Tenzer, E. Z. (2018). *Crowd-shipping of small parcels in a physical internet* (Tech. Rep.).

Solomon, M. M. (1987). Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations Research*.

Sun, Y., & Lang, M. (2015). Bi-objective optimization for multi-modal transportation routing planning problem based on pareto optimality. *Journal of Industrial Engineering and Management*, *8*(4), 1195–1217.

Vakulenko, Y., Hellström, D., & Hjort, K. (2018). What's in the parcel locker? Exploring customer value in e-commerce last mile delivery. *Journal of Business Research*, *88*(June 2017), 421–427. doi: 10.1016/j.jbusres.2017.11.033

van Duin, R., Wiegmans, B., Arem, B. V., & van Amstel, Y. (2019). From home delivery to parcel lockers: a case study in amsterdam. *Transportation Research Procedia*, *46*(June), 88–96.

Veenstra, M., Roodbergen, K. J., Coelho, L. C., & Zhu, S. X. (2018). A simultaneous facility location and vehicle routing problem arising in health care logistics in the Netherlands. *European Journal of Operational Research*, *268*(2), 703–715.

Voccia, S. A., Campbell, A. M., & Thomas, B. W. (2013, 5). The probabilistic traveling salesman problem with time windows. *EURO Journal on Transportation and Logistics*, *2*(1-2), 89–107.

Yang, X., Strauss, A. K., Currie, C. S., & Eglese, R. (2016). Choice-based demand management and vehicle routing in E-fulfillment. *Transportation Science*, *50*(2), 473–488.

Yuen, K. F., Wang, X., Ng, L. T. W., & Wong, Y. D. (2018). An investigation of customers intention to use self-collection services for last-mile delivery. *Transport Policy*, *66*, 1–8.

Appendices

A
Results Solomon Instances

***Table A.1:** Computational results for Solomon R instances*

Instance	Solver		Total	Epsilon 1	Epsilon 2	Epsilon 3	Epsilon 4	Epsilon 5	Epsilon 6	Epsilon 7	Epsilon 8	Epsilon 9	Epsilon 10	Epsilon 11
R101_20rec_8Ql		**Epsilon**		1.09	15.10	29.11	43.12	57.13	71.14	85.15	99.17	113.18	127.19	141.20
	Gurobi	**True attraction**		3.66	17.62	31.22	45.16	58.52	72.26	86.05	99.94	113.85	127.42	141.20
		Best LB		1.39	1.42	1.39	1.46	1.52	1.74	1.87	2.09	2.36	2.68	2.97
		Best		1.39	1.42	1.51	1.69	1.97	2.13	2.39	2.67	2.81	3.06	3.28
		Gap LB		0.0%	0.0%	8.8%	16.0%	30.1%	22.4%	27.8%	28.0%	18.8%	14.3%	10.4%
		Run Time [sec]	34,704											
	ALNS	**True attraction**		11.19	17.99	31.58	58.72	58.72	72.53	85.92	100.44	113.60	127.59	141.20
		Best		1.51	1.65	1.88	2.03	2.03	2.34	2.41	2.84	2.95	3.16	3.28
		Average		1.61	1.76	1.92	2.08	2.14	2.36	2.45	2.87	2.99	3.19	3.29
		Gap LB		8.0%	16.6%	35.5%	38.7%	33.4%	34.6%	28.8%	36.0%	24.6%	18.0%	10.4%
		Avg. Run Time [sec]	1,191											
	Improvement ALNS - Gurobi			8.0%	16.6%	26.7%	22.8%	3.4%	12.2%	1.0%	8.0%	5.9%	3.7%	0.0%
R101_20rec_6Ql		**Epsilon**		1.09	15.10	29.11	43.12	57.13	71.14	85.15	99.17	113.18	127.19	141.20
	Gurobi	**True attraction**		3.66	17.62	31.22	45.16	58.52	72.26	86.05	99.94	113.85	127.42	141.20
		Best LB		1.32	1.35	1.39	1.46	1.52	1.74	1.87	2.09	2.36	2.67	2.97
		Best		1.39	1.42	1.51	1.69	1.97	2.13	2.39	2.67	2.81	3.06	3.28
		Gap LB		5.3%	5.2%	8.3%	15.9%	30.0%	22.4%	27.7%	28.0%	18.8%	14.3%	10.4%
		Run Time [sec]	34,577											
	ALNS	**True attraction**		4.59	18.21	38.37	45.38	58.87	73.09	86.17	100.34	113.70	127.48	141.20
		Best		1.67	1.67	1.79	1.91	2.12	2.38	2.56	2.74	2.95	3.13	3.28
		Average		1.67	1.75	1.87	1.96	2.22	2.43	2.60	2.80	2.99	3.16	3.29
		Gap LB		25.8%	24.1%	28.3%	31.0%	39.7%	36.4%	36.4%	31.2%	24.7%	17.0%	10.4%
		Avg. Run Time [sec]	1,184											
	Improvement ALNS - Gurobi			20.6%	18.9%	20.1%	15.1%	9.7%	14.1%	8.7%	3.2%	5.9%	2.6%	0.0%
R101_40rec_16Ql		**Epsilon**		1.81	29.87	57.93	85.99	114.05	142.11	170.17	198.22	226.28	254.34	282.40
	Cplex	**True attraction**		14.56	35.55	63.12	89.64	117.66	144.37	172.41	200.14	227.09	254.97	282.40
		Best LB		0.99	1.09	1.16	1.41	1.70	2.04	2.36	2.71	3.06	3.49	4.10
		Best		1.63	1.63	1.93	2.10	2.32	2.64	3.02	3.42	3.81	4.05	4.48
		Gap LB		64.1%	49.4%	66.8%	49.4%	36.1%	29.5%	27.8%	26.4%	24.2%	16.1%	9.4%
		Run Time [sec]	252,313											
	ALNS	**True attraction**		11.18	51.47	78.52	105.53	119.37	146.39	207.22	207.22	234.50	275.45	282.40
		Best		2.58	2.85	2.88	3.11	3.47	3.55	3.76	3.76	4.28	4.62	4.76
		Average		2.60	2.91	2.98	3.25	3.51	3.69	3.88	4.04	4.40	4.65	4.77
		Gap LB		159.8%	161.5%	148.5%	121.1%	103.8%	74.1%	59.0%	38.7%	39.7%	32.2%	16.1%
		Avg. Run Time [sec]	3,736											
	Improvement ALNS - Cplex			95.7%	112.1%	81.6%	71.7%	67.7%	44.6%	31.2%	12.3%	15.5%	16.1%	6.7%
R101_40rec_12Ql		**Epsilon**		1.81	29.87	57.93	85.99	114.05	142.11	170.17	198.22	226.28	254.34	282.40
	Cplex	**True attraction**		21.18	35.17	62.13	89.98	117.50	144.74	172.72	199.84	227.31	254.77	282.40
		Best LB		1.08	1.02	1.19	1.42	1.74	1.99	2.36	2.71	3.10	3.48	4.10
		Best		1.61	1.63	1.80	2.10	2.43	2.66	3.06	3.42	3.70	4.08	4.48
		Gap LB		48.6%	59.3%	51.0%	48.1%	39.7%	33.7%	29.6%	26.2%	19.4%	17.2%	9.4%
		Run Time [sec]	283,556											
	ALNS	**True attraction**		11.18	51.56	65.23	92.16	132.80	146.30	200.19	200.19	228.01	254.91	282.40
		Best		2.45	2.65	2.92	3.13	3.23	3.61	3.77	3.77	4.26	4.41	4.80
		Average		2.55	2.73	3.00	3.20	3.34	3.67	3.84	3.95	4.33	4.60	4.82
		Gap LB		125.9%	159.9%	145.3%	121.1%	85.8%	81.1%	59.3%	38.9%	37.6%	26.6%	17.2%
		Avg. Run Time [sec]	10,181											
	Improvement ALNS - Cplex			77.3%	100.6%	94.3%	72.9%	46.1%	47.4%	29.7%	12.8%	18.2%	9.3%	7.8%
R101_80rec_32Ql		**Epsilon**		3.24	59.39	115.55	171.71	227.86	284.02	340.18	396.33	452.49	508.64	564.80
	Cplex	**True attraction**		32.42	60.26	116.21	174.67	331.06	-	352.55	399.61	454.52	509.83	564.80
		Best LB		0.86	0.88	1.03	1.26	1.67	-	2.24	2.94	3.43	3.98	4.96
		Best		2.37	2.49	2.66	2.67	21.62	-	6.27	12.82	22.78	13.00	9.74
		Gap LB		174.5%	183.7%	157.8%	111.6%	1195.7%	-	179.8%	336.3%	564.6%	226.5%	96.6%
		Run Time [sec]	133,811											
	ALNS	**True attraction**		31.33	91.23	137.49	177.07	249.38	316.24	350.15	423.25	463.59	510.70	564.80
		Best		3.79	4.00	4.26	4.37	4.56	4.80	5.05	5.33	5.65	6.05	6.60
		Average		4.00	4.18	4.33	4.54	4.73	4.96	5.21	5.58	5.86	6.33	6.73
		Gap LB		338.7%	355.2%	312.5%	246.1%	173.5%	-	125.6%	81.4%	64.8%	52.1%	33.1%
		Avg. Run Time [sec]	26,159											
	Improvement ALNS - Cplex			164.2%	171.5%	154.7%	134.5%	-1022.2%	-	-54.3%	-254.8%	-499.8%	-174.4%	-63.5%
R101_80rec_24Ql		**Epsilon**		3.24	59.39	115.55	171.71	227.86	284.02	340.18	396.33	452.49	508.64	564.80
	Cplex	**True attraction**		38.12	59.98	115.74	171.72	230.07	366.38	340.34	402.49	454.86	509.65	564.80
		Best LB		0.99	0.94	1.10	1.35	1.62	2.06	2.27	2.96	3.60	3.98	4.96
		Best		2.37	2.46	2.54	3.08	3.57	20.41	3.89	10.41	22.86	11.38	8.19
		Gap LB		139.7%	161.1%	131.8%	128.3%	120.1%	891.2%	71.2%	251.2%	535.4%	185.9%	65.4%
		Run Time [sec]	302,698											
	ALNS	**True attraction**		31.33	71.05	137.52	177.87	230.91	289.29	396.21	402.90	477.28	557.96	564.80
		Best		3.79	3.85	4.24	4.34	4.44	4.86	5.14	5.62	6.03	6.27	6.29
		Average		3.92	4.17	4.33	4.52	4.63	4.99	5.40	5.65	6.15	6.44	6.49
		Gap LB		283.3%	308.7%	286.2%	222.0%	174.1%	136.2%	125.9%	89.6%	67.6%	57.5%	26.9%
		Avg. Run Time [sec]	25,807											
	Improvement ALNS - Cplex			15.6%	13.8%	17.2%	12.7%	9.0%	-32.3%	14.1%	-24.3%	-43.9%	-28.5%	-18.4%

Table A.2: *Computational results for Solomon RC instances*

Instance	Solver		Total	Epsilon 1	Epsilon 2	Epsilon 3	Epsilon 4	Epsilon 5	Epsilon 6	Epsilon 7	Epsilon 8	Epsilon 9	Epsilon 10	Epsilon 11
RC101_20rec_8QI		**Epsilon**		0.52	14.58	28.65	42.72	56.79	70.86	84.93	98.99	113.06	127.13	141.20
	Gurobi	**True attraction**		27.47	27.49	34.31	47.78	61.02	74.08	88.32	100.79	113.93	127.38	141.20
		Best LB		1.65	1.52	1.65	1.70	1.68	1.55	1.63	1.81	2.18	2.54	2.86
		Best		3.27	3.27	3.28	3.30	3.35	3.43	3.67	3.61	3.74	3.86	4.13
		Gap LB		98.3%	114.8%	98.9%	93.4%	99.4%	122.0%	124.9%	100.0%	71.5%	51.9%	44.4%
		Run Time [sec]	39,612											
	ALNS	**True attraction**		8.25	14.87	35.44	47.55	60.79	73.81	88.48	107.98	114.30	127.70	141.20
		Best		3.28	3.29	3.35	3.42	3.49	3.53	3.60	3.82	3.86	3.96	4.13
		Average		3.28	3.30	3.37	3.45	3.51	3.60	3.71	3.84	3.93	3.97	4.14
		Gap LB		98.9%	116.1%	103.3%	100.5%	107.5%	128.1%	120.9%	111.5%	76.9%	55.8%	44.4%
		Avg. Run Time [sec]	1,037											
	Improvement ALNS - Gurobi			0.6%	1.3%	4.4%	7.0%	8.1%	6.0%	-4.0%	11.5%	5.4%	4.0%	0.0%
RC101_20rec_6QI		**Epsilon**		0.52	14.58	28.65	42.72	56.79	70.86	84.93	98.99	113.06	127.13	141.20
	Gurobi	**True attraction**		27.47	27.49	34.31	47.78	61.02	74.08	88.32	100.79	113.93	127.38	141.20
		Best LB		1.65	1.52	1.65	1.70	1.68	1.55	1.63	1.81	2.18	2.55	2.86
		Best		3.27	3.27	3.28	3.30	3.35	3.43	3.67	3.61	3.74	3.86	4.13
		Gap LB		98.6%	114.9%	99.0%	93.9%	99.1%	121.9%	124.5%	99.3%	71.2%	51.7%	44.5%
		Run Time [sec]	39,615											
	ALNS	**True attraction**		14.38	15.17	34.10	47.21	67.11	80.26	88.44	100.71	113.93	127.73	141.20
		Best		3.28	3.30	3.37	3.43	3.48	3.52	3.75	3.81	3.84	3.91	4.13
		Average		3.28	3.31	3.38	3.44	3.50	3.56	3.77	3.85	3.88	3.96	4.15
		Gap LB		98.9%	116.8%	104.9%	101.8%	106.7%	127.7%	129.7%	110.2%	76.1%	53.7%	44.5%
		Avg. Run Time [sec]	2,519											
	Improvement ALNS - Gurobi			0.3%	1.8%	5.9%	7.9%	7.6%	5.8%	5.2%	11.0%	4.9%	2.0%	0.0%
RC101_40rec_16QI		**Epsilon**		1.04	29.17	57.31	85.45	113.58	141.72	169.85	197.99	226.13	254.26	282.40
	Cplex	**True attraction**		43.88	57.77	58.66	91.78	116.81	146.17	173.53	200.09	227.46	254.80	282.40
		Best LB		0.99	1.02	1.05	1.02	1.08	1.15	1.44	1.88	2.32	2.81	3.76
		Best		2.50	2.62	2.67	2.68	2.77	3.73	4.18	3.97	4.28	4.67	5.24
		Gap LB		152.0%	156.6%	153.1%	162.2%	155.5%	224.9%	190.0%	111.8%	84.4%	66.5%	39.4%
		Run Time [sec]	45,769											
	ALNS	**True attraction**		17.82	76.98	76.98	97.28	116.95	149.62	176.47	223.40	229.10	275.49	282.40
		Best		3.83	3.93	3.93	4.01	4.25	4.40	4.56	4.72	4.83	5.16	5.25
		Average		3.91	3.97	4.00	4.16	4.29	4.45	4.61	4.82	4.89	5.20	5.32
		Gap LB		286.8%	285.5%	273.0%	292.2%	291.9%	283.2%	216.2%	151.9%	108.1%	83.9%	39.5%
		Avg. Run Time [sec]	3,588											
	Improvement ALNS - Cplex			134.8%	128.9%	119.9%	130.0%	136.4%	58.3%	26.2%	40.1%	23.7%	17.4%	0.2%
RC101_40rec_12QI		**Epsilon**		1.04	29.17	57.31	85.45	113.58	141.72	169.85	197.99	226.13	254.26	282.40
	Cplex	**True attraction**		44.45	43.85	57.90	91.00	117.82	144.13	172.23	199.57	227.41	254.85	282.40
		Best LB		1.14	0.99	1.03	1.02	1.08	1.19	1.46	1.81	2.24	2.80	3.76
		Best		2.50	2.50	2.62	2.62	3.02	3.23	3.53	4.05	4.19	4.52	5.24
		Gap LB		118.8%	153.2%	153.1%	156.2%	180.6%	170.8%	142.7%	124.0%	86.8%	61.5%	39.3%
		Run Time [sec]	47,255											
	ALNS	**True attraction**		17.82	37.43	70.59	110.47	117.17	156.73	176.92	202.25	229.03	255.92	282.40
		Best		3.83	3.87	4.02	4.04	4.24	4.33	4.42	4.60	4.79	5.09	5.34
		Average		3.97	4.02	4.08	4.15	4.35	4.45	4.52	4.67	4.87	5.19	5.41
		Gap LB		235.8%	292.3%	288.9%	294.4%	293.3%	263.1%	203.5%	154.7%	113.6%	81.9%	41.8%
		Avg. Run Time [sec]	8,877											
	Improvement ALNS - Cplex			117.1%	139.1%	135.8%	138.2%	112.7%	92.3%	60.8%	30.7%	26.8%	20.5%	2.5%
RC101_80rec_32QI		**Epsilon**		1.87	30.01	58.14	86.28	114.42	142.55	170.69	198.83	226.96	255.10	564.80
	Cplex	**True attraction**		62.88	76.40	125.58	-	-	285.21	339.84	404.94	509.85	510.35	564.80
		Best LB		1.06	0.88	1.10	-	-	1.88	2.08	2.61	3.94	3.29	4.87
		Best		4.19	4.70	5.85	-	-	7.90	8.87	25.53	13.60	11.45	10.16
		Gap LB		293.8%	434.2%	431.4%	-	-	320.2%	327.0%	876.5%	245.4%	247.7%	108.8%
		Run Time [sec]	172,419											
	ALNS	**True attraction**		39.19	39.19	84.69	137.31	137.31	193.47	193.47	241.06	241.06	262.17	564.80
		Best		5.39	5.39	5.52	5.56	5.56	5.74	5.74	5.78	5.78	5.92	7.09
		Average		5.53	5.53	5.71	5.72	5.72	5.80	5.80	5.94	5.95	6.16	7.23
		Gap LB		406.8%	512.9%	401.3%	-	-	205.5%	176.4%	121.0%	46.7%	79.7%	45.8%
		Avg. Run Time [sec]	23,069											
	Improvement ALNS - Cplex			112.9%	78.7%	-30.0%	-	-	-114.7%		-755.5%	-198.7%	-168.0%	-63.1%
RC101_80rec_24QI		**Epsilon**		1.87	30.01	58.14	86.28	114.42	142.55	170.69	198.83	226.96	255.10	564.80
	Cplex	**True attraction**		56.88	82.31	138.45	172.28	-	284.70	-	401.60	455.75	509.55	564.80
		Best LB		0.95	0.92	1.05	1.35	-	1.88	-	2.99	3.38	3.90	4.87
		Best		4.17	4.23	3.69	8.46	-	6.44	-	11.86	21.75	6.74	9.51
		Gap LB		338.0%	359.7%	252.5%	528.7%	-	242.1%	-	296.8%	543.8%	72.9%	95.5%
		Run Time [sec]	187,097											
	ALNS	**True attraction**		138.04	138.04	138.04	138.04	138.04	216.09	216.09	216.09	229.16	334.66	564.80
		Best		5.78	5.78	5.78	5.78	5.78	5.83	5.83	5.83	5.93	5.96	7.20
		Average		5.84	5.84	5.84	5.84	5.84	5.89	5.91	5.94	5.99	6.06	7.37
		Gap LB		506.6%	527.4%	452.0%	329.2%	-	210.0%	-	95.2%	75.4%	52.9%	47.9%
		Avg. Run Time [sec]	40,589											
	Improvement ALNS - Cplex			168.6%	167.7%	199.5%	-199.4%	-	-32.1%	-	-201.6%	-468.4%	-20.0%	-47.6%

B

Results Case Study

B.1. Base Scenario

Table B.1: *Results for Base Scenario*

Index in Pareto Frontier	Total Cost	Total Attraction	Service Level	Transportation Distance	Locker Rent	Lockers In Use	Locker Capacity Usage	Number of receivers traveling a distance (in km) of						
	(EUR)	(-)	(%)	(km)	(EUR)	(num.)	(%)	0 km*	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	> 0.5
0	27.95	67.5	10.3%	46.2	0.22	11	34.1%	5	14	42	11	5	3	0
1	28.65	174.3	28.4%	47.5	0.16	8	36.9%	21	12	32	9	4	2	0
2	28.82	304.5	51.1%	47.8	0.16	8	24.4%	41	5	22	5	4	2	1
3	29.21	311.0	52.5%	48.5	0.12	6	31.7%	42	6	20	6	4	2	0
4	29.67	311.8	52.0%	49.2	0.14	7	27.1%	42	7	21	4	4	2	0
5	29.71	349.2	54.7%	49.1	0.22	11	15.0%	47	10	23	0	0	0	0
6	29.80	442.8	76.4%	49.6	0.04	2	45.0%	62	0	9	4	3	2	0
7	29.94	466.8	79.5%	49.7	0.10	5	15.0%	65	6	9	0	0	0	0
8	29.98	558.1	97.8%	49.9	0.02	1	5.0%	79	0	1	0	0	0	0
9	30.14	564.8	100%	50.2	0.00	0	0.0%	80	0	0	0	0	0	0

B.2. Locker Capacity

Table B.2: *Results for 15 Locker Capacity*

Index in Pareto Frontier	Total Cost	Total Attraction	Service Level	Transportation Distance	Locker Rent	Lockers In Use	Locker Capacity Usage	Number of receivers traveling a distance (in km) of						
	(EUR)	(-)	(%)	(km)	(EUR)	(num.)	(%)	0 km*	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	> 0.5
0	29.06	233.8	35.9%	48.0	0.28	14	17.9%	30	11	27	6	3	2	1
1	29.30	337.5	57.6%	48.7	0.10	5	34.0%	46	7	11	6	4	4	2
2	29.39	356.5	61.3%	48.9	0.08	4	38.8%	49	5	10	6	4	4	2
3	29.82	551.7	95.2%	49.6	0.04	2	5.0%	78	1	1	0	0	0	0
4	29.85	564.8	100%	49.7	0.00	0	0.0%	80	0	0	0	0	0	0

Table B.3: *Results for 20 Locker Capacity*

Index in Pareto Frontier	Total Cost	Total Attraction	Service Level	Transportation Distance	Locker Rent	Lockers In Use	Locker Capacity Usage	Number of receivers traveling a distance (in km) of						
	(EUR)	(-)	(%)	(km)	(EUR)	(num.)	(%)	0 km*	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	> 0.5
0	29.15	125.8	18.9%	48.0	0.32	16	20.9%	13	20	44	3	0	0	0
1	29.21	139.0	21.0%	48.2	0.30	15	21.7%	15	20	42	3	0	0	0
2	29.22	145.6	22.1%	48.2	0.30	15	21.3%	16	19	42	2	1	0	0
3	29.51	204.9	32.0%	48.8	0.24	12	22.9%	25	17	36	1	0	1	0
4	29.53	211.8	33.0%	48.8	0.24	12	22.5%	26	17	36	1	0	0	0
5	29.70	218.1	34.7%	49.1	0.22	11	24.1%	27	16	36	1	0	0	0
6	29.74	230.2	36.3%	49.2	0.24	12	21.3%	29	14	35	1	1	0	0
7	29.79	301.5	48.8%	49.2	0.24	12	16.7%	40	10	26	0	1	3	0
8	29.79	359.4	55.3%	49.2	0.26	13	11.9%	49	4	27	0	0	0	0
9	29.98	472.4	77.5%	49.7	0.14	7	10.0%	66	3	11	0	0	0	0
10	30.02	564.8	100%	50.0	0.00	0	0.0%	80	0	0	0	0	0	0

B.3. Number of Lockers

Table B.4: *Results for 15 Lockers*

Index in Pareto Frontier	Total Cost	Total Attraction	Service Level	Transportation Distance	Locker Rent	Lockers In Use	Locker Capacity Usage	Number of receivers traveling a distance (in km) of						
	(EUR)	(-)	(%)	(km)	(EUR)	(num.)	(%)	0 km*	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	> 0.5
0	28.26	118.4	19.3%	46.8	0.18	9	49.6%	13	8	38	16	1	2	2
1	28.67	119.0	19.1%	47.4	0.20	10	44.7%	13	9	38	16	1	2	1
2	28.79	150.2	23.4%	47.6	0.26	13	32.3%	17	16	41	6	0	0	0
3	28.93	304.3	52.3%	48.1	0.08	4	65.0%	41	7	14	10	4	3	1
4	29.22	305.0	52.4%	48.5	0.10	5	52.0%	41	8	14	10	3	4	0
5	29.26	311.9	53.5%	48.6	0.10	5	50.7%	42	8	14	10	3	3	0
6	29.59	315.5	52.6%	49.0	0.16	8	31.7%	42	10	26	2	0	0	0
7	29.63	387.6	63.7%	49.1	0.16	8	22.5%	53	7	19	1	0	0	0
8	29.64	419.9	69.2%	49.2	0.14	7	21.0%	58	6	12	2	1	1	0
9	29.77	425.1	68.0%	49.3	0.18	9	15.6%	59	1	18	2	0	0	0
10	29.78	433.3	74.5%	49.5	0.10	5	26.7%	60	5	13	2	0	0	0
11	29.79	440.0	73.1%	49.4	0.12	6	21.1%	61	6	11	0	1	1	0
12	29.82	451.2	72.7%	49.4	0.16	8	14.2%	63	0	15	2	0	0	0
13	29.92	498.6	82.2%	49.7	0.12	6	11.1%	70	3	4	1	1	0	1
14	29.98	525.1	88.4%	49.8	0.08	4	10.0%	74	1	4	1	0	0	0
15	30.01	558.1	97.9%	50.0	0.02	1	6.7%	79	0	1	0	0	0	0
16	30.09	564.8	100%	50.2	0.00	0	0.0%	80	0	0	0	0	0	0

Table B.5: *Results for 10 Lockers*

Index in Pareto Frontier	Total Cost	Total Attraction	Service Level	Transportation Distance	Locker Rent	Lockers In Use	Locker Capacity Usage	Number of receivers traveling a distance (in km) of						
	(EUR)	(-)	(%)	(km)	(EUR)	(num.)	(%)	0 km*	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	> 0.5
0	27.38	89.0	14.4%	45.3	0.18	9	80.0%	8	16	39	15	2	0	0
1	27.64	127.9	21.2%	45.8	0.16	8	82.5%	14	13	38	15	0	0	0
2	27.65	154.9	24.5%	45.8	0.18	9	68.9%	18	14	33	14	1	0	0
3	27.72	166.7	27.2%	45.9	0.16	8	75.0%	20	11	35	12	2	0	0
4	27.77	182.6	30.2%	46.0	0.14	7	82.9%	22	15	32	10	1	0	0
5	27.85	200.4	33.5%	46.2	0.14	7	78.6%	25	10	32	12	1	0	0
6	28.00	266.5	44.2%	46.4	0.14	7	64.3%	35	9	22	14	0	0	0
7	28.45	287.9	48.5%	47.2	0.10	5	84.0%	38	11	24	6	1	0	0
8	28.48	300.2	51.3%	47.3	0.10	5	80.0%	40	9	22	7	1	1	0
9	28.55	333.0	56.0%	47.4	0.12	6	58.3%	45	7	17	11	0	0	0
10	28.73	333.2	55.9%	47.7	0.10	5	70.0%	45	8	19	6	2	0	0
11	28.76	367.2	63.0%	47.8	0.08	4	75.0%	50	8	16	6	0	0	0
12	28.90	374.0	64.1%	48.0	0.08	4	72.5%	51	8	16	5	0	0	0
13	29.12	386.3	66.4%	48.4	0.08	4	67.5%	53	6	13	7	1	0	0
14	29.19	399.9	68.9%	48.5	0.06	3	83.3%	55	6	13	6	0	0	0
15	29.21	492.7	85.5%	48.6	0.04	2	55.0%	69	3	5	3	0	0	0
16	29.45	498.4	87.9%	49.1	0.02	1	100.0%	70	2	5	3	0	0	0
17	29.60	499.2	85.6%	49.2	0.06	3	33.3%	70	3	5	2	0	0	0
18	29.67	518.4	89.6%	49.4	0.04	2	35.0%	73	1	4	2	0	0	0
19	29.71	525.1	92.0%	49.5	0.02	1	60.0%	74	1	3	2	0	0	0
20	29.94	564.8	100%	49.9	0.00	0	0.0%	80	0	0	0	0	0	0

B.4. Locker Rent

Table B.6: *Results for 0.05 Rent*

Index in Pareto Frontier	Total Cost	Total Attraction	Service Level	Transportation Distance	Locker Rent	Lockers In Use	Locker Capacity Usage	Number of receivers traveling a distance (in km) of						
	(EUR)	(-)	(%)	(km)	(EUR)	(num.)	(%)	0 km*	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	> 0.5
0	28.67	145.7	22.3%	46.9	0.55	11	28.6%	17	10	32	14	3	4	0
1	28.71	289.4	48.5%	47.4	0.25	5	41.0%	39	4	22	6	4	2	3
2	28.86	302.8	51.1%	47.7	0.25	5	39.0%	41	3	21	7	4	2	2
3	29.59	313.5	52.8%	48.8	0.30	6	31.7%	42	7	25	4	2	0	0
4	29.92	349.5	59.4%	49.5	0.20	4	40.0%	48	2	17	7	5	1	0
5	29.96	564.8	100%	49.9	0.00	0	0.0%	80	0	0	0	0	0	0

Table B.7: *Results for 0 Rent*

Index in Pareto Frontier	Total Cost	Total Attraction	Service Level	Transportation Distance	Locker Rent	Lockers In Use	Locker Capacity Usage	Number of receivers traveling a distance (in km) of						
	(EUR)	(-)	(%)	(km)	(EUR)	(num.)	(%)	0 km*	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	> 0.5
0	24.99	27.2	4.1%	41.6	0.00	8	50.0%	0	14	32	5	4	6	19
1	25.35	33.6	5.2%	42.3	0.00	8	49.4%	1	13	29	13	4	4	16
2	25.59	47.5	7.5%	42.7	0.00	9	42.8%	3	14	30	9	3	2	19
3	25.67	94.5	15.7%	42.8	0.00	7	50.0%	10	13	26	6	5	3	17
4	25.67	94.5	15.7%	42.8	0.00	7	50.0%	10	13	26	6	5	3	17
5	25.95	156.1	25.1%	43.3	0.00	6	50.0%	20	5	17	9	5	4	20
6	26.12	161.2	27.1%	43.5	0.00	6	50.0%	20	10	26	3	1	3	17
7	26.18	163.1	27.8%	43.6	0.00	6	50.0%	20	11	28	6	2	1	12
8	26.51	163.1	27.1%	44.2	0.00	8	37.5%	20	12	26	3	2	0	17
9	26.65	285.7	46.0%	44.4	0.00	4	50.0%	40	0	0	1	2	4	33
10	26.98	285.7	46.4%	45.0	0.00	4	50.0%	40	0	0	2	2	3	33
11	27.28	288.2	46.9%	45.5	0.00	4	50.0%	40	1	6	3	1	0	29
12	27.33	290.6	48.7%	45.6	0.00	4	50.0%	40	3	7	4	2	2	22
13	27.54	291.5	49.0%	45.9	0.00	4	50.0%	40	4	9	2	4	1	20
14	27.65	342.0	55.3%	46.1	0.00	5	32.0%	48	2	0	0	1	0	29
15	27.65	348.4	57.4%	46.1	0.00	4	38.8%	49	1	0	0	1	0	29
16	28.01	357.8	60.8%	46.7	0.00	3	50.0%	50	1	5	0	3	0	21
17	28.34	417.9	70.7%	47.2	0.00	3	35.0%	59	0	0	0	2	0	19
18	28.43	425.9	73.2%	47.4	0.00	2	50.0%	60	0	2	2	1	1	14
19	28.47	426.6	73.0%	47.5	0.00	2	50.0%	60	1	2	2	1	1	13
20	28.56	428.0	74.0%	47.6	0.00	2	50.0%	60	2	3	1	3	0	11
21	28.59	432.8	74.3%	47.6	0.00	2	47.5%	61	1	0	1	0	1	16
22	28.83	439.7	75.5%	48.0	0.00	2	45.0%	62	1	0	1	0	0	16
23	29.31	445.5	76.4%	48.9	0.00	2	42.5%	63	0	0	0	0	0	17
24	29.67	455.3	78.6%	49.4	0.00	2	40.0%	64	2	2	2	0	1	9
25	29.68	465.5	76.1%	49.5	0.00	7	10.7%	65	2	11	0	0	0	2
26	29.75	494.8	86.3%	49.6	0.00	1	50.0%	70	0	0	0	0	0	10
27	29.89	495.3	86.6%	49.8	0.00	1	50.0%	70	0	1	1	0	0	8
28	29.90	497.1	86.0%	49.8	0.00	2	25.0%	70	0	4	3	2	1	0
29	30.00	558.3	97.0%	50.0	0.00	1	5.0%	79	1	0	0	0	0	0
30	30.00	564.8	100%	50.0	0.00	0	0.0%	80	0	0	0	0	0	0

B.5. Home Delivery Attraction

Table B.8: *Results for 0.3 Un*

Index in Pareto Frontier	Total Cost	Total Attraction	Service Level	Transportation Distance	Locker Rent	Lockers In Use	Locker Capacity Usage	Number of receivers traveling a distance (in km) of						
	(EUR)	(-)	(%)	(km)	(EUR)	(num.)	(%)	0 km*	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	> 0.5
0	29.10	34.4	28.0%	48.0	0.30	15	23.7%	9	16	43	4	6	1	1
1	29.16	34.8	31.4%	48.2	0.24	12	20.4%	31	14	35	0	0	0	0
2	29.36	40.1	25.2%	48.3	0.40	20	19.8%	1	22	55	1	0	1	0
3	29.48	40.3	25.5%	48.5	0.40	20	20.0%	0	22	56	2	0	0	0
4	34.88	40.4	25.6%	57.5	0.40	20	19.8%	1	22	56	1	0	0	0
5	35.43	40.4	25.6%	58.4	0.40	20	19.5%	2	22	56	0	0	0	0

Table B.9: *Results for 0.8 Un*

Index in Pareto Frontier	Total Cost	Total Attraction	Service Level	Transportation Distance	Locker Rent	Lockers In Use	Locker Capacity Usage	Number of receivers traveling a distance (in km) of						
	(EUR)	(-)	(%)	(km)	(EUR)	(num.)	(%)	0 km*	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	> 0.5
0	27.86	30.0	21.5%	46.1	0.20	10	40.0%	0	10	42	16	9	3	0
1	27.88	30.7	22.3%	46.1	0.20	10	39.5%	1	10	42	16	9	2	0
2	28.37	38.0	35.2%	47.1	0.12	6	49.2%	21	5	33	11	8	2	0
3	28.93	44.9	25.2%	47.7	0.34	17	19.7%	13	19	47	1	0	0	0
4	29.10	47.2	29.0%	48.0	0.30	15	20.0%	20	18	41	1	0	0	0
5	29.42	48.1	32.9%	48.6	0.24	12	23.3%	24	17	37	1	0	1	0
6	29.60	50.2	36.1%	49.0	0.22	11	22.3%	31	15	34	0	0	0	0
7	29.74	52.1	38.3%	49.2	0.20	10	22.5%	35	15	30	0	0	0	0
8	29.85	54.7	42.7%	49.4	0.20	10	15.5%	49	7	24	0	0	0	0
9	29.86	57.0	46.0%	49.5	0.18	9	13.3%	56	5	19	0	0	0	0
10	29.89	64.0	100%	49.8	0.00	0	0.0%	80	0	0	0	0	0	0
11	30.58	64.0	90.8%	50.9	0.02	1	5.0%	79	1	0	0	0	0	0
12	30.64	64.1	91.9%	51.0	0.02	1	5.0%	79	1	0	0	0	0	0
13	30.82	64.1	88.3%	51.3	0.02	1	5.0%	79	1	0	0	0	0	0
14	31.26	64.2	95.0%	52.1	0.02	1	5.0%	79	1	0	0	0	0	0
15	32.39	64.2	93.8%	54.0	0.02	1	5.0%	79	1	0	0	0	0	0

B.6. Distance Factor

Table B.10: *Results for -1.5 utility*

Index in Pareto Frontier	Total Cost (EUR)	Total Attraction (-)	Service Level (%)	Transportation Distance (km)	Locker Rent (EUR)	Lockers In Use (num.)	Locker Capacity Usage (%)	Number of receivers traveling a distance (in km) of						
								0 km*	**0.0 - 0.1**	**0.1 - 0.2**	**0.2 - 0.3**	**0.3 - 0.4**	**0.4 - 0.5**	**> 0.5**
0	24.95	141.8	9.9%	41.3	0.16	8	50.0%	0	14	28	8	4	5	21
1	25.01	141.8	9.9%	41.4	0.16	8	50.0%	0	14	28	8	4	5	21
2	25.15	143.8	9.9%	41.6	0.16	8	50.0%	0	14	31	6	5	5	19
3	25.41	146.9	10.2%	42.1	0.16	8	49.4%	1	13	29	7	5	4	21
4	25.73	147.7	10.4%	42.6	0.16	8	49.4%	1	14	28	8	4	5	20
5	25.80	153.6	10.9%	42.7	0.16	8	48.8%	2	14	28	8	4	4	20
6	25.81	193.6	14.6%	42.8	0.14	7	50.0%	10	11	25	7	5	4	18
7	25.83	233.9	19.3%	42.9	0.12	6	50.0%	20	6	15	2	3	5	29
8	26.13	246.3	21.0%	43.3	0.12	6	50.0%	20	10	23	6	1	2	18
9	26.32	246.6	21.0%	43.7	0.12	6	50.0%	20	9	21	12	3	2	13
10	26.48	248.0	21.0%	43.9	0.12	6	50.0%	20	12	21	3	3	3	18
11	26.56	249.4	21.2%	44.1	0.12	6	50.0%	20	12	21	5	3	4	15
12	26.68	295.2	25.0%	44.3	0.12	6	42.5%	29	9	19	7	1	1	14
13	26.89	300.6	27.9%	44.7	0.10	5	50.0%	30	9	20	5	1	0	15
14	26.98	329.2	32.4%	44.8	0.08	4	50.0%	40	0	0	2	2	3	33
15	27.18	343.8	34.7%	45.2	0.08	4	50.0%	40	4	9	2	2	3	20
16	27.46	348.6	36.5%	45.6	0.08	4	50.0%	40	5	13	2	2	5	13
17	27.70	352.5	36.3%	46.0	0.08	4	50.0%	40	8	16	1	0	0	15
18	28.09	353.6	30.5%	46.6	0.12	6	33.3%	40	8	15	3	1	2	11
19	28.17	394.2	45.0%	46.9	0.06	3	50.0%	50	2	5	1	2	0	20
20	28.43	439.5	50.0%	47.3	0.06	3	35.0%	59	0	0	0	2	0	19
21	28.56	443.7	56.4%	47.5	0.04	2	50.0%	60	0	0	0	0	0	20
22	28.61	444.6	57.0%	47.6	0.04	2	50.0%	60	0	0	0	0	0	20
23	28.70	450.3	58.4%	47.8	0.04	2	50.0%	60	1	3	1	1	0	14
24	28.72	450.3	52.3%	47.8	0.06	3	35.0%	59	2	6	3	0	2	8
25	28.81	450.5	58.4%	47.9	0.04	2	50.0%	60	1	3	1	2	1	12
26	28.83	455.3	59.5%	48.0	0.04	2	50.0%	60	2	5	3	0	2	8
27	28.97	460.8	59.7%	48.2	0.04	2	45.0%	62	0	2	2	1	1	12
28	29.50	469.9	61.3%	49.1	0.04	2	42.5%	63	1	3	2	1	2	8
29	29.55	475.9	62.0%	49.2	0.04	2	40.0%	64	1	3	2	1	2	7
30	30.00	497.8	56.6%	49.9	0.06	3	21.7%	67	2	4	3	3	1	0
31	30.01	505.1	64.9%	49.9	0.04	2	27.5%	69	1	3	2	2	0	3
32	30.09	516.0	77.0%	50.1	0.02	1	40.0%	72	0	0	0	0	0	8
33	30.13	559.6	84.7%	50.2	0.02	1	5.0%	79	0	1	0	0	0	0
34	30.20	564.8	100%	50.3	0.00	0	0.0%	80	0	0	0	0	0	0

Table B.11: *Results for -0.5 utility*

Index in Pareto Frontier	Total Cost (EUR)	Total Attraction (-)	Service Level (%)	Transportation Distance (km)	Locker Rent (EUR)	Lockers In Use (num.)	Locker Capacity Usage (%)	Number of receivers traveling a distance (in km) of 0 km*	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	> 0.5
0	24.97	261.9	10.6%	41.4	0.16	8	50.0%	0	14	31	6	5	5	19
1	25.51	262.3	10.6%	42.3	0.16	8	50.0%	0	10	29	19	3	5	14
2	25.73	264.8	10.7%	42.6	0.16	8	49.4%	1	14	28	8	4	4	21
3	25.77	324.1	14.5%	42.7	0.14	7	43.6%	19	6	17	2	3	4	29
4	25.92	327.4	16.5%	43.0	0.12	6	50.0%	20	6	15	2	3	4	30
5	26.07	333.5	16.9%	43.3	0.12	6	50.0%	20	9	21	6	2	3	19
6	26.13	335.7	17.0%	43.3	0.12	6	50.0%	20	10	23	6	1	1	19
7	26.13	335.8	17.0%	43.3	0.12	6	50.0%	20	10	23	6	1	1	19
8	26.23	338.0	17.0%	43.5	0.12	6	50.0%	20	10	27	5	2	1	15
9	26.35	339.9	17.0%	43.7	0.12	6	50.0%	20	11	29	6	3	0	11
10	26.39	361.1	18.1%	43.8	0.12	6	42.5%	29	4	13	1	2	3	28
11	26.63	396.8	26.1%	44.2	0.08	4	50.0%	40	0	1	2	2	2	33
12	27.01	406.1	26.8%	44.9	0.08	4	50.0%	40	3	11	4	2	1	19
13	27.45	412.8	27.4%	45.6	0.08	4	50.0%	40	8	16	3	0	1	12
14	27.87	413.1	27.5%	46.3	0.08	4	50.0%	40	8	16	3	0	2	11
15	27.94	440.5	34.6%	46.5	0.06	3	50.0%	50	0	1	2	2	2	23
16	28.13	443.0	29.2%	46.7	0.08	4	38.8%	49	3	10	1	1	3	13
17	28.32	481.9	46.5%	47.1	0.04	2	50.0%	60	1	2	1	0	1	15
18	28.44	482.5	46.6%	47.3	0.04	2	50.0%	60	1	2	2	1	1	13
19	28.58	485.0	47.0%	47.6	0.04	2	50.0%	60	2	5	1	1	0	11
20	29.01	485.2	47.0%	48.3	0.04	2	50.0%	60	2	3	2	3	1	9
21	29.23	489.4	47.6%	48.7	0.04	2	50.0%	60	4	6	1	2	2	5
22	29.26	489.9	47.7%	48.7	0.04	2	50.0%	60	4	5	3	4	1	3
23	29.46	499.4	48.3%	49.0	0.04	2	40.0%	64	1	3	0	2	1	9
24	29.60	517.6	49.7%	49.3	0.04	2	27.5%	69	0	0	1	0	0	10
25	29.90	524.6	65.7%	49.8	0.02	1	50.0%	70	1	1	1	0	1	6
26	30.02	530.5	51.2%	50.0	0.04	2	22.5%	71	1	1	2	1	2	2
27	30.06	560.3	70.1%	50.1	0.02	1	5.0%	79	0	0	0	0	0	1
28	30.10	561.1	70.6%	50.1	0.02	1	5.0%	79	0	1	0	0	0	0
29	30.18	564.8	100%	50.3	0.00	0	0.0%	80	0	0	0	0	0	0

C

Pseudocode for Destroy & Repair Operators

Pseudocode Destroy Operators

Algorithm C.1 Receivers random removal

```
input: x^c
x ← x^c
n ← random_number(rec)
M ← random_sample(rec, n)
for i ∈ M do
    x ← remove(i, x)
end for
for l ∈ L do
    if l = ∅ then
        x ← remove(l, x)
    end if
end for
output: x
```

Algorithm C.2 Receiver worst cost removal

```
input: x^c
x ← x^c
c ← removal_costs(x)
i ← choose_max(c)
x ← remove(i, x)
for l ∈ L do
    if r ∈ l then
        l ← ∅
    end if
end for
output: x
```

Algorithm C.3 Receiver worst utility removal

```
input: x^c
x ← x^c
u ← removal_utilities(x)
i ← choose_min(u)
x ← remove(i, x)
for r ∈ M do
    for l ∈ L do
        if l ∈ r then
            l ← ∅
        end if
    end for
    x ← remove(r, x)
end for
output: x
```

Algorithm C.4 Receiver elated removal

```
input: x^c
x ← x^c
n ← random_number(x)
dis ← max(distances)*degree_destruction
N ← receivers_in(dis,rec)
for i ∈ N do
    x ← remove(i, x)
end for
for r ∈ M do
    for l ∈ L do
        if l ∈ r then
            l ← ∅
        end if
    end for
    x ← remove(r, x)
end for
output: x
```

Algorithm C.5 Route random removal

```
input: x^c
x ← x^c
n ← random_number(rou)
M ← random_sample(rou, n)
for r ∈ M do
    x ← remove(r, x)
    for l ∈ L do
        if l ∈ r then
            l ← ∅
        end if
    end for
end for
output: x
```

Algorithm C.6 Route worst cost removal

```
input: x^c
x ← x^c
c ← removal_costs(x)
r ← choose_max(c)
x ← remove(r, x)
for l ∈ L do
    if l ∈ r then
        l ← ∅
    end if
end for
output: x
```

Algorithm C.7 Route worst utility removal

```
input: x^c
x ← x^c
u ← removal_utilities(x)
r ← choose_min(u)
x ← remove(r, x)
for l ∈ L do
    if l ∈ r then
        l ← ∅
    end if
end for
output: x
```

Algorithm C.8 Route cheapest cost removal

```
input: x^c
x ← x^c
c ← removal_costs(x)
r ← choose_min(c)
x ← remove(r, x)
for l ∈ L do
    if l ∈ r then
        l ← ∅
    end if
end for
output: x
```

Algorithm C.9 Route cheapest utility removal

```
input: x^c
x ← x^c
u ← removal_utilities(x)
r ← choose_max(u)
x ← remove(r, x)
for l ∈ L do
    if l ∈ r then
        l ← ∅
    end if
end for
output: x
```

Algorithm C.10 Locker random removal

```
input: x^c
x ← x^c
n ← random_number(loc)
M ← random_sample(loc, n)
for l ∈ M do
    l ← remove(l, x)
    l ← ∅
end for
output: x
```

Algorithm C.11 Locker worst cost removal

```
input: x^c
x ← x^c
c ← removal_costs(x)
l ← choose_max(c)
x ← remove(l, x)
l ← ∅
output: x
```

Algorithm C.12 Locker worst utility removal

```
input: x^c
x ← x^c
u ← removal_costs(x)
l ← choose_min(u)
x ← remove(l, x)
l ← ∅
output: x
```

Algorithm C.13 Locker random removal

```
input: x^c
x ← x^c
l ← random_choice(loc)
l ← ∅
for r ∈ R do
    if l ∈ r then
        x ← remove(r, x)
    end if
end for
output: x
```

Pseudocode Repair Operators

Algorithm C.14 Greedy receiver insertion in routes

```
input: x
M ← relocate(x)
for i ∈ M do
    R_a ← available_routes (x)
    r, p ← greedy_insert_route (Ra)
    x ← insert (i, r, p)
end for
output: x
```

Algorithm C.15 Best receiver insertion in routes

```
input: x
M ← relocate(x)
while M ≠ ∅ do
    R_a ← available_routes (x)
    i, r, p ← best_insert_route (Ra)
    x ← insert (i, r, p)
end while
output: x
```

Algorithm C.16 Regret receiver insertion in routes

```
input: x
M ← relocate(x)
while M ≠ ∅ do
    R_a ← available_routes (x)
    i, r, p ← regret_insert_route (Ra)
    x ← insert (i, r, p)
end while
output: x
```

Algorithm C.17 Greedy receiver insertion in maximum utility locker

```
input: x
M ← relocate(x)
for i ∈ M do
    L_a ← available_lockers (x)
    l ← greedy_locker (La)
    x ← insert(i, l)
end for
if cap(R) violated  then
    x ← delete_lockers(x)
end if
for l ∈ L do
    if l ≠ ∅ then
        if l ∉ R then
            R_a ← available_routes_for_locker(x, l)
            r, p ← greedy_insert_route (Ra)
            x ← insert (l, r, p)
        end if
    end if
end for
output: x
```

Algorithm C.18 Best receiver insertion in maximum utility lockers

```
input: x
M ← relocate(x)
while M ≠ ∅ do
    L_a ← available_lockers (x)
    i, l ← best_maxU_locker (La)
    x ← insert(i, l)
end while
if cap(R) violated then
    x ← delete_lockers(x)
end if
for l ∈ L do
    if l ≠ ∅ then
        if l ∉ R then
            R_a ← available_routes_for_locker(x, l)
            r, p ← greedy_insert_route (Ra)
            x ← insert (l, r, p)
        end if
    end if
end for
output: x
```

Algorithm C.19 Regret receiver insertion in maximum utility lockers

```
input: x
M ← relocate(x)
while M ≠ ∅ do
    L_a ← available_lockers (x)
    i, l ← regret_maxU_locker (La)
    x ← insert(i, l)
end while
if cap(R) violated then
    x ← delete_lockers(x)
end if
for l ∈ L do
    if l ≠ ∅ then
        if l ∉ R then
            R_a ← available_routes_for_locker(x, l)
            r, p ← greedy_insert_route (Ra)
            x ← insert (l, r, p)
        end if
    end if
end for
output: x
```

Algorithm C.20 Greedy receiver insertion in cheapest lockers

```
input: x
M ← relocate(x)
for i ∈ M do
    L_a ← available_lockers (x)
    l ← greedy_cheapest_locker (La)
    x ← insert(i, l)
end for
if cap(R) violated then
    x ← delete_lockers(x)
end if
for l ∈ L do
    if l ≠ ∅ then
        if l ∉ R then
            R_a ← available_routes_for_locker(x, l)
            r, p ← greedy_insert_route (Ra)
            x ← insert (l, r, p)
        end if
    end if
end for
output: x
```

Algorithm C.21 Regret receiver insertion in cheapest lockers

```
input: x
M ← relocate(x)
while M ≠ ∅ do
    L_a ← available_lockers (x)
    i, l ← regret_cheapest_locker (La)
    x ← insert(i, l)
end while
if cap(R) violated then
    x ← delete_lockers(x)
end if
for l ∈ L do
    if l ≠ ∅ then
        if l ∉ R then
            R_a ← available_routes_for_locker(x, l)
            r, p ← greedy_insert_route (Ra)
            x ← insert (l, r, p)
        end if
    end if
end for
output: x
```

D
Scientific Paper

Implementation of Receiver Preferences in a Parcel Locker Network for Last Miles Deliveries

Alba Genius Coca

Delft University of Technology

Abstract. With the current growth of e-commerce, couriers need to serve a bigger demand and it is often the case that receivers are not at the location when their parcel is delivered. The use of parcel lockers is seen as a good option for improving the problem of failed deliveries. However, implementing a parcel locker network has an impact on both couriers and receivers, which still prevents couriers from directly adopting this technology. The aim of this research is to develop a new tool that helps couriers analyse the impact of using a parcel locker network taking also into account receiver preferences to pick up parcels from lockers. An optimization model is combined with a choice behaviour model to determine the trade-offs between delivering to parcel lockers or to end-users, in terms of service level and total transportation costs. In order to solve this model for large instances, an Adaptive Large Neighbourhood Search algorithm has been adapted with operators and criteria specific for the problem presented. Computational experiments were carried in a set of the Solomon instances and show that the problem can be solved efficiently with the proposed algorithm. Moreover, the algorithm was applied in a small delivery area in Rotterdam, showing the sensitivity of the model to the preferences of receivers in the area.

Keywords: parcel locker, routing, choice behaviour, ALNS

1 Introduction

E-commerce is significantly growing amongst nowadays society and a lot of parcels have to be moved from a depot to the locations specified by the receivers. This means that the B2C couriers need more vehicles and longer travelling distances to serve a bigger demand. Moreover, it is often the case that the receiver is not at the location when the parcels are delivered and this has an impact on the efficiency of the delivery routing process.

There are different ways in which this issue can be tackled, for example, telling the receiver in advance the delivery time period or asking the receiver beforehand during what time is possible to find him/her at the location. However, there is always some probability of the receiver not being at the location at the given period of time. For this reason, some research [13, 19, 20] is already being done trying to take into account these probabilities when defining the delivery routes.

Another line of research is focused on the Physical Internet concept [9] and the use of parcel lockers [2, 10]. Using these parcel lockers is considered to be positive because the B2C couriers can serve multiple receivers at a single point, which reduces travelling costs and at the same time eliminates the problem of failed deliveries. Moreover, parcel lockers are usually placed in locations opened 24h a day, giving consumers more flexibility. Not to forget, they also help to diminish congestion in cities and make the last mile delivery more environmentally friendly [2, 5, 21]. On the other hand, the main consequence is that consumers are the ones covering part of the last mile delivery. Therefore, their willingness to go to the locker is an important factor to take into account.

Many companies have already implemented the use of parcel lockers for the last mile delivery in various countries. [5] state that *InPost* has installed more than 3000 parcel lockers in different countries. In similar terms, [10] remarks that *DHL* has also implemented in Germany 2500 parcel lockers, which allows them to state that 90% of the German population is within 10 minutes of a parcel-locker. [2] also mention the use of parcel-lockers from *Amazon* and the *Canada Post*. In the Netherlands, [3] present a pilot project of *PostNL* in Amsterdam.

[11] determine factors that are important for identifying the behaviour of online consumers. [17] studied the value of parcel-lockers for consumers in Sweden, they mention that consumer value is created when a service of delivery or pick-up takes place and they conclude that future interactions with the last mile delivery services are affected by the meaning of previous services. [5] did a survey about the use of parcel-lockers and concluded that their location has an important effect on their efficiency. Their survey gives an overview of parcel-locker users in Poland. [6] get some insights on the locations of parcel-lockers in Australia. They identify clusters within the current locations and state that the majority of them are located on commercial streets and shopping centres.[2] focus on the design of a parcel-network, which in the end, is also related to determine the best location of the lockers. However, their research is from a quantitative perspective. They develop a mathematical model to determine how many parcel-lockers to open, where to locate them in order to maximise the profit of the operating courier.

Following on the quantitative research on lockers, [18] define a location-routing problem for delivering health care medication in the Netherlands. They determine which lockers to open and the routes to visit the lockers and the routes that visit the patients, minimizing the routing and opening costs.

In line with [18], this research wants to solve a routing problem to deliver parcels from a depot to parcel lockers or homes with the aim of reducing the impact on costs for the courier and the receivers. Therefore, this research contributes to the current literature by taking into account the preferences of the receivers when deciding the routes. The objective of this type of problems is different in the existing literature, where the main goal is to minimize the total transportation costs (TTC) for the couriers.

Specifically, a routing problem is combined with a choice behaviour model, to deliver parcels from a depot to parcel lockers or homes, minimizing the total travel costs and maximizing the utilities of the receivers going to the parcel lockers. Besides, given the nature of the routing problems, solving them with an exact method usually requires a high computational time which leads to the necessity of using heuristics. This research uses the Adaptive Large Neighbourhood Search (ALNS) heuristics [14] for solving the optimization model and contributes with the design of repair and destroy operators specifics for this model.

2 Problem Description

The problem consists of a B2C courier which has to distribute a set of parcel requests ($n \in R$) from a depot to a set of parcel lockers ($l \in L$) or to several home locations. Specifically, the depot has an homogeneous fleet of vehicles ($k \in K$) with capacity Q_V available to cover the daily demand. There is an existing network of lockers with a limited capacity Q_L which can be rented by the

B2C courier, who has to determine which lockers to use together with the delivery routes. A fixed renting cost C_{rent} per request is assumed.

As not all receivers are willing to go to all the lockers, the utility of a receiver picking up a parcel in a specific locker is an important factor to take into account. Preferences of receivers are described in terms of probabilities to go to a certain locker. These probabilities, as described later on, are a function of the utilities.

Following this, the service level of a courier can be understood as the degree to which the courier adjusts to the preferences of the receivers. In mathematical terms, the service level $SL = \sum_{i \in R} P_{ij}/n$ offered by the courier is defined as the average of the probability of each receiver to go to the locker where its parcel is being delivered. Therefore, in order to give a better service level, the aim of the courier will be to deliver the parcel to the locker giving the maximum utility to the receiver or to deliver the parcel at their home. This reasoning is in line with the utility maximization theory [8].

The probability P_{ij} of a receiver i to go to one of the lockers j will be determined using a discrete choice model, the Multinomial Logit (MNL), which has already been used in literature in the context of parcel lockers by [1, 7, 12], where they tried to model the preferences of the people to go to the parcel lockers. P_{ij} is defined by the MNL model by $P_{ij} = e^{U_{ij}}/(\sum_{j \in L} e^{U_{ij}} + e^{U_H})$, where U_{ij} is the utility of receiver i to go to locker j and U_H is the utility of home delivery.

The utility functions from [7] are going to be used for the MNL model. [7] estimated the parameters for two different utility U_{ij} functions depending on whether the receiver is located in a residential area or in a commercial area. The attributes included in them are travel distance d_{ij} and type of locker $type_j$ ($type_j = 1$ if locker j is located nearby a shopping center and a train/ subway/ tram station). They defined the attraction A_{ij} of a locker j to receiver i as the exponential of the utility function. The utility functions were estimated with data of an area in Singapore and the lockers were located in distances smaller than 1 km. They also estimated the attraction A_H values of not going to any locker (home delivery) for both type of receivers.

$$Residential\ area: \ U_{ij} = log(A_{ij}) = -4.59\ d_{ij}^{1/3} + 1.5\ type_j, \quad A_H = 7.06$$
$$Comercial\ area: \ U_{ij} = log(A_{ij}) = -4.47\ d_{ij}^{1/3} + 0.52\ type_j, \quad A_H = 17.79$$

Each parcel request has a consideration set of lockers for the receiver $L_i \subseteq L$. This set of lockers specific for each receiver is used to limit the choices available to the receivers, as it is not expected that they want to go to lockers which are located further away. Therefore, the consideration sets of lockers are going to be limited to the lockers that give a minimum attraction value of A_{min}.

There is a service time s associated to the time spend to put a parcel in a locker, which has to be taken into account when determining the total routing time and cannot exceed a specific amount of hours T_{max} (driver working hours).

There are two main objectives in this problem, 1) minimize the total transportation costs of the courier while 2) maximizing the utilities of each receiver. In most cases these are conflicting objectives because delivering the parcels to a locker where only a few people is willing to go comes with an additional cost for the courier. Therefore, in order to balance the two objectives, obtaining a Pareto frontier [16] is proposed.

The problem is first solved with each of the objective functions independently. The results for the second objective function in both cases are used to define the upper and lower boundaries of the Pareto frontier. Then, the problem is solved with only the first objective function and adding the second objective as a constraint limited by an ε value. This ε is a value between the two boundaries previously found. In order to obtain the Pareto Frontier, the difference between the two boundaries is divided by a number of intervals in order to obtain multiple ε with which to solve the problem.

2.1 Graphical example

In this section, a small example is presented. The transportation network consists of a depot and 5 parcel-lockers available to cover a demand of 10 receivers. Therefore, the problem is represented with a graph of 17 nodes in total, where the blue node is the depot, the light green nodes are the parcel-lockers and the dark green nodes are the receivers.

Figure 1 shows the solution of the problem solved for the first objective function. As can be seen in the figure, only lockers are visited by vehicles. This is expected to happen because the objective is to minimise the total transportation costs. Contrarily, in figure 3, only receivers are visited, which happens as a result of solving the problem with the second objective function.

Figure 2 illustrates another solution, where the trade-offs between the previous two cases can be observed. In this case, the problem is solved for the first objective function and having the second objective as a constraint delimited by an ε. As a result, some receivers are assigned to lockers but others have home delivery.

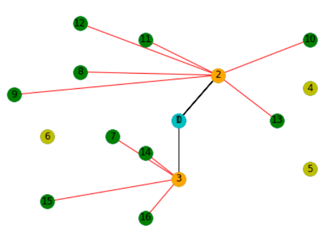


Fig. 1: Solution obtained minimising the TTC.

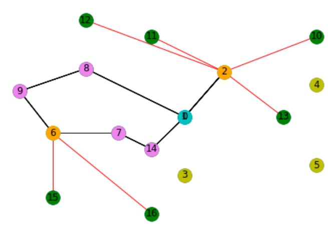


Fig. 2: Solution obtained minimising the TTC with an ε constraint.

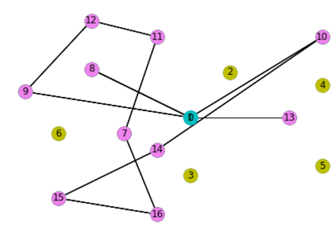


Fig. 3: Solution obtained maximizing the utilities of the receivers.

2.2 Mathematical Model

This problem is defined under a directed graph $\mathcal{G}(N, A)$ where $N = R \cup L \cup O$ is the set of nodes and $A = A(R) \cup A(O) \cup A(L)$ is the set of arcs. $A(R) = \{(i,j)|i \in R \cup L \wedge j \in R \cup L\}$; $A(O) = \{(i,j)|i \in \{0\} \wedge j \in R \cup L \vee i \in R \cup L \wedge j \in \{1\}\}$; $A(L) = \{(i,j)|i \in R \wedge j \in L_i\}$. The sets R and L correspond to all the receivers and lockers locations and set $O = \{0, 1\}$ includes two nodes that correspond to the depot (departure, arrival). Each arc $(i,j) \in A$ has associated some cost, which is travel distance d_{ij}.

Let binary variables y_j be equal to 1 if locker j is rented, w_i be equal to 1 if receiver i has home delivery, z_{ij} be equal to 1 if receiver i is assigned to locker j, g_i^k be equal to 1 if parcel from request i is delivered by vehicle k, r_j^k be equal to 1 if node j is visited by vehicle k, x_{ij}^k be equal to 1 if vehicle k moves from i to j. Lastly, t_j^k is the accumulated time of vehicle k having served node j.

The problem consists of two objective functions, Function (1) minimizes the total travelling costs, which includes the travelling distance costs (C_{km}) and the rent of the lockers (C_{rent}) and Function (2) maximizes the attraction of the receivers, which comes from a locker delivery(A_{ij}) or a home delivery(A_H).

$$minimize \sum_{(i,j)\in A} C_{km}\ d_{ij}\ x_{ij}^k + \sum_{i\in R}\sum_{j\in L_i} C_{rent}\ z_{ij} \tag{1}$$

$$maximize \sum_{i\in R}\sum_{j\in L_i} A_{ij}\ z_{ij} + \sum_{i\in R} A_H\ w_i \tag{2}$$

Subject to:

$$z_{ij} \le y_j \qquad \forall i \in R, j \in L_i \tag{3}$$

$$y_j \le \sum_{(i,j)\in A(L)} z_{ij} \qquad \forall j \in L \tag{4}$$

$$\sum_{j\in L_i} z_{ij} + w_i = 1 \qquad \forall i \in R \tag{5}$$

Constraints (3) and (4) make sure that the receivers are only assigned to lockers that are rented and lockers can only be rented if there is at least one receiver assigned to it. Constraint (5) ensures that each receiver is either assigned to one locker or has home delivery.

$$\sum_{j\in R\cup L} x_{0j}^k - \sum_{j\in R\cup L} x_{j,1}^k = 0 \qquad \forall k \in K \tag{6}$$

$$\sum_{j\in R\cup L\cup\{1\}} x_{ij}^k - \sum_{j\in R\cup L\cup\{0\}} x_{ji}^k = 0 \qquad \forall k \in K, i \in R\cup L \tag{7}$$

$$\sum_{j\in R\cup L} x_{0j}^k \le 1 \qquad \forall k \in K \tag{8}$$

$$t_j^k \ge t_i^k + \frac{d_{ij}}{v} + s\sum_{n\in C} g_n^k - M(1 - x_{ij}^k) \qquad \forall i \in R\cup L\cup\{0\}, j \in R\cup L, k \in K \tag{9}$$

$$t_1^k \ge t_i^k + \frac{d_{ij}}{v} - M(1 - x_{ij}^k) \qquad \forall i \in R\cup L, k \in K \tag{10}$$

$$t_1^k \le T_{max} \qquad \forall k \in K \tag{11}$$

$$t_0^k = 0 \qquad \forall k \in K \tag{12}$$

The flow conservation constraints are included in constraints (6 - 8). The consistency of the time variables is ensured by constraints (9 - 12), which at the same time eliminate possible subtours. Constraint (11) makes sure that the route duration does not exceed the working time T_{max}.

$$\sum_{i\in R\cup L\cup\{0\}} x_{ij}^k = r_j^k \qquad \forall j \in R\cup L, k \in K \tag{13}$$

$$r_j^k \le y_j \qquad \forall j \in L, k \in K \tag{14}$$

$$y_j \le \sum_{k\in K} r_j^k \qquad \forall j \in L \tag{15}$$

$$\sum_{k\in K}\sum_{j\in R\cup L\cup\{1\}} x_{ij}^k = w_i \qquad \forall j \in R \tag{16}$$

$$\tag{17}$$

$$g_i^k \geq z_{ij} + r_j^k - 1 \qquad \forall k \in K, i \in R, j \in L_i \tag{18}$$

$$g_i^k \geq w_i + r_i^k - 1 \qquad \forall k \in K, i \in R, j \in L_i \tag{19}$$

$$\sum_{k \in K} g_i^k = 1 \qquad \forall i \in R \tag{20}$$

Constraints (13 - 20) are the linking constraints. Specifically, constraints (14) and (15) enforce that vehicles only visit lockers that are rented and constraint (16) ensures that receivers with home delivery are visited by a vehicle. Constraint (20) forbids that a parcel for a receiver is carried for more than one vehicle.

$$\sum_{i \in R} g_i^k \leq Q_V \qquad \forall k \in K \tag{21}$$

$$\sum_{i \in R | j \in Li} z_{ij} \leq Q_L \qquad \forall j \in L \tag{22}$$

$$y_j \in \{0,1\} \qquad \forall j \in L \tag{23}$$

$$w_i \in \{0,1\} \qquad \forall i \in R \tag{24}$$

$$z_{ij} \in \{0,1\} \qquad \forall i \in R, \forall j \in L_i \tag{25}$$

$$g_i^k \in \{0,1\} \qquad \forall i \in R \cup L, \forall k \in K \tag{26}$$

$$r_j^k \in \{0,1\} \qquad \forall j \in R \cup L, \forall k \in K \tag{27}$$

$$t_j^k \geq 0 \qquad \forall j \in N, \forall k \in K \tag{28}$$

$$x_{ij}^k \in \{0,1\} \qquad \forall i \in N \backslash \{1\}, \forall j \in N \backslash \{0\}, \forall k \in K \tag{29}$$

Finally, constraints (21) and (22) enforce the vehicle and lockers capacity restrictions, respectively and constraints (23 - 29) define the nature and range of the decision variables.

3 Multi-objective Adaptive Large Neighborhood Search

The Mathematical Model presented in Section 2.2 is not possible to be solved for large instances within a short time period. Therefore, an Adaptive Large Neighborhood Search (ALNS) heuristic is proposed as a solution method.

The ALNS described by [14] is an adaptation of the Large Neighborhood Search (LNS), where multiple destroy and repair heuristics are used in the same search. Hence, the main components of the ALNS are: destroy operators, repair operators and an adaptive mechanism, which controls the usage of the operators according to their performance in the previous iterations.

The solution method starts by giving an initial solution x^i, to which the ALNS algorithm is applied. This means that part of the solution is destroyed and repaired. Later, the acceptance criteria is used to evaluate whether the new solution is accepted and a weight is assigned to the destroy/repair operators used, to control how they perform. This is an iterative process that searches for better solutions and finishes after N iterations [4].

The initial solution given in order to start applying the ALNS algorithm is usually obtained by applying one of the repair operators (*in this case: Greedy receiver insertion in lockers*).

Among the different acceptance criteria used within literature, Simulated Annealing (SA) is the one mostly applied when using ALNS. As described by [4], the temporary solution x is accepted if $f(x) \leq f(x^c)$ and otherwise, it is accepted with probability $P = e^{(f(x^c)-(f(x))/T}$. The temperature $(T > 0)$ is updated at each iteration i using a cooling rate α $\{T_i = \alpha\ T_{i-1} \mid 0 \leq \alpha \leq 1\}$. An initial and end temperature must be given to the algorithm as well.

The adaptive selection and weight adjustments described by [4] are used for the ALNS algorithm. In this case, as there are two objectives functions (minimise total transportation $f(x)$ costs and maximise total attractions$f_2(x)$), the ALNS works with a pool of best solutions instead of only one best. This is because the purpose is to find a Pareto Frontier. The Acceptance and Weight (A&W) criteria followed are presented in Algorithm 1.

Algorithm 1 A&W criteria

input: $pool^b, x, x^c, (\omega_1, \omega_2, \omega_3, \omega_4), T_{i-1}, T_{end}, \alpha$
if $f(x) > f(x^c) \& f_2(x) < f_2(x^c)$ **then**
    $z \leftarrow SA(x, x^c, T_{i-1}, T_{end}, \alpha)$
    if z = Accepted **then**
        $x^c, \Psi \leftarrow x, \omega_3 \quad (ACCEPTED)$
    else
        $x^c, \Psi \leftarrow x^c, \omega_4 \quad (REJECTED)$
    end if
end if
for $x^b \in pool^b$ **do**
    if $f(x) >= f(x^b) \& f_2(x) <= f_2(x^b)$ **then**
        $S \leftarrow add(1)$
    end if
end for
if $S >= 1$ **then**
    $x^c, \Psi \leftarrow x, \omega_2 \quad (BETTER)$
else
    $x^c, \Psi \leftarrow x, \omega_1 \quad (BEST)$
    $pool^b \leftarrow add(x)$
end if
Output: $pool^b, x^c, \Psi$

As already mentioned, some of the following repair and destroy operators have been designed specifically for solving the mathematical model presented in Section 2.2.

3.1 Destroy operators

Receiver random removal: Randomly removes a number of receivers from the given solution. The number is determined by the product of the number of receivers and the degree of destruction. These receivers could be part of the route or inside a locker.

Receiver worst cost removal: Removes the receiver with the highest cost of having it in one of the given solution routes. Having a receiver in a locker is given a zero cost value.

Receiver worst utility removal: Removes the receiver with the lowest utility of having it in one of the lockers or visiting it.

Receiver related removal: Randomly chooses a receiver and removes all the receivers within a given distance. This distance is determined by the product of the maximum distance between the nodes and the degree of destruction.

Routes random removal: Randomly removes a number of routes from the given solution. The number is determined by the product of the number of routes and the degree of destruction.

Routes worst cost removal: Removes the route with the highest cost in the given solution.

Routes worst utility removal: Removes the route with the lowest utilities in the given solution.

Routes cheapest cost removal: Removes the route with the lowest cost in the given solution.

Routes cheapest utility removal: Removes the route with the highest utilities in the given solution.

Locker random removal: Randomly removes a number of lockers from the given solution. The number is determined by the product of the number of lockers and the degree of destruction.

Locker worst cost removal: Removes the locker with the highest cost in the given solution.

Locker worst utility removal: Removes the locker with the lowest utilities in the given solution.

Locker random removal plus route: Randomly chooses a locker and removes the entire route visiting it.

For all these operators, if when removing a receiver a locker is emptied, this locker is taken out of the route. If a route is removed and there were lockers in it, these ones are emptied. If a locker is removed, this one is emptied.

3.2 Repair operators

Greedy receiver insertion in routes Inserts the receivers that are not in the given destroyed solution by taking a receiver from the list, checking the cost of locating it in the less costly position at each of the available routes and then choosing the route with the lowest insertion cost. Once the best route is determined, the operator inserts the receiver in this route and repeats the procedure until all receivers have been placed.

Best receiver insertion in routes Inserts the receivers that are not in the given destroyed solution by checking the cost of locating each receiver in the less costly position at each of the available routes and then choosing the receiver and the route with the lowest insertion cost. Later, the operator inserts the receiver in the route and repeats the procedure until all receivers have been placed.

Regret receiver insertion in routes Inserts the receivers that are not in the given destroyed solution by checking the regret of inserting each receiver. The regret of a receiver is defined as the difference between the costs of locating the receiver in the two cheapest routes. Later, The operator inserts the receiver with the highest regret in the route and repeats the procedure until all receivers have been placed.

Greedy receiver insertion in maximum utility lockers Inserts the receivers that are not in the given destroyed solution by taking a receiver from the list, checking the utility of locating it in each of the available lockers and then choosing the locker giving the maximum utility. Once the best locker is determined, the operator adds the receiver to this locker and repeats the procedure until all receivers have been placed.

Greedy receiver insertion in cheapest lockers Inserts the receivers that are not in the given destroyed solution by taking a receiver from the list, checking the cost of locating it in each of the available lockers and then choosing the cheapest locker. Once the best locker is determined, the operator adds the receiver to this locker and repeats the procedure until all receivers have been placed.

Best receiver insertion in maximum utility lockers Inserts the receivers that are not in the given destroyed solution by checking the utility of locating each receiver in each of the available lockers and then choosing the receiver and the locker that give the maximum utility. Later, the operator adds the receiver in the chosen locker and repeats the procedure until all receivers have been placed.

Regret receiver insertion in maximum utility lockers Inserts the receivers that are not in the given destroyed solution by checking the regret of inserting each receiver. In this case, the regret of a receiver is defined as the difference between the utilities of locating the receiver in the two lockers with the highest utilities. Later, the operator adds the receiver in the chosen locker and repeats the procedure until all receivers have been placed.

Regret receiver insertion in cheapest lockers Inserts the receivers that are not in the given destroyed solution by checking the regret of inserting each receiver. In this case, the regret of a receiver is defined as the difference between the costs of locating the receiver in the two cheapest lockers. Later, the operator adds the receiver in the chosen locker and repeats the procedure until all receivers have been placed.

For all the operators that insert receivers in lockers, the following applies. If there is any locker that is filled with receivers and is not part of any route, then this locker is added to one of the available routes, taking into account the amount of receivers inside it. If there are no available routes for that, all lockers are deleted from the routes and are inserted following the greedy insertion method. Moreover, a check is done at the end, in case the parcels could be rearranged to lockers with higher utilities, keeping the number of receivers in each locker.

4 Experimental Setup

In this section a computational experiment is presented to check the computational efficiency of the ALNS implementation explained in the previous section. Particularly, the software implementation of the exact method and the ALNS algorithm are compared. The ALNS has been implemented in Python and the mathematical model defined in Section 2.2 has also been implemented in Python using the optimization solver Gurobi (for 20 receivers) and Cplex (for 40 and 80 receivers).

4.1 Data description and parameters of ALNS

The performance of the exact method and the ALNS is evaluated on a set of the Solomon instances [15], which have 80 requests. They are divided into different types depending on the distribution of the nodes. Experiments have been performed with R (random) and RC (mix of random and clustered) instances to verify the ALNS method. Specifically, instances with three different sizes (20, 40 and 80 requests) were considered. The following characteristics of the instances are defined as a proportion of the requests(r). A total of 0.25r number of lockers with a capacity of 0.3r or 0.2r, and a total of 0.2r vehicles available with a capacity of 0.4r.

The parameters used for running the ALNS with the previously presented instances are shown in Table 1. For Simulated Annealing, the initial temperature is set in such a way that the probability of accepting a 2 times worst solution than the initial solution is 50% and the final temperature is determined with the following function $T_e = T_i \ \alpha^{\#iterations}$. Each instance is run three times for a total of 5,000 iterations x 6 epsilons. That means that a total of 35,000 iterations are executed for each instance and run. For each of the epsilons, a Pareto Frontier is obtained and later all of them are combined into a single one.

Table 1: Parameters used in ALNS.

Parameter	Description	Value
λ	decay parameter	0.95
N	number of iterations	5000
e	number of epsilons	6
ε	Penalty value for violating the Utility constraint	1000
$\omega_1, \omega_2, \omega_3, \omega_4$	Score weights	(4, 3, 2, 0.5)
α	cooling rate	0.9998

4.2 Computational Performance

In this section the software implementation of the exact method and the ALNS algorithm are compared. Because solving the model with the exact method requires a considerable amount of computational time, a time limit was used. Specifically, 1 hour per epsilon with the instances of 20 receivers (using Gurobi). For instances with 40 and 80 receivers, the Cplex runs were performed with different strategies, to achieve the best lower bound (LB) with a time limit of 12h per epsilon and to achieve the best solution with a time limit of 3 hours per epsilon. This was done in order to get better results combining the two. However, it is important to keep in mind that the exact method was stopped with a time limit and the gaps with the LB are rather high in general.

Table 2 presents an average of the differences between the gaps of the ALNS minus the gaps of the exact method, which gives the general improvements achieved with the ALNS for each Pareto Frontier. It should be noted that all gaps are calculated with respect to the best LB. The positive improvements mean that the ALNS performs better than the exact method and the negative improvements mean the that the ALNS performed indeed worse.

Table 2: ALNS average run time and improvement achieved with respect to the exact method for R and RC instances.

Instances	**R results**		**RC results**	
	Run Time	**Improvement**	**Run Time**	**Improvement**
20rec_8Ql	3.4%	-9.8%	2.6%	-4.0%
20rec_6Ql	3.4%	-10.8%	6.4%	-4.8%
40rec_16Ql	1.5%	-50.5%	7.8%	-74.2%
40rec_12Ql	3.6%	-46.9%	18.8%	-79.7%
80rec_32Ql	19.5%	144.4%	13.4%	143.2%
80rec_24Ql	8.5%	82.1%	21.7%	48.2%

Therefore, for the 20 receivers instances, within a 2.4%-6.4% of the Gurobi running time, the ALNS is able to find a solution that is only 4.0%-10.8% worst than the exact model. For the 40 receiver instances, the ALNS run time varies more, from 1.5% -18.8% and the results from the ALNS are further away from the solutions of the exact method. For the 80 receiver instances, the ALNS is able to find a solution for all the epsilons within 8.5%-21.7% of the exact running time, while the exact method was not able to find solutions for all the epsilons given the computation time limit. Moreover, on average the ALNS improves significantly the solutions from the exact method.

Figures 4 to 6 present the results in the form of Pareto Frontiers for a number of representative cases only, as there are no significant differences between the results for the same number of receivers but different locker capacities.

Figure 4 shows the Pareto Frontiers for one of the 20 receiver instances, where the ALNS is really close to the exact solutions. However, Figure 5 confirms what was observed in the previous tables, that the ALNS solutions are at a further distance from the exact method solutions. Figure 6 shows that the exact method is not able to find good solutions within the given time limit whereas the ALNS can find better solutions than the exact method.

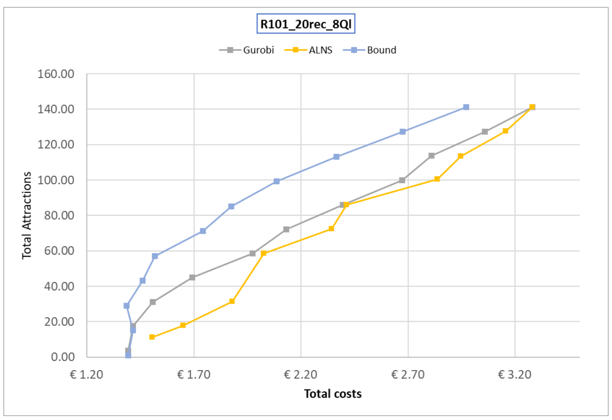


Fig. 4: Pareto Frontiers obtained for instance R101_20rec_8Ql.

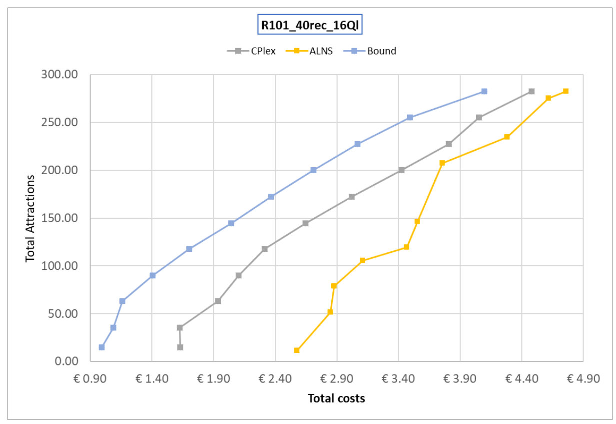


Fig. 5: Pareto Frontiers obtained for instance R101_40rec_16Ql.

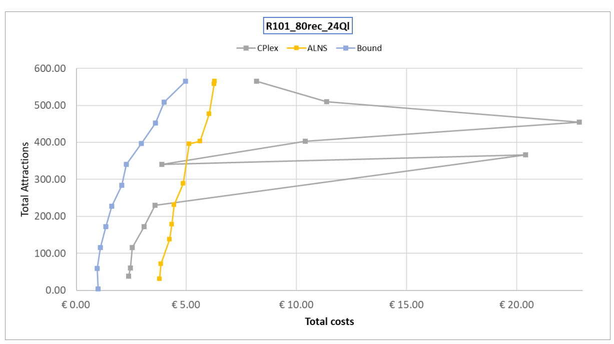


Fig. 6: Pareto Frontiers obtained for instance R101_80rec_24Ql.

Figures 4, 5 also show that the exact model finds smoother Pareto Frontiers, meaning that probably the ALNS operators are not able to find all possible solutions. This shows room for improving the ALNS algorithm.

To conclude, the ALNS can be used for solving the mathematical problem presented previously in Section 2.2. The ALNS algorithm is not able to find better solutions than the exact method for the smaller instances - at least for the selected running times - whereas it is able to find some better solutions for the bigger instances. Therefore, for instances equal or bigger than 80 receivers, the ALNS improves the performance of the exact method with a significant reduction of the running time, given the time limitation of 12h per epsilon in the exact method.

4.3 Impact of spatial distribution on delivery performance

In this section some general observations regarding differences between the R (uniformly distributed) and RC (mixed of uniformly distributed and clusters) are pointed out.

First, R instances costs are lower than the RC instances. This difference of cost is due to the spatial distribution, as for RC there are more receivers located further away from the center than in R. The RC Pareto Frontiers are steeper than the ones from R. This means that adding home deliveries is cheaper for the courier delivering to RC distribution networks.

In general, the lockers are used at low capacity and the number of lockers used does not seem to differ much regarding the different distributions as well. Therefore, these parameters are not affected for having different receivers distributions.

Finally, when the lockers are located in the clusters, receivers have to travel shorter distances to pick up their parcels, whereas in the R instances they have to travel longer distances.

5 Case study

The previous ALNS heuristics algorithm has been applied to a case study using data from the company DPD, in The Netherlands. Specifically, a small area in the city center of Rotterdam was chosen and the number of requests was limited to 80 parcels. In this case, the DPD depot is not located inside the area where the requests are located but around 5.5 km to the North of the study area.

The following parameters have been selected for a base scenario. 20 lockers with a capacity of 10 parcels, so that the algorithm has enough freedom to use more or less lockers, more or less full. The attraction function of a residential area presented in Section 2 is used. Given the dimensions of the study area, a fleet of 6 vehicles with a capacity of 20 parcels each, was considered. A fictional driving cost of 0.6 €/km is assumed together with a driving speed of 30 km/h inside the study area (between receivers and/or lockers) and 80 km/h between the depot and the study area. The maximum duration of a route is limited to 8h in line with the drivers' working hours. The service time is assumed to be 2 min per parcel. Moreover, only parcel lockers that give an attraction higher than 0.1 to the receivers are taken into account.

Lastly, the ALNS has been slightly modified, as for the case study, the renting cost is per locker instead of per parcel (inside the locker). A rent cost of 0.02 €/locker is used. This value was chosen because the Pareto Frontier is sensitive to the rent. For cases where the rent is high in comparison with the distances between receivers, the cheapest result with the highest service level would always be delivering all the parcels at home.

Different scenarios were created to see the effect on the whole system of the renting costs of the lockers, the number of lockers and their capacity and a change in preferences of the end-users. The parameter with the most significant effect is the preferences of the end-users, which is represented with variations on the home delivery attraction and the distance parameter in the attraction function. This effect is presented below.

5.1 Effect of home delivery attraction and distance parameter

When calculating the probabilities of a receiver to go to a specific locker, the probability function (Section 2) takes into account the attraction of all the lockers that are opened, as well as the attraction of home delivery. For this reason, the probabilities obtained tend to be low when there are many lockers opened or when the home attraction is high compared to the locker attractions, as they are competing options from which the receiver could choose from. For the same reason, when all the parcels are delivered at home, the receivers have no other option to choose from as there are no lockers opened. Therefore, the probability of them choosing the home delivery option is 1.

Due to this behaviour, an adjustment of the service level was needed (see Figure 8) to show the effect of the attraction function variations. This adjusted SL is the average of the attraction of each receiver with respect to the possible attraction range. Particularly, this is required for two scenarios: when varying the home delivery attraction and the distance parameter.

To see the effect of the home delivery attraction, two scenarios were tested: reducing this parameter from 7.06 in the base scenario to 0.8 and 0.3, and to see the effect of the distance parameter, two other scenarios were tested: reducing this parameter from -4.59 in the base scenario to -1.5 and -0.5.

When reducing the distance parameters, the adjusted SL curves become less steep than the base scenario as can be seen in Figure 7. This implies that the courier needs to invest a little more in order to see a significant improvement on the SL. However, this figure also shows that even though any change is applied to the network, the courier is able to provide a higher SL with the same cost if the receivers are less sensitive to the distance (-0.5 utility). Just to provide a 50% SL in the -0.5 utility case, the courier reduces the travelling distance 5km and the total transportation costs 3€ from the base scenario.

More parcels will be delivered to lockers that are further away from the receivers, allowing to reduce the routing distances, but still getting a similar service level. The fact that the parcels are located to lockers that are further away is shown with Figure 9, where the dark green area is quite significant. In these scenarios, still, home delivery is preferred because the difference in attraction is high (maximum locker attraction 2.8 vs home attraction 7.06).

On the other hand, when reducing the value of home delivery attraction, the lockers can compete with the home delivery and that is why the SL curve is different. Contrarily to the other two cases, where the maximum SL is provided when delivering all the parcels at homes, in this scenario, the maximum SL is provided delivering all the parcels to lockers. Specifically, to lockers located at less than 200m from the receivers, as observed in Figure 10.

From this, the courier can see the importance of knowing the type of receivers present in their network. For example, if the receivers are willing to make the extra effort of going to a locker further away over receiving the parcel at home – which can be associated with sustainability consciousness or convenience of the parcel locker system – the courier will be able to provide a high SL while reducing the TTC to serve the same network.

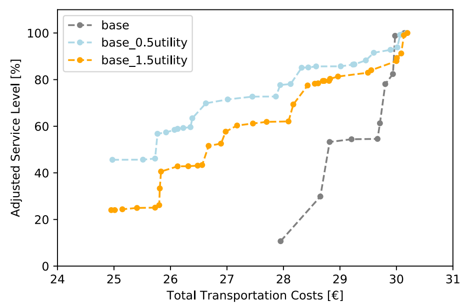


Fig. 7: Adjusted SL for the base scenario (-4.59 dist. param.) and two other scenarios of -1.5 and -0.5 dist.param.

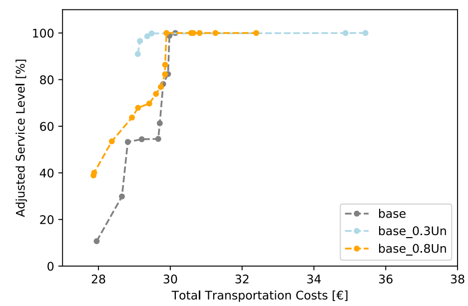


Fig. 8: Adjusted SL for the base scenario (7.06 Home attraction) and two other scenarios of 0.3 and 0.8 home attraction.

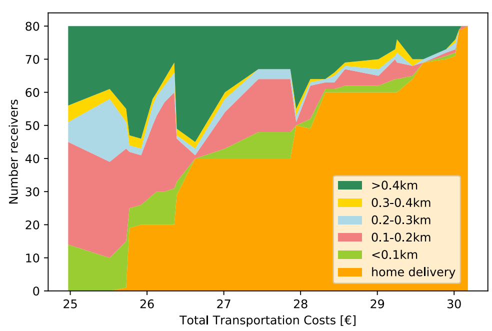


Fig. 9: Receiver distribution by distance to locker for -0.5 distance parameter.

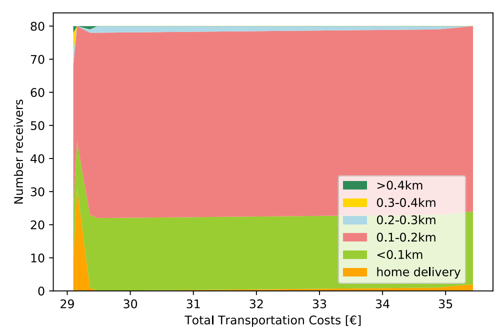


Fig. 10: Receiver distribution by distance to locker for 0.3 home attraction.

5.2 Key findings

The following remarks can be highlighted based on the analysis of the results. First of all, it is important to keep in mind that similar SL and TTC can be obtained for significantly different routes, making this a complex system to analyse. When looking at the shape of the Pareto Frontiers, a steep slope means that the SL can be easily improved with a small impact on the total costs. On the other hand, a flat section in the Pareto Frontier means that a significant amount of money is required to further increase the SL. When looking at the relevance of the parameters analysed, the percentage of home deliveries is one of the main drivers for increasing the SL when home delivery attraction is high. The capacity of lockers does not have a big impact on the results, while low renting costs help to provide a specific SL at lower TTC. In general, using less lockers at a higher capacity helps to reduce costs.

It is crucial for the couriers to study what type of receivers belong to their delivery network before deciding on the implementation of parcel lockers. For example, if receivers are more sustainable, the resulting parcel locker network will enhance the use of more lockers, reducing the general distance from the receivers to the lockers. Also, if receivers are less sensitive to the distance to the lockers, the resulting parcel locker network will reduce the number of lockers used, increasing the distance to the lockers from the receivers side.

6 Conclusions

A new problem has been defined incorporating receivers' choice behaviour into a vehicle routing problem. This problem has been formulated in a Mathematical Model that can be solved numerically. A multi-objective ALNS algorithm with some operators specific for this problem is proposed. This heuristics were compared with an exact method and the ALNS algorithm proved to be able to solve the problem for large instances (100 nodes) efficiently.

A network of parcel lockers for the last mile delivery has been modeled for a case study in a small urban area in Rotterdam. The impact of using parcel lockers on both couriers and receivers is evaluated with a Pareto Frontier obtained from implementing the proposed ALNS algorithm. The results proved to be significantly sensitive to the utility functions. Therefore, it is crucial for the couriers to study what type of receivers belong to their delivery network before deciding on the implementation of parcel lockers.

Bibliography

[1] Collins, A.: Travel behaviour in the context of parcel pickups. ITLS (2015)
[2] Deutsch, Y., Golany, B.: A parcel locker network as a solution to the logistics last mile problem. International Journal of Production Research **56**(1-2), 251–261 (2018)
[3] van Duin, R., Wiegmans, B., Arem, B.V., van Amstel, Y.: From home delivery to parcel lockers: a case study in amsterdam. Transportation Research Procedia **46**(June), 88–96 (2019)
[4] Hillier, F.S., Price, C.C., Austin, S.F.: Handbook of Metaheursitics, vol. 173. Springer (2010)
[5] Iwan, S., Kijewska, K., Lemke, J.: Analysis of Parcel Lockers' Efficiency as the Last Mile Delivery Solution - The Results of the Research in Poland. Transportation Research Procedia **12**(June 2015), 644–655 (2016)
[6] Lachapelle, U., Burke, M., Brotherton, A., Leung, A.: Parcel locker systems in a car dominant city: Location, characterisation and potential impacts on city planning and consumer travel access. Journal of Transport Geography **71**(July), 1–14 (2018)
[7] Lyu, G., Teo, C.p.: Last Mile Innovation : The Case of the Locker Alliance Network. SSRN pp. 1–51 (2019)
[8] McFadden, D.: Disaggregate Behavioral Travel Demand's RUM Side A 30-Year Retrospective. Travel behaviour research : the leading edge **2000**(July), 17–64 (2001)
[9] Montreuil, B., Meller, R.D., Ballot, E.: Physical Internet foundations, vol. 472. IFAC (2012)
[10] Morganti, E., Seidel, S., Blanquart, C., Dablanc, L., Lenz, B.: The Impact of E-commerce on Final Deliveries: Alternative Parcel Delivery Services in France and Germany. Transportation Research Procedia **4**(0), 178–190 (2014)
[11] Nguyen, D.H., de Leeuw, S., Dullaert, W.E.: Consumer Behaviour and Order Fulfilment in Online Retailing: A Systematic Review. International Journal of Management Reviews **20**(2), 255–276 (2018)
[12] Oliveira, L.K.d., Morganti, E., Dablanc, L., Oliveira, R.L.M.d.: Analysis of the potential demand of automated delivery stations for e-commerce deliveries in Belo Horizonte, Brazil. Research in Transportation Economics **65**, 34–43 (2017)

[13] Pan, S., Giannikas, V., Han, Y., Grover-Silva, E., Qiao, B.: Using customer-related data to enhance e-grocery home delivery. Industrial Management and Data Systems **117**(9), 1917–1933 (2017)
[14] Pisinger, D., Ropke, S.: A general heuristic for vehicle routing problems. Computers and Operations Research **34**(8), 2403–2435 (2007)
[15] Solomon, M.M.: Algorithms for the vehicle routing and scheduling problems with time window constraints. Operations Research (1987)
[16] Sun, Y., Lang, M.: Bi-objective optimization for multi-modal transportation routing planning problem based on pareto optimality. Journal of Industrial Engineering and Management **8**(4), 1195–1217 (2015)
[17] Vakulenko, Y., Hellström, D., Hjort, K.: What's in the parcel locker? Exploring customer value in e-commerce last mile delivery. Journal of Business Research **88**(June 2017), 421–427 (2018). https://doi.org/10.1016/j.jbusres.2017.11.033
[18] Veenstra, M., Roodbergen, K.J., Coelho, L.C., Zhu, S.X.: A simultaneous facility location and vehicle routing problem arising in health care logistics in the Netherlands. European Journal of Operational Research **268**(2), 703–715 (2018)
[19] Voccia, S.A., Campbell, A.M., Thomas, B.W.: The probabilistic traveling salesman problem with time windows. EURO Journal on Transportation and Logistics **2**(1-2), 89–107 (5 2013)
[20] Yang, X., Strauss, A.K., Currie, C.S., Eglese, R.: Choice-based demand management and vehicle routing in E-fulfillment. Transportation Science **50**(2), 473–488 (2016)
[21] Yuen, K.F., Wang, X., Ng, L.T.W., Wong, Y.D.: An investigation of customers' intention to use self-collection services for last-mile delivery. Transport Policy **66**(September 2017), 1–8 (2018)