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„Efficiency of parcel lockers in a two-tier city logistics context“

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Abstract

Worldwide urbanization, climate change and the rise of e-commerce as well as steadily increasing shipment volumes have caused major players in the CEP-market (Courier, Express and Parcel) to come up with more cost-efficient and environmentally friendlier delivery methods. A concept that has emerged from this is commonly referred to as "two-tier city logistics". This delivery concept usually comprises the shipment of goods by bigger vehicles from a central depot located outside the city center to smaller depots located inside the city as a first tier delivery process. From there on, environmentally friendly delivery vehicles like cargo-bikes, different public transport modes or drones are used to either deliver to a customer‘s home or to pick-up points for the second tier. This thesis studies the efficiency of parcel-lockers regarding a practical application to the 7$^{\text{th}}$ district of Vienna. A 4-step solution approach is used to assess and test locker efficiency in combination with different micro-hub locations and sizes. Finally, a fitting measure for parcel-locker efficiency is provided as well as practical recommendations.

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1 Introduction

The last-mile delivery and specifically the delivery of shipments to private customers in urban areas has become a very interesting and thoroughly studied topic over the last few years, as it comprises up to 53% of the total delivery costs for a logistics provider (Shelagh, 2018). This trend was mainly triggered by the following challenges:
Due to the ongoing urbanization and the steady rise of the e-commerce sector, the demand for last-mile delivery services is rising faster than ever. It is estimated that by 2050, 70% of the world‘s population could be living in major cities (Boysen et al., 2020).
Increasing parcel demands in urban areas cause more delivery vans to be routed through cities, which not only burdens existing infrastructure and increases traffic, but also negatively impacts peoples‘ health due to increasing pollution. This has led governments to start banning vehicles driven by internal combustion engines and reward environmentally friendly alternatives like cargo-bikes, whose use as a last-mile delivery method has increased significantly in recent years (Boysen et al., 2020).
Costs are another major driving force, as traditional attended home delivery via vans is very expensive. Reasons for this are a lack of parking spaces, vehicle operating costs, congestion and high first delivery failures. The major cost-driver is workforce and the time it spends stuck in traffic or searching for parking lots, creating high additional costs for CEP-providers. As logistics providers usually operate under small margins and in highly competitive situations, every achievable saving can be of competitive advantage (Boysen et al., 2020).
As customer expectations have increased over the past years and e-commerce and most recently Covid-19 skyrocketed parcel volumes, most retailers nowadays offer next- or same-day delivery. This causes increasing costs due to tight delivery time-windows, which can have major impacts on workloads and efficiency for logistics providers. This fact requires last-mile delivery methods to be easily scalable on short notice (Boysen et al., 2020).
The CEP-industry still requires a lot of human resources, which are very costly. This fact combined with the problem of an aging workforce that is usually completing physically demanding tasks has led companies to put emphasis on research for alternative delivery methods such as using parcel-lockers instead of delivering directly to a customer‘s home. While this concept is already commonly applied to urban areas, fully automated delivery processes like autonomously driving vehicles and drones are thoroughly researched. Although fully automated delivery methods are already entering testing-phases, it will take some time until existing infrastructure will be able to handle such huge amounts of live data. Furthermore, legal restrictions and frameworks need to be laid out for new technologies, possibly slowing

down the process of enrollment (Boysen et al., 2020).

The status-quo delivery concept broadly applied all over the world for processing the vast majority of shipments of goods is based on a truck or van departing from a central depot and delivering to customers‘ homes along a predefined tour. This concept can be denoted as **central depot → truck/van → man → @home** (Boysen et al., 2020).
Problems arising regarding today‘s CEP-market, especially for large cities, force logistics providers to come up with more cost-efficient and environmentally friendly solutions, resulting in a new approach better suited for today‘s market requirements. This concept is broadly referred to as "two-tier city logistics". It differs from the traditional delivery method in a way that it divides the process into two main parts (tiers). The first tier comprises the transportation of goods from a central depot located outside the city center to smaller depots (or micro-depots/hubs) located in the inner city. From there on, shipments are conducted by environmentally friendly transportation modes like cargo-bikes, drones, public transport etc., which deliver goods to customers‘ homes or specific delivery points, where customers are able to collect their parcels themselves (Boysen et al., 2020). The two-tier concept unifies the efficiency of transporting large amounts of goods by trucks/vans at higher speeds from outside a city to micro-depots and the flexibility of smaller delivery vehicles inside the city. As second tier vehicles do not require parking spaces and are often able to escape parts of heavy traffic by using e.g. bike-lanes, the "idle" times and therefore total vehicle and workforce costs can be drastically reduced (Boysen et al., 2020).
A basic two-tier logistics concept can be denoted as **central depot → truck/van → hubs → cargo-bike → man → @home** (Boysen et al., 2020). Additionally, a parcel-delivery to pick-up locations, where a customer can collect the parcel on his/her own terms can be included and denoted as **central depot → truck/van → hubs → cargo-bike → man → @home/parcel-locker** (Boysen et al., 2020). This notation represents the basic concept considered for this thesis, where trucks deliver to hubs for the first tier and cargo-trikes deliver to customers at home or parcel-lockers for the second tier. The following figure depicts the basic underlying concept considered for this work:

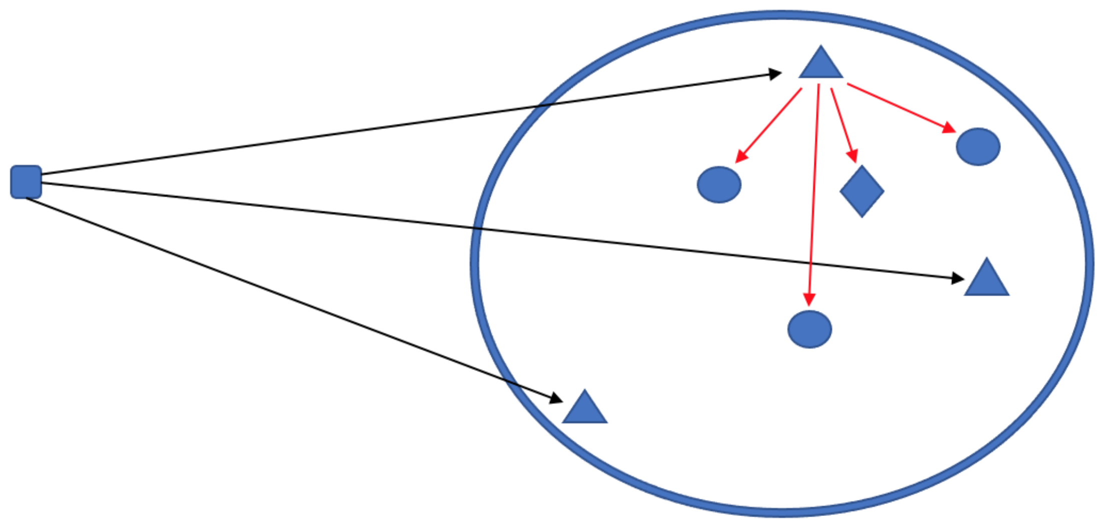


Figure 1: Two-tier city logistics with second tier delivery to homes/lockers

Figure 1 illustrates the two-tier delivery process. The square denotes the central depot, triangles represent hubs and circles/diamonds represent customers‘ homes/parcel-lockers.

This thesis aims at conducting a two-tier city logistics study for the CEP-market, specifically the parcel delivery process, based on a real-world scenario for the city of Vienna and its 7^{th} district called "Neubau" with an emphasis on the efficiency of parcel-lockers in this process.
For the first tier, trucks deliver parcels from a central depot located outside the city to hubs that are situated in "Neubau". For the second tier, cargo-trikes are used to deliver shipments to either customers directly or to parcel-lockers, where the customer then collects the parcel him/herself. The study will be conducted as a 4-step process by:

1. Determining the number of hubs to be opened by stating and solving a Single Source Capacitated Plant Location Problem (Jamshidi, 2009) with Gurobi and establishing delivery areas for each hub.

2. Stating and solving a variant of the Facility Location Problem - the Covering Problem (Fallah et al., 2009) - with Gurobi for allocating customers to either a parcel-locker or home delivery service.

3. Solving different routing scenarios for the second tier with the Erdoğan VRP-Solver (Erdoğan, 2017).

4. Solving different routing scenarios for the first tier with the Erdoğan VRP-Solver (Erdoğan, 2017).

Concluding the study, solution tables showing different routing scenarios and respective costs are provided as well as a fitting measure for parcel-locker efficiency in the context of two-tier city logistics.

The contributions of this thesis are:

1. Highlighting the efficiency of parcel-lockers in urban areas.

2. Presenting findings regarding number and size of micro-hubs.

3. Comparing total costs of different routing scenarios by solving a 4-step solution process with a total of 600 customers located in "Neubau".

2 State of the art

2.1 Relevant literature

Literature chosen for this section studies the effects of an implementation of micro-hubs, cargo-bikes and parcel-lockers on different measures like total distance driven, internal and external costs as well as emissions by conducting various studies using different metaheuristic approaches, simulations and surveys. This section focuses on practical implications of relevant literature that give impetus on why to study the efficiency of parcel-lockers in a two-tier logistics context in the first place. This thesis uses a different approach compared to relevant literature in this filed, where metaheuristic approaches are prevalent. Reason for this is that the development and testing of an all encompassing metaheuristic approach (combining first and second tier operations for hubs, parcel-lockers and home delivery) is very complex and has not been studied until recent years (Zhou et al., 2018). Additionally, problem instances with multiple micro-depots, parcel-lockers and hundreds of customers further add complexity that is beyond the scope of this thesis.

Browne et al. (2011) evaluate the efficiency of micro-consolidation centers in the City of London in combination with the use of cargo-tricycles for a second tier delivery. They conclude that even in a supply chain with already highly consolidated goods further reductions in total distance traveled and greenhouse emissions through additional city consolidation centers and the use of electric delivery vehicles can be achieved. They find that the total distance traveled can be reduced by 20%, while the CO2-emissions decrease by 54%.
Fikar et al. (2018) provide a decision support system to facilitate urban last-mile distribution. They explore the efficiency of using micro-hubs and cargo-bikes within a food delivery setting. Results indicate that providing urban consolidation centers, such as micro-hubs, is particularly beneficial in terms of delay of shipments in a high demand setting where cargo-bikes are highly utilized.They also point out that average travel distances per shipment increase as detours to reach micro-hubs occur.

Sheth et al. (2019) model four different scenarios based on variables gathered by data collection and literature review as well as assumptions in order to highlight route/cost trade-offs between electrically assisted cargo-bikes and delivery trucks in dense urban areas. They conclude that cargo-bikes are more cost-efficient than delivery trucks for deliveries close to a distribution center or depot (6 miles for a delivery route with less than 10 parcels per

stop), where there exists a high density of residential units and low delivery volumes per stop. Delivery trucks are found to be more effective for longer distances and large volume deliveries per stop.
A. Anderluh et al. (2017) develop a two-echelon city distribution scheme with temporal and spatial synchronization between cargo-bikes and vans and solve it via a greedy randomized adaptive search procedure with path relinking and test it based on a real-world scenario in Vienna. They conclude that for some instances the combined use of cargo-bikes and vans can reduce costs compared to a delivery by vans alone. Additionally, the use of cargo-bikes reduces emissions by substituting vans.

Arnold et al. (2018) conduct a case study by simulating the current state of delivery in Antwerp and compare it to a simulation of self-pickup and of bike-deliveries based on a real-world demand data-set and cost values. They find that using self-pickup locations is very cost-efficient regarding operating costs, but increases external costs compared to a traditional home delivery by vans as more customers have to travel to a pickup location themselves and therefore increase traffic. They also simulate the effects of using cargo-bikes as a second tier delivery method and discover opposite effects on costs compared to the pick-up location case. Operating costs increased due to lower speeds and capacities of cargo-bikes, while external costs decreased, as fewer vans had to drive into the inner city. They conclude that neither pick-up locations nor cargo-bikes alone are beneficial for their underlying real-world scenario, but that a combination of the two could be beneficial for both service providers as well as government stakeholders.
Zhou et al. (2016) consider a simultaneous home and pick-up location second tier delivery for a real-world instance for the city Shapingba, a district in Chongquing city. They solve the problem using a hybrid evolution search algorithm combined with a Genetic Algorithm (GA) and a Local Search (LS). They conclude that introducing pick-up locations reduces operating costs and the number of vehicles used compared to a home delivery only scenario.
Zhou et al. (2018) consider a two-echelon vehicle routing problem with vans delivering shipments from depots outside a city to so called "satellites" within the city. From there, cargo-bikes deliver goods to either pick-up facilities or directly to a customer‘s home. They propose a hybrid multi-population genetic algorithm to tackle this problem. Results obtained by solving a real-world problem instance show that combining pick-up and home delivery services can reduce the total number of vehicles on the second tier as well as operating costs.
Enthoven et al. (2020) introduce a two-echelon vehicle routing problem with covering op-

tions, where trucks deliver goods from a single depot to either parcel-lockers or ”satellite locations”, where goods are transferred to zero-emission vehicles, which deliver directly to customers. They solve different problem instances via an Adaptive Large Neighborhood Search Heuristic (ALNS) specifically tailored to the problem. Results show that covering locations are able to reduce total operating costs with the degree of improvement depending on the connection-cost structure between a covering location and a potential customer.
Song et al. (2009) study the impact of installing a network of collection points on total routing costs regarding certain percentages of failed first deliveries for attended home deliveries in West Sussex (UK). They find that a network of locker sites located in supermarkets, railway stations, gas-stations etc. functions most effectively in terms of overall traveling costs if the share of first-time home delivery failures is ≥20%. They also point out significant reductions in processing costs per parcel due to reduced overall attempted multiple home deliveries.
Iwan et al. (2016) conduct pilot surveys concerning different aspects of parcel-lockers in Poland. For the respondents (n=83), time, price, localization and 24h availability are the most important reasons for parcel-locker utilization, with shares between 18% to 27%. Additionally, participants desire a locker to be close to home (33%) or on their way to work (21%). Safety was the topmost important issue for 11% of the respondents.

2.2 Relevant concepts

2.2.1 Micro-hubs

Today, logistics providers are facing challenges like increasing customer expectations such as same-day delivery, providing perishable goods within small time-frames etc. as well as increasing pollution of central urban areas, which leads governments to start banning combustion engines in certain heavily polluted parts of cities. Trends towards environmentally sustainable delivery methods triggered the up and coming use of cargo-bicycles in inner cities. As ranges, speeds and capacities of cargo-bikes are of limited nature compared to vans or trucks, the concept of micro-depots in urban areas has emerged over the last few years (Industrie- und Handelskammer Mittlerer Niederrhein, 2019).

A micro-depot, or micro-hub, can be defined as a storage area located at a predefined spot in an inner city, where delivery goods are stored and commissioned in order to be further distributed via environmentally friendly transportation modes such as cargo-bikes, drones, public transport etc. Usually, micro-hubs are integrated into the two-tier city logistics concept, where they serve as the connecting entity between the first and the second tier. Goods are delivered via trucks or vans to micro-hubs, where they are consolidated and further transported to the customer via e.g. cargo-bikes. Micro-hubs have the potential of reducing the cost of the "Last-Mile" (Industrie- und Handelskammer Mittlerer Niederrhein, 2019), which makes up a major part of the total delivery costs for logistics providers (up to 53%) (Shelagh, 2018).

There are two different technical implementations of micro-hubs: immobile and mobile hubs. Immobile refers to a fixed location like a parking-garage, parking-lot or a designated spot somewhere in the inner city, where a stationary hub can be set up and operated. Mobile refers to a hub not having a stationary position, meaning that it can be moved between locations. Examples for mobile hubs are containers and truck trailers that can be delivered in the morning and picked up in the afternoon. Both concepts have their pros and cons: immobile hubs can be bigger in size, as a trailer‘s capacity is limited to a certain extent. Mobile hubs are better suited for reacting to fluctuations in demand, legal regulations etc., as they can be moved to another location. The problem with mobile hubs is that a lot of cities do not want public sites and cultural hot-spots to be plastered by containers and trailers. This fact does not allow for mobile micro-hubs in certain inner cities (Industrie- und Handelskammer Mittlerer Niederrhein, 2019).
Next, micro-hub concepts can be implemented as either "Greenfield" or "Brownfield" solutions. "Greenfield" refers to building new logistics-centers in inner cities, which are specifically tailored to the purposes of logistics providers. As these projects are not only very costly, but also hardly ever realizable because of the required space, "Brownfield" solutions are the common way of installing micro-hubs. "Brownfield" refers to using existing infrastructure like empty buildings, vending areas, parking-garages etc., as these storage areas come a lot cheaper and are fast to remodel and set up (HTC Hanseatic Transport Consultancy, 2019).
Furthermore, micro-hubs can be operated as either single- or multi-user hubs. In this context, a single-user hub is only used by a single logistics provider, whereas a multi-user hub is collectively used among multiple service providers. Multi-user hubs are beneficial, as service providers profit from economies of scale in terms of management and administrative effort. Furthermore, this concept makes it easier to open new facilities, as financing is divided among multiple stakeholders. Additionally, available storage capacities and resources are used more efficiently, as fluctuations in demands are balanced by providers among themselves. The biggest problem, which is also the reason why this concept is hardly ever found

in practice nowadays, is the exact allocation of resources, maintenance costs, profits, legal issues etc. to all providers involved. Common practice has shown that multi-user hubs create too much friction and conflicts of interests (Industrie- und Handelskammer Mittlerer Niederrhein, 2019).

Nowadays, a lack of suitable locations for micro-hubs is the major obstacle preventing a faster enrollment of this concept. Basic requirements for a potential micro-hub location are the need of an area between 15 and $\geq$150 qm, depending on the number of potential users and shipment volume. These areas should provide access at ground level, suitable storage and commissioning areas as well as a good traffic link. Furthermore, the rent should be at a moderate level. Additionally, the inclusion of other services like a small cafe, kiosk or parcel returning area can help to better include micro-hub concepts into urban areas, as combined solutions fit better into cityscapes and are more likely to be accepted by government officials (HTC Hanseatic Transport Consultancy, 2019).

2.2.2 Cargo-bikes

Inner city centers, where pollution, traffic and population density is the highest, have been seeking alternative delivery methods in order to reduce these burdens. Cargo-bikes, which can be either electrically, manually or hybridly operated, have become a quite fitting and popular solution in recent years. The lack of an internal combustion engine makes a cargo-bike a sustainable and environmentally friendly delivery method for city logistics (Boysen et al., 2020).

There are two main types the general term cargo-bike usually refers to: cargo-bicycles and cargo-tricycles. Cargo-bicycles have two wheels and the storage area is usually situated between a driver and the front or back wheel. A cargo-tricycle has three wheels end the freight is usually placed behind the driver on a rear axle while a single wheel in the front is used for steering. This makes cargo-tricycles bigger and slightly harder to maneuver, but enables them to carry a lot more freight both in terms of volume and weight (Choubassi et al., 2016). Additionally, so-called cubicycles are emerging among logistics providers, which have four wheels and carry the freight on the rear axle. In terms of volume and weight to be transported, cubicycles do not significantly differ from tricycles (DHL, 2019).
Furthermore, there are two types of electric propulsion systems, namely pedelecs and e-cycles. Pedelecs are usually equipped with small electric motors and require the rider to be

pedaling in order to produce power. E-cycles are equipped with electric batteries and can operate without the driver needing to pedal all the time. As cargo-tricycles equipped with batteries have the highest ranges and capacities among the range of possible bike-variants, it has evolved to be the commonly used type of "cargo-bike" for CEP-logistics providers in inner cities (Choubassi et al., 2016).

The success of an implementation of a cargo-bike delivery network depends greatly on the urban context it is embedded in. Flat urban areas with high population ($\geq$100000 inhabitants), high population densities (min. 10000 inhabitants per km^2 (Bogdanski, 2017)), high congestion levels, limited parking spaces and good bicycle street networks have proven to be the best conditions for cargo-bikes, which are not only environmentally friendlier than conventional Diesel-vans, but also potentially cheaper to operate under these conditions, as their capital, operating and maintenance costs are reduced due to lower insurance costs, less need for storage and fuel savings (Choubassi et al., 2016).
Cargo-bikes also come with limitations such as lower ranges due to battery capacities (30-50km), which does not qualify them to be used for longer trips. Weather conditions as well as the topography of a city (e.g. hilly regions) can also have an influence on the feasibility of cargo-bikes (M. A. Anderluh & Hemmelmayr, 2016). Furthermore, capacities and maximum loads are significantly smaller compared to traditional vans. Additionally, there are still problems occurring regarding smooth operations of cargo-bikes, as they tend to have problems of their own such as drive-train and battery issues. As cargo-bikes are implemented in an increasing number of cities, research will help solving these problems as well as enabling an increase in battery life-spans and ranges (Choubassi et al., 2016).

2.2.3 Parcel-lockers

As the e-commerce market is steadily growing, parcel-locker networks have become a common method implemented in larger cities. Parcel-lockers can be advantageous for multiple stakeholders, as they reduce city logistics flows, the number of vehicles needed by taking advantage of consolidation opportunities as well as the number of failed deliveries. Additionally, they offer flexible delivery locations and collecting hours (Deutsch & Golany, 2018). In the context of this work the term parcel-locker is used to comprise a parcel-locker-bank, which consists of groups of single reception locker boxes that are combined into one larger locker-bank and operated by a central control unit (Iwan et al., 2016).

Parcel-locker-banks can be of either fixed or modular nature: fixed-configuration smart locker banks, as they are also referred to, are the current status-quo in practice all over the world. Due to their standard design and dimensions fixed locker-banks offer the opportunity for economies of scale. Furthermore, it is possible to move entire banks from one location to another without any structural modifications required, as fixed banks come in the same shapes and sizes. The main problem with fixed lockers is that they can neither efficiently adapt to changes in shipment volumes nor package-size mixes (Faugere & Montreuil, 2017). Modular towers on the other hand offer opportunities to be readjusted over time by adding or removing modules from the bank. Contrary to fixed locker-banks, modular lockers do have one central control unit whereas fixed banks come with a control unit per bank. This fact offers high flexibility concerning stochastic demands and also reduces total costs as one central unit per location suffices. One downside of modular banks is the need for a modular tower inventory management that adds and removes lockers from sites based on customer demand patterns. Additionally, modular towers still have a fixed mix of package sizes per tower, which causes difficulties when adapting to changes in overall parcel-size distributions (Faugere & Montreuil, 2017).

3 Methodology

This thesis aims at illustrating the efficiency of embedding a set of parcel-lockers into a two-tier city logistics context regarding variable costs comprised of distance- and time- related costs. Customer service-times will be added as an additional cost-driver in later sections. Furthermore, a specific measure for parcel-locker efficiency is developed. The following 4-step solution process is proposed in order to investigate on locker efficiency in this work‘s context based on a real-world scenario in Vienna (Austria):

3.1 Allocation of delivery areas to hubs

First, customers and parcel-lockers need to be allocated to respective micro-hub delivery areas. This problem can be subsumed under the Facility Location Problems, specifically the Location-Allocation (LA) Problems. Location-Allocation Problems try to optimize the number of new facilities to build out of a set of available facilities that can be opened at predefined areas, which minimize the total distance driven between all customers and all selected facilities while satisfying total customer demand (Azarmand & Neishabouri, 2009). Facilities are characterized mainly by their number, type and costs as well as profits and capacity. The number of new facilities to build is one of the main properties of Location-Allocation Problems, where the type of facility built and services offered can vary between locations within a single model. The set of possible locations can be represented as either discrete, continuous or as a network. The demands of customers are either deterministic or probabilistic (Azarmand & Neishabouri, 2009).
The general model of an Location-Allocation Problem uses 4 variables in order to minimize total costs: The total number of facilities, the total number of possible locations, the amount of allocation of facilities to customers and the capacity of each facility. The general model assumes the solution space to be continuous, each customer‘s demand to be possibly served by multiple facilities, facilities to be uncapacitated, parameters to be deterministic supplying all the demand and no relationship between new facilities. The inputs for the model are the number of customers and existing facilities, a single customer‘s demand as well as the coordinates of customers and facilities (Azarmand & Neishabouri, 2009).
The basic model minimizes the total transportation cost by allocating each customer to the closest available facility while satisfying total customer demands, as no capacity constraints for the facilities are introduced (Azarmand & Neishabouri, 2009):

Sets

I	set of facilities
J	set of customers
N	set of nodes, $N = I + J$
A	set of arcs, $A = \{(i,j) : i,j \in N\}$

Parameters

d_{ij}	$(i,j) \in A$	total distance traveled on arc (i,j)
a_j	$j \in J$	demand of a customer $j \in J$

Variables

w_{ij}	$(i,j) \in A$	quantity supplied to customer $j \in J$ by facility $i \in I$

Objective

$$\min \sum_{(i,j) \in A} w_{ij} d_{ij} \tag{1}$$

Constraints

$$\sum_i w_{ij} = a_j \qquad \forall j \in J \tag{2}$$

$$w_{ij} \geq 0 \qquad \forall i,j \in N \tag{3}$$

The objective function (1) minimizes total transportation costs, while constraint (2) ensures that the demand of every customer is satisfied. Equation (3) states the quantity supplied to a customer $j \in J$ by a facility $i \in I$ to be ≥ 0.

The basic model can be altered in a way that each customer is only covered by a single facility by introducing a binary variable x_{ij} indicating whether or not a customer $j \in J$ is served by a facility $i \in I$:

$$\sum_i x_{ij} = 1 \qquad \forall j \in J$$

Additionally, facility opening costs as well as stochastic demands can be introduced (Azarmand & Neishabouri, 2009).
The main problem identified with the Location-Allocation Problems are Median Problems. The objective of Median Problems is to find the median candidate point(s) (1-Median or P-Median) so that total costs can be minimized. For a standard P-Median Problem, a number of facilities has to be built on potential locations under the objective of minimizing total costs while satisfying the demands of all customers. The P-Median Problem can be referred to as Plant Location Problem in the context of this work (Jamshidi, 2009).
With the additional introduction of capacity constraints for facilities (b_i), the problem can be described as a Capacitated Plant Location Problem:

$$\sum_j w_{ij} \leq b_i \qquad \forall i \in I$$

If each customer is supposed to be served by exactly one facility, the problem is called a Single Source Capacitated Plant Location Problem (Jamshidi, 2009).
For the practical part of this thesis, a variant of the Single Source Capacitated Plant Location Problem (Jamshidi, 2009) is used with a single facility type (micro-hub) implementable within an individual scenario. Possible micro-hub and parcel-locker locations remain the same throughout scenarios as well as customer locations and demands. The problem is modeled and solved for a total demand of 600 parcels for different hub-sizes with the Gurobi/Python application. Distances and locations are collected using Excel VBA (Erdoğan, 2017) and Bing Maps Distance Matrix API (Bing Maps Dev Center, 2021). The delivery areas for each hub are fixed by plotting numerous random draws of customers onto a first partition of delivery areas established by solving the Single Source Capacitated Plant Location Problem. Additionally, parcel-lockers are assigned accordingly:

Let G be a network comprised of a set of nodes N consisting of a set of customers I and a set of hubs J, as well as a set of arcs A. Set $A = \{(i, j) : i, j \in N\}$ is a set of edges connecting each pair of nodes in N with associated total distance traveled on arc d_{ij}. The capacity of a hub is represented as b_j and the demand of a single customer as a_i. $open_j$ denotes the number of hubs to be opened and $workload_{min}$ and $workload_{max}$ are used to preset the min. and max. possible workload of hubs. Additionally, a $BigM$ constant is introduced and set sufficiently high. The model features two binary variables: $x_{ij} \in \{0,1\}$ equals 1 if a customer $i \in I$ is assigned to a hub $j \in J$ and 0 otherwise. $y_j \in \{0,1\}$ equals 1 if a hub $j \in J$ is built and 0 otherwise. The continuous variable $w_j \in \mathbb{R}^+[0,1]$ states the workload of hubs to be between 0 and 1.

Sets

I	set of customers
J	set of hubs
N	set of nodes, $N = I + J$
A	set of arcs, $A = \{(i,j) : i,j \in N\}$

Parameters

d_{ij}	$(i,j) \in A$	total distance traveled on arc (i,j)
b_j	$j \in J$	capacity of a hub
a_i	$i \in I$	demand of a customer
$open_j$	$j \in J$	number of hubs to be opened
M	10000	BigM
$workload_{min}$	≥ 0	min. workload of hubs
$workload_{max}$	≤ 1	max. workload of hubs

Variables

x_{ij}	$\in \{0,1\}$	$\forall i,j \in A$
y_j	$\in \{0,1\}$	$\forall j \in J$
w_j	$\in \mathbb{R}^+[0,1]$	$\forall j \in J$

Objective

$$\min \quad \sum_{(i,j) \in A} x_{ij} d_{ij} \tag{1}$$

Constraints

$$\sum_i a_i * x_{ij} \geq b_j * workload_{min} * y_j \qquad \forall j \in J \qquad (2)$$

$$\sum_i a_i * x_{ij} \leq b_j * workload_{max} + M * (1 - y_j) \qquad \forall j \in J \qquad (3)$$

$$\sum_j x_{ij} = 1 \qquad \forall i \in I \qquad (4)$$

$$\sum_j y_j \leq open_j \qquad (5)$$

$$x_{ij} - y_j \leq 0 \qquad \forall (i,j) \in N \qquad (6)$$

$$w_j \leq 1 \qquad \forall j \in J \qquad (7)$$

$$w_j = (\sum_i a_i * x_{ij})/b_j \qquad \forall j \in J \qquad (8)$$

The objective function (1) minimizes the sum of all distances between all hubs opened and all customers. Constraints (2) and (3) are able to steer the minimum and maximum workloads of opened hubs. Constraint (4) assigns each customer to exactly one hub. Constraint (5) is supposed to control the maximum amount of hubs to be opened. Constraint (6) defines that a customer cannot be assigned to a hub if it is not opened. Constraint (7) does not allow the workload of a single hub to exceed its capacity, while constraint (8) determines the variable w_j as the quotient between the total demand assigned to a hub and its capacity.

3.2 Allocation of customers to lockers

Services that customers receive depend on the distance between a customer and a facility in many covering problems. In a covering problem, a critical value D_C is introduced indicating the maximum possible distance between a potential customer and a facility. If this covering distance is exceeded, the customer cannot be served by that respective facility. Covering problems are, like Median Problems, a variant of the Facility Location Problem (Fallah et al., 2009):

Sets

I	set of customers
J	set of covering points
N	set of nodes, $N = I + J$
A	set of arcs, $A = \{(i,j) : i,j \in N\}$

Variables

$$a_{ij} \quad \in \{0,1\} \quad \forall i,j \in A$$
$$x_j \quad \in \{0,1\} \quad \forall j \in J$$

Objective

$$\min \quad \sum_{j \in J} x_j \tag{1}$$

Constraints

$$\sum_{j} a_{ij} * x_j \geq 1 \qquad \forall i \in I \tag{2}$$

The objective function (1) minimizes the total number of covering points $j \in J$ to be built in order to cover all customers $i \in I$ in combination with equation (2). Binary variable a_{ij} states if a covering point $j \in J$ can cover a customer $i \in I$ or not, depending on a maximum coverage distance D_C. Binary variable x_j states if a covering location is built or not.

By introducing a distance measure d_{ij}, indicating the distance traveled on an arc $(i,j) \in A$, the objective function can be formulated as a distance minimizing function:

$$\min \quad \sum_{(i,j) \in A} a_{ij} d_{ij}$$

This thesis considers a basic Covering Problem with capacitated warehouses of uniform capacity (b_j) and type (parcel-lockers) that can be built on numerous pre-selected locations. The demand of a single customer is set to 1, constraining the model to allocate a single customer to exactly one facility or none, as not every customer assigned to a locker service has to be served by a locker (see section 4.3.2):

$$\sum_j a_{ij} * x_j \leq 1 \qquad \forall i \in I$$

There are two kinds of services offered: attended home delivery or a delivery to a locker, where a customer picks up the freight on his/her own. For this, customers are randomly assigned to either service based on a certain probability of demand for each service. The model is, contrary to the standard Covering Problem, seeking to maximize the total workload of all parcel-lockers opened. Reason for this is that for this work, possible locker customers do not necessarily have to be covered by a locker due to later introduced minimum workload requirements as well as the imposed maximum covering radius.

For the testing, customers are assigned to either service using a randomized drawing implemented in Microsoft Excel. Then, the Covering Problem (Fallah et al., 2009) is modeled and solved via the Gurobi/Python interface in order to assign customers to lockers. Different minimum workloads for parcel-lockers are set and tested as well:

Let G be a network comprised of a set of nodes N consisting of a set of customers I and a set of parcel-lockers J, as well as a set of arcs A. Set $A = \{(i, j) : i, j \in N\}$ is a set of edges connecting each pair of nodes in N with associated total distance traveled on arc d_{ij}. The capacity of a parcel-locker is represented as b_j and the demand of a single customer as a_i. $workload_{min}$ and $workload_{max}$ are used to determine the min. and max. possible workload of parcel-lockers. Additionally, a $BigM$ constant is introduced and set sufficiently high. Furthermore, a parameter r_j representing the maximum covering radius of a single parcel-locker is introduced. li assigns each customer an assignment cost to a parcel-locker of either 1 or 20, depending on whether the customers is drawn to be a parcel-locker customer or not. If a customer is determined to be demanding parcel-locker service, he/she is assigned a value of 1 and 20 otherwise. The model features two binary variables: $x_{ij} \in \{0, 1\}$ equals 1 if a customer $i \in I$ is assigned to a locker $j \in J$ and 0 otherwise. $y_j \in \{0, 1\}$ equals 1 if a locker $j \in J$ is built and 0 otherwise. The continuous variable $w_j \in \mathbb{R}^+[0, 1]$ states the workload of lockers to be between 0 and 1.

Sets

I	set of customers
J	set of parcel-lockers
N	set of nodes, $N = I + J$
A	set of arcs, $A = \{(i,j) : i,j \in N\}$

Parameters

d_{ij}	$(i,j) \in A$	total distance traveled on arc (i,j)
b_j	$j \in J$	capacity of a parcel-locker
a_i	$i \in I$	demand of a customer
M	10000	BigM
$workload_{min}$	≥ 0	min. workload of a parcel-locker
$workload_{max}$	≤ 1	min. workload of a parcel-locker
r_j	$j \in J$	max. covering radius
l_i	$choice(1,20)$	assignment costs

Variables

x_{ij}	$\in \{0,1\}$	$\forall i,j \in A$
y_j	$\in \{0,1\}$	$\forall j \in J$
w_j	$\in \mathbb{R}^+[0,1]$	$\forall j \in J$

Objective

$$\max \quad \sum_{j \in J} w_j \tag{1}$$

Constraints

$$\sum_i a_i * x_{ij} \geq b_j * workload_{min} * y_j \qquad \forall j \in J \qquad (2)$$

$$\sum_i a_i * x_{ij} \leq b_j * workload_{max} + M * (1 - y_j) \qquad \forall j \in J \qquad (3)$$

$$\sum_j x_{ij} \leq 1, if : l_i = 1 \qquad \forall i \in I \qquad (4)$$

$$\sum_j x_{ij} = 0, if : l_i > 1 \qquad \forall i \in I \qquad (5)$$

$$x_{ij} - y_j \leq 0 \qquad \forall (i, j) \in N \qquad (6)$$

$$w_j \leq 1 \qquad \forall j \in J \qquad (7)$$

$$w_j = (\sum_i a_i * x_{ij})/b_j \qquad \forall j \in J \qquad (8)$$

$$x_{ij} * d_{ij} \leq r_j * y_j \qquad \forall (i, j) \in N \qquad (9)$$

The objective function (1) maximizes the sum of all workloads of all parcel-lockers opened. Constraints (2) and (3) are able to steer the minimum and maximum workload of opened lockers. Constraint (4) and (5) define that if a customer demands a parcel-locker service, it qualifies to be possibly served by a maximum of one locker, depending on a parcel-locker‘s capacity and covering radius. As a few parcel-locker customers are excluded due to r_j, not every customer demanding a locker service has to be served. In combination with the maximizing objective function, the model still seeks to assign as many customers as possible to lockers. Constraint (6) defines that a customer cannot be assigned to a locker if it is not opened. Constraint (7) does not allow the workload of a single locker to exceed its capacity, while constraint (8) determines the variable w_j as the quotient between the total demand assigned to a locker and its capacity. Constraint (9) does not allow a customer to be assigned to an opened locker if it is further away than the maximum covering radius r_j.

3.3 Second tier routing

The simplest form of routing problems is the Traveling Salesman Problem (TSP), where all customers are covered by a single vehicle completing a single tour. In the standard TSP, the distribution of goods starts from a single depot, mostly denoted as point 0, to a set of customers, $N = \{1, 2, ..., n\}$. The amount of freight to be delivered to a customer $i \in N$ can be written as a scalar q_i and is set to be ≥ 0 for each customer. A vehicle starts and ends its trip at the depot, while moving on an arc $A = \{(i, j) : i, j \in V\}$ incurs travel costs c_{ij} by traveling a distance d_{ij}. The objective of the basic TSP is to minimize the total distance driven under the constraints of serving each customer via a single vehicle (Liu et al., 2014). A basic TSP-formulation can be stated as follows (Dantzig et al., 1954):

Sets

N	set of clients
V	set of vertices,$V = \{0\} + N$
A	set of arcs, $A = \{(i, j) : i, j \in V : i \neq j\}$

Parameters

d_{ij}	$(i, j) \in A$	total distance traveled on arc (i, j)

Variables

x_{ij}	$\in \{0, 1\}$	$\forall i, j \in A$

Objective

$$\min \quad \sum_{(i,j)\in A} x_{ij} d_{ij} \tag{1}$$

Constraints

$$\sum_{j\in V, j\neq i} x_{ij} = 1 \qquad \forall i \in V \tag{2}$$

$$\sum_{i\in V, i\neq j} x_{ij} = 1 \qquad \forall j \in V \tag{3}$$

$$\sum_{i\in Q} \sum_{j\neq i, j\in Q} x_{ij} \leq |Q| - 1 \qquad \forall Q \subsetneq \{0, ..., v\}, |Q| \geq 2 \tag{4}$$

The objective function (1) minimizes the total distance driven to all customers. Constraints (2) and (3) are flow conservation constraints and define that each node is only left and visited once. Constraint (4) ensures that no subset Q can form a subtour, resulting in a single complete tour returned instead of multiple smaller tours. Binary variable x_{ij} states if an arc $(i, j) \in A$ is visited by a vehicle on a tour or not.
By adding a maximum capacity parameter to the TSP, the problem can be described as a Vehicle Routing Problem (VRP), where capacity constraints are imposed on a single or multiple vehicles such that various routes occur instead of a single one. Further complexity can be added by introducing both delivery and collection, time-windows, multiple depots, multiple trips, different vehicle types, maximum route length etc. (Irnich et al., 2014).

For determining routes between micro-hubs, parcel-lockers and customers for this thesis, a variant of the Vehicle Routing Problem (VRP), the Capacitated Vehicle Routing Problem (CVRP) (Miller et al., 1960), is first modeled and solved with the Gurobi/Python-Interface. As a homogeneous fleet with equal vehicles and capacities is used for each tier, the CVRP can also be formulated as a cycled VRP, where each cycle belongs to a single vehicle:

Let G be a network consisting of arcs $A = \{(i, j) \in V^2 : i \neq j\}$ and a set of vertices $V = (\{0\} + N)$, where N denotes a set of customers $i \in N$ and $\{0\}$ a single micro-hub. All parcel-locker locations within the delivery area of a respective micro-hub are contained in the customer set as well. The distance traveled on an arc is denoted by d_{ij}, the demand of a single customer by q_i and the capacity of a cargo-trike by Q. The binary variable x_{ij} defines if an arc $i, j \in A$ is used or not. The flow variable u_i denotes the accumulated customer demand at customer $i \in N$ on a single tour.

Sets

N	set of customers
V	set of vertices,$V = \{0\} + N$
A	set of arcs, $A = \{(i, j) : i, j \in V : i \neq j\}$

Parameters

d_{ij}	$(i,j) \in A$	total distance traveled on arc (i,j)
Q		capacity of a vehicle
q_i	$i \in N$	demand of a customer

Variables

x_{ij}	$\in \{0,1\}$	$\forall i,j \in A$
u_i	$\in \mathbb{N}^+, \leq \sum_{i \in N} q_i$	$\forall i \in N$

Objective

$$\min \quad \sum_{(i,j) \in A} x_{ij} d_{ij} \tag{1}$$

Constraints

$$\sum_{j \in V, j \neq i} x_{ij} = 1 \qquad \forall i \in N \tag{2}$$

$$\sum_{i \in V, i \neq j} x_{ij} = 1 \qquad \forall j \in N \tag{3}$$

$$if: x_{ij} = 1 \Rightarrow u_i + q_j = u_j \qquad i,j \in A : j \neq 0, i \neq 0 \tag{4}$$

$$q_i \leq u_i \leq Q \qquad \forall i \in N \tag{5}$$

The objective function (1) minimizes the total distance driven to all customers. Constraints (2) and (3) are flow conservation constraints and define that each customer is only left and visited once. Constraints (4) and (5) are the Miller-Tucker-Zemlin subtour-elimination constraints (Miller et al., 1960). Constraint (4) states that if an arc $(i,j) \in A$ is used, the cumulative demand u_j at customer j is the sum of u_i and q_i, except for node $\{0\}$. Constraint (5) defines the accumulated demand on a route u_i to be between the demand of a single customer $i \in N$ and the capacity of a cargo-trike.

As it turns out after a test run with 100 customers, solving an Integer Programming Model (see section 4.3.3) to optimality is not a suitable approach for calculating routes for the underlying practical application of this thesis. Reason for this is that problem instances are too big to be solvable within appropriate time. For this reason, the Erdoğan VRP-Spreadsheet-Solver is used to do the routing for this thesis. The Erdoğan solver uses a variant of the Adaptive Large Neighborhood Search embedded within the Excel VBA environment, which delivers reliable results in a fraction of the time that is needed using an IP-Solver (Erdoğan, 2017).

3.4 First tier routing

The first tier routing is done the same way as the second tier routing, but with alternated depot and customer sets (see section 4.3.4)

3.5 Scenarios

Concluding, three main scenarios are compared by total costs:

1. First tier delivery to hubs and second tier delivery only to customers at home (no customers are assigned to parcel-lockers).

2. First tier delivery to hubs and second tier delivery to customers at home and parcel-lockers.

3. First tier delivery to hubs and parcel-lockers and second tier delivery only to customers at home (same customers that are assigned to parcel-lockers in (2.) are now serviced by first tier vehicles, which deliver parcels to lockers).

Additionally, different minimum locker workloads are tested as well for each scenario. Furthermore, a fitting measure for parcel-locker efficiency is developed based on findings of all routing scenarios with customer service-time being a major cost- and efficiency-driver.

All computations within this work are done using an Apple MacBook Pro (Mid 2014) with a 2,2 GHz Quad-Core Intel Core i7 Processor with 16 GB of RAM.

4 A two-tier city logistics concept for the 7th district of Vienna

4.1 Specifications of "Wien Neubau"

The 7th district of Vienna, also commonly referred to as "Neubau", belongs to the inner districts close to the city center, where deliveries are a bigger challenge due to increased population density and concentration of workplaces. In fact, districts 1-9 and 20 make up 30% of Vienna‘s total parcel demand volume, while all 10 districts combined only make up about 10% of Vienna‘s total area (Wirtschaftskammer Wien, 2020).

In order for a cargo-trike delivery method to be competitive, the stop-rate needs to be reasonably high and the number of parcels delivered per address should not exceed 3 parcels (A. Anderluh & Hemmelmayr, 2018). Bogdanski (2017) refers to a population density of at least 10000 inhabitants per km^2. "Neubau" has a total area of 1,61 km^2 with a total of around 32000 inhabitants, which equals a population density per km^2 of about 19900 (Wien.gv.at, 2021a), which is nearly double the minimum requirement. Futhermore, "Neubau" is a considerably flat district, which is a very favorable fact concerning an implementation of cargo-trikes with limited battery capacities and ranges (Google Maps, 2021).

Following the classification scheme developed by A. Anderluh & Hemmelmayr (2018), it can be seen that most parts of the 7th district are allocated between 3 and 6, which lists "Neubau" among the most suitable districts for urban consolidation centers in Vienna. The score ranges from 0 to 6 with 6 being the highest. It takes into account population density, average age of the population as well as level of education. Each of the three variables is assigned a score, whereas the sum builds the overall total score. Scores increase with higher population density, an average age structure of under 40 (as people between 16 and 44 seem to be the most frequent online-shoppers) as well as higher levels of education, as people with higher education tend to earn more money and shop more online (A. Anderluh & Hemmelmayr, 2018).

"Neubau" is surrounded by stations of different subway-lines like Thaliastraße (U6), Burggasse-Stadthalle (U6), Volkstheater (U3), Museumsquartier (U2), Zieglergasse (U3), Neubaugasse (U3) and equipped with supermarkets of various chains (Spar, Billa, Merkur, Hofer, Etsan), banks and post offices, where installments of parcel-locker banks are considered for this work.

Additionally, "Neubau" features numerous parking-garages, which are considered as possible micro-hub locations, as they do not interfere with the cityscape (Google Maps, 2021).
"Neubau" also exhibits numerous bike-paths and bike-friendly streets, where it is possible to drive in opposite directions to one-ways (Google Maps, 2021). Additionally, there is a general lack of parking space in the 7th district due to ongoing construction work, outside gardens on the streets in summer as well as the creation of new "cool-zones", which are green spaces along the streets (Wien.gv.at, 2021b). This also supports an introduction of cargo-trikes, as they do not need dedicated parking spaces to deliver carried goods.

4.2 Assumptions

4.2.1 Demands and Addresses

The demand of a single customer for the testing-phase is determined using the demand of parcels per address. In 2019, the shipment volume for parcels for Vienna was about 95,7 million with a B2C-share of around 71 percent (Wirtschaftskammer Wien, 2020).
As the parcel volume grew by around 16,7 percent in 2020 and the trend is expected to continue in a similar fashion in 2021, a volume of around 130 million parcels by the end of 2021 can be assumed reasonably (Branchenradar.com Marktanalyse GmbH, 2021).
In 2019, 30 percent of the total parcel volume was delivered within the inner districts of Vienna (1st,2nd,3rd,4th,5th,6th,7th,8th,9th and 20th district)(Wirtschaftskammer Wien, 2020).
Furthermore, it is assumed that the total number of delivery days per year ranges from 250 to 280 days. Using the total population of "Neubau" and all inner districts of Vienna, the following formula can be stated an the population-ratio for "Neubau" compared to the total inner districts can be derived:

$$\frac{\sum inhabitants_{Neubau}}{\sum districts_{Inner}} = \frac{31961}{518795} = 6,16\%$$

Including all parameters above, the following formula is stated:

$$\frac{\sum deliveries_{Vienna} * share_{InnerDistricts} * share_{B2C} * share_{Inhabitants}}{\sum deliverydays * \sum addresses}$$

$$\frac{130000000 * 0,30 * 0,71 * 0,0616}{\mathbf{280} * 2099} = \mathbf{2{,}90}$$

$$\frac{130000000 * 0,30 * 0,71 * 0,0616}{\mathbf{250} * 2099} = \mathbf{3{,}25}$$

Results show that, on average, each address in "Neubau" receives approximately 3 parcels per delivery day ($\frac{2{,}90+3{,}25}{2} = 3,075$).

As this thesis considers a real-world scenario, real addresses of "Neubau" are used for all the testing. This is done by extracting all addresses of the 7th district from Wien.gv.at, which sum up to 2099 total addresses. For simplicity reasons, it is assumed that all addresses are private customer addresses and that all addresses comprise about the same amounts of individual households.

4.2.2 Parcel-lockers

The capacity of a single parcel-locker is set to 20 parcels, which roughly equals the size of a single modular locker bank (Faugere & Montreuil, 2017). It is assumed that this is a reasonably small size to be implemented in all 50 possible predetermined locations for "Neubau".

Furthermore, the maximum covering radius, which states the maximum distance between a customer and a parcel-locker, is set to 600 meters. Zhou et al. (2016) conducted a real-world Location Routing Problem with Simultaneous Home Delivery and Customer‘s Pickup Points (LRPSHC) with 47 candidate parcel-locker locations and 136 customers for the last-mile distribution system of Shapingba, a district in Chongqing city. They conclude that a covering-radius of 600 meters is the most acceptable distance regarding cost-efficiency. 600 meters therefore appears to be a fitting measure to be used for this work as well. Additionally, it can be stated that an even larger radius usually does not offer large jumps in terms of efficiency, especially in densely populated areas, but with increasing distances to potential customers the willingness to pick up parcels decreases accordingly (Zhou et al., 2016).

Maximum capacities of respective lockers as well as the percentage of demand for this service can also impact efficiency, but for this work no variations to the radius and locker capacities are considered. Reason for this is that the defined values for capacity and radius appear to work well already, as a single locker is hardly ever fully occupied and only a handful of customers are rejected due to the maximum covering radius. Furthermore, it is assumed that each customer collects his/her parcel within 24 hours (or opening hours) and that each locker is filled at the same time each day.

4.2.3 Hubs

Two single-user hub concepts are further analyzed for an application to "Neubau". Reasons for not using multi-user concepts are the added complexity and the reduced practicability. These concepts are highly desired by urban stakeholders, but not very common in practice due to their complex planning and distributing of resources among multiple service providers in an "anti-conflict" manner (HTC Hanseatic Transport Consultancy, 2019).
The two types of micro-depots used for this work are a single-user micro-hub "Basic" and a single-user micro-hub "Max", which will be referred to as a "small" and a "big" hub scenario in the following sections (HTC Hanseatic Transport Consultancy, 2019).
A "small" hub requires at least 15-20 qm of package sorting area as well as electricity, a nearby loading area and some additional area for fitting 7,5t trucks for parking and turning. Furthermore, there must be some lockable storage area for cargo-trikes and included charging points. Possible locations for this type of micro-hub are parking-garages as well as retail spaces. The delivery radius should be $\leq$2 kilometers and the shipment volume per hub should be at least around 120 parcels per day, which represents 80 percent of its maximum capacity of 150 parcels (HTC Hanseatic Transport Consultancy, 2019).
A "big" hub requires at least 60-70 qm of package sorting area as well as additional logistics area of 10-20 qm. Furthermore, electricity and nearby loading areas are needed for fitting a truck with a maximum of 14t loading capacity. There must also exist lockable storage area for cargo-trikes and included charging points. Possible locations for this type of micro-hub are parking-garages, dedicated logistic areas as well as retail spaces. The delivery radius should be $\leq$2 kilometers and the shipment volume per hub should be at least around 300 parcels per day, which represents 60 percent of its maximum capacity of 500 parcels (HTC Hanseatic Transport Consultancy, 2019).

4.2.4 Vehicles, capacities and speeds

For the first tier delivery process, trucks are used. In the literature different parcel-capacities are assumed for first tier delivery vehicles. A. Anderluh et al. (2017) consider delivery vans with capacities of 100 parcels each. Arnold et al. (2018) consider medium-sized Diesel-vans with a capacity of 300, whereas Sheth et al. (2019) consider delivery trucks with a capacity of 400 parcels. For this thesis, a capacity of a 7,5t delivery truck is assumed to amount to 400 parcels.
Concerning traveling speeds of delivery vans and trucks, Arnold et al. (2018) assume 17 km/h for their simulation, whereas Bogdanski & Cailliau (2020) set speeds between 17,7 and 20,3 km/h in inner cities. As the central depot considered for the testing in this thesis is situated in a less congested area and a substantial part of the total distance traveled is not situated in the inner city, an average traveling speed of 30 km/h for trucks is assumed for this work.

For the second tier delivery process, cargo-trikes are used. A. Anderluh et al. (2017) assume a cargo-bike‘s capacity to be 16 parcels. Arnold et al. (2018) assume a capacity of 10 parcels, whereas both Sheth et al. (2019) and Assmann et al. (2019) assume a capacity of 40 parcels per vehicle. For the testing in this thesis, e-cargo-trikes will be used with an assumed capacity of 30 parcels, which seems reasonable as tricycles are usually able to carry more shipments than bicycles (Arnold et al., 2018).
Traveling speeds for cargo-bikes vary from 12 km/h (A. Anderluh et al., 2017) up to 15 km/h for Assmann et al. (2019) and Arnold et al. (2018). For this work, the average traveling speed of a cargo-trike is set to 15 km/h.

4.2.5 Costs

For the determination of the total costs for all scenarios, variable vehicle and driver costs as well as service-times per customer are considered. Regarding this work, routing costs refer to variable vehicle and driver costs, while total costs also include service-times per customer.

In the literature variable costs for a delivery van or truck vary between 0.18 (Arnold et al., 2018) and 0.40 Euro (A. Anderluh et al., 2017) per km, whereas variable costs for a cargo-bike are set to about 0.04 Euro per km, (A. Anderluh et al., 2017) which only resembles up to a tenth of a van‘s variable costs. Reasons for this are for instance the cargo-bike‘s reduced maintenance, insurance and fueling costs.

For the driver, costs of between 0.30 (Arnold et al., 2018) and 0.33 Euro (A. Anderluh et al., 2017) per minute are considered.
For this work, an average 0.30 Euro per km is considered for a delivery truck and 0.04 Euro for a cargo-trike. It is assumed that a cargo-trike has the same variable costs as a cargo-bike. Furthermore, a driver‘s cost per minute is set to 0.30 Euro. These costs combined will be referred to as routing costs in further sections. Fixed vehicle costs are not included for this work. Service-times per customer are assumed to be 2,5 minutes for a home delivery (Arnold et al., 2018) and 1 minute for a parcel-locker delivery.

4.3 Results

For this section, samples of 6x200 and 1x600 addresses are randomly drawn from a total 2099 addresses of "Neubau" via a random function implemented in Microsoft-Excel and numbered as testing sets 1 to 7, which are needed for determining delivery areas for each hub (see section 3.1). The testing for sections 4.3.2 to 4.3.4 is done using a single test set of 200 addresses ("Run 6") and multiplying each address with 3 (as every address receives 3 parcels (see section 4.2.1)) in order to reach 600 customers, which represents the defined sample size for this thesis. The reason for multiplying addresses is that in reality it is more likely that three different households per address receive one parcel per delivery day instead of one household receiving three parcels. For simplicity reasons it is assumed that all 600 parcels for individual customers can be transported via cargo-trike. In this setting, a demand of 600 parcels represents about 10% of the total daily parcel volume shipped to "Neubau"(Wirtschaftskammer Wien, 2020).

4.3.1 Allocation of delivery areas to hubs

For the underlying case of "Neubau", customers can be assigned to a maximum of 9 possible hub locations for small and big hubs. Distances are obtained via Excel VBA using the Erdoğan VRP-Spreadsheet Solver (Erdoğan, 2017) and Bing Maps Distance Matrix API (Bing Maps Dev Center, 2021).

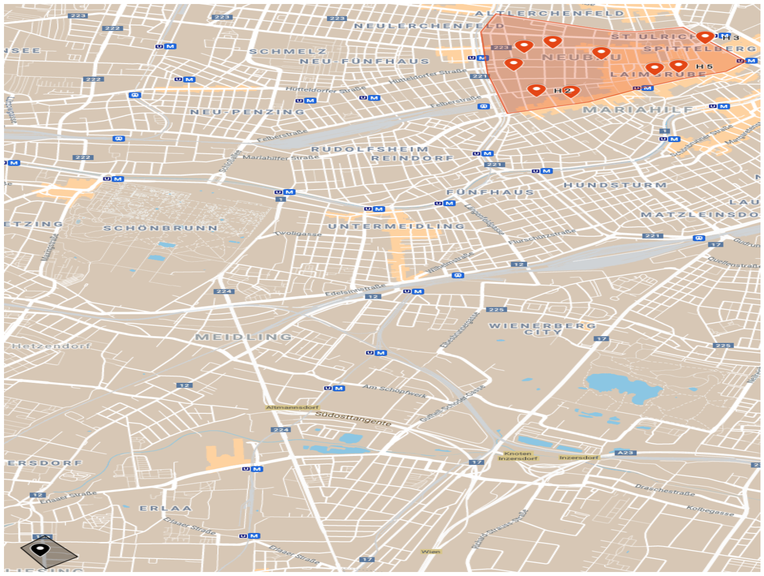


Figure 2: Central depot and "Neubau" (Google Maps, 2021)

Figure 2 illustrates the central depot as well as the area and possible hub locations of "Neubau".

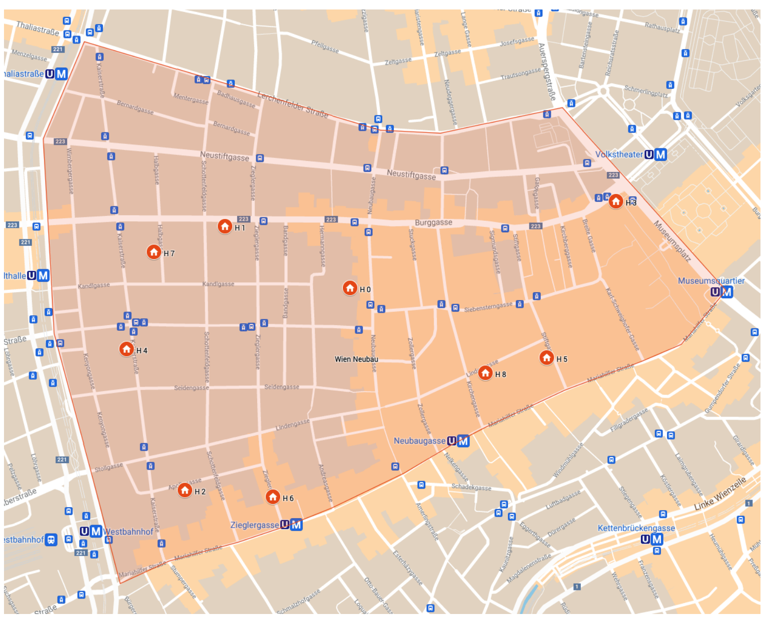


Figure 3: Overview hubs (Google Maps, 2021)

Figure 3 shows the 9 possible hub locations numbered from 0 to 8 as well as the total area of "Neubau".

First, $workload_{min}$ and $workload_{max}$ are set to 0 and 1 in order to not interfere with the objective function depicted in section 3.1, as specific requirements for workloads can increase total distances. It has to be mentioned that due to the VRP-Solver‘s restriction to a maximum of 201 locations (Erdoğan, 2017), only 192 randomly drawn customers of ”Run 1” are used for the testing via the Integer Program (as 9 hubs are also included in the matrix). The residual 8 customers are assigned by randomly doubling the demand of 8 out of the random 192 customers. Numerous repetitions show that deviations in distances and hubs assigned according to different workload ranges are only marginal and do not interfere with final partitions of delivery areas and outcomes in later sections. The IP-Model is solved for both the small and the big hub scenario:

Table 1: Efficiency table small hubs

Nr. of Hubs	**Hubs selected**	**Costs (km)**	**Efficiency gain (%)**	**Avg. workloads (%)**
1	none	0	0	0
2	none	0	0	0
3	none	0	0	0
4	0,1,2,3	112.31	0	100.00
5	0,1,2,3,4	104.46	6.99	80.00
6	0,1,2,3,4,8	97.02	7.12	66.66
7	0,1,2,3,4,6,8	93.62	3.50	57.14
8	0,1,2,3,4,5,6,8	91.76	1.99	50.00
9	0,1,2,3,4,5,6,7,8	90.50	1.37	44.44

Table 1 shows that no less than 4 small hubs are necessary in order to cope with the total demand of 600 parcels. With an increasing number of hubs, the total distance driven decreases as well as the efficiency gains per additional hub and average workloads. As the average workload of a small hub is supposed to be at least about 80 percent, only 4 or 5 hubs with respective average workloads of 100% and 80% are considered. As fluctuations in demand have to be factored into a model, a 4-hub scenario is not practical in a real-world application with designated delivery areas in this case, as each hub on average is fully occupied, which does not allow for any fluctuations in demand to be compensated by another hub. For this reason, a 5-hub scenario is considered for further investigation:

Table 2: Different workload ranges small hubs

Range (workload)	Costs (km)	Hubs selected	Avg. workloads (%)
0-90	105.17	1,2,3,4,8	80.00
50-90	105.51	1,2,3,4,8	80.00
60-90	105.68	0,1,2,3,4	80.00
70-90	106.01	0,1,2,3,4	80.00
80-90	107.72	0,1,2,3,4	80.00

Table 2 shows the number and ID of small hubs selected for each range of workload, as well as respective distances. It can be seen that with increasingly balanced workloads throughout selected hubs the number of hubs selected as well as distances slightly change. The maximum capacity of a single hub is set to 90% of its total capacity. The reason for this is that by randomly drawing and plotting addresses on a map and respective delivery areas, fluctuations in demand can occur that need to be balanced throughout hubs, as a single hub is not allowed to be more than fully occupied at any time.

With an allowed range of a hub between 0% and 90%, hubs 1,2,3,4,8 are selected with a total distance driven of around 105 km. With the highest and smallest possible range of 80%-90%, hubs 0,1,2,3,4 are selected with a total distance driven of around 107 km. It has to be mentioned that these costs refer to the total distance driven from all hubs to all customers, meaning that each customer is visited separately. If the total costs are doubled, the result reflects the total distance driven for "Neubau" comprised of only single tours from a hub to a customer and back. As a result, the total distance driven is about 4-5 km lower for the largest range, while after combining tours for a Vehicle Routing Problem the difference in total distance driven may even be considerably smaller to a degree where it can be neglected. With tighter ranges, hubs can be planned to adapt to future increases in demand. The reason for this is that with balanced workloads throughout hubs, changes in demand do not lead to a single hub being overly occupied while others are still capable of serving more customers. A 5-hub scenario for the underlying case has a maximum overall capacity of 750 parcels per delivery day, while 600 total parcels are considered for the testing. This means that this scenario could possibly, under perfect conditions, turn over 25% more parcels in the future. As distances are only slightly longer for a tighter workload range, while adaptability to increasing future demand is much higher, a determination and partition of delivery areas is attempted to be as evenly distributed as possible in terms of workloads. For further analysis, hubs 0,1,2,3,4 will be considered, as this represents the best possible small hub scenario for tighter workload ranges.

Table 3: Efficiency table big hubs

Nr. of Hubs	Hubs selected	Costs (km)	Efficiency gain (%)	Avg. workloads (%)
1	none	0	0	0
2	3,4	138.17	0	60.00
3	1,2,3	117.94	14.64	40.00
4	0,1,2,3	109.12	7.48	30.00
5	0,1,2,3,8	103.02	5.59	24.00
6	0,1,2,3,4,8	97.02	5.82	20.00
7	0,1,2,3,4,6,8	93.62	3.50	17.14
8	0,1,2,3,4,5,6,8	91.76	1.66	15.00
9	0,1,2,3,4,5,6,7,8	90.50	1.37	13.33

Table 3 shows that no less than 2 big hubs are possible in order to cope with the total demand. With increasing number of hubs, the total distance driven as well as the efficiency gains per additional hub and the average workloads decrease. As the average workload of a big hub is supposed to be about 60 percent, only a 2-hub scenario with selected hubs 3 and 4 is considered for further investigation:

Table 4: Different workload ranges big hubs

Range (workload)	Costs (km)	Hubs selected	Avg. workloads (%)
0-90	138.17	3,4	60.00
60-90	141.39	3,4	60.00
70-90	0	not possible	0
80-90	0	not possible	0

Table 4 highlights the number and ID of big hubs selected for each range of workload as well as respective distances. It can be seen that due to the capacity of a single hub of 500 parcels, the tightest workload range possible is between 60%-90%. As with the 5-hub scenario, the total distance driven between bigger and smaller ranges increases ever so slightly,

while the ability to adapt to future increases in demand is heightened by an even distribution of demand throughout delivery areas. For this reason, partitions of delivery areas will yield even distributions of workloads for hubs 3 and 4 for the big hub scenario.

For the first random draw of 200 addresses ("Run 1"), delivery areas for both small and big hub scenarios are roughly allocated for a primary division by solving the Integer Program depicted above in section 3.1. 4 further runs of 200 randomly drawn addresses ("Runs 2-5") are used to further tune delivery area divisions by plotting all addresses onto a map to realign certain areas between different hubs selected. Following this, another random draw of 200 addresses ("Run 6") is selected for independent further testing in sections 4.3.2-4.3.4. Additionally, a seventh run ("Run 7") with 600 randomly drawn addresses is also drawn in order to highlight the accuracy and reliability of dividing delivery areas based on 200 addresses. This is done in order to determine reliable and accurate delivery area partitions that would deliver good results regardless of the random underlying draws of addresses.
Another way to establish accuracy would be to do all the testing for multiple draws of 200 addresses by optimally assigning them to their respective hubs and services and then performing the second and first tier routing. While this way of testing delivers optimal results and assigning delivery areas to hubs does not due to the nature of fixing delivery areas before drawing and plotting addresses, it is beyond the scope of this work to repeat the 4-step process multiple times. Additionally, the results obtained by assigning delivery areas to hubs are still comparable to one another and deliver good insights on efficiency of hubs and parcel-lockers regarding total driving distances, driving times and overall costs. Furthermore, this method delivers final partitions of delivery areas, while repeated optimal solving via the Integer Program does not. For determining workloads for each hub the demand per address for "Run 1-6" is set to 3 in order to represent 3 customers per address, while for "Run 7" it is set to 1 (see section 4.2.1).

Table 5: Delivery areas small hubs

Hub	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Average
0	78.00	78.00	84.00	88.00	90.00	84.00	82.00	83.43
1	78.00	82.00	72.00	100.00	78.00	84.00	76.00	81.43
2	80.00	80.00	88.00	62.00	62.00	88.00	82.66	77.53
3	74.00	84.00	80.00	86.00	76.00	74.00	80.00	79.14
4	90.00	76.00	76.00	64.00	74.00	70.00	79.33	75.62

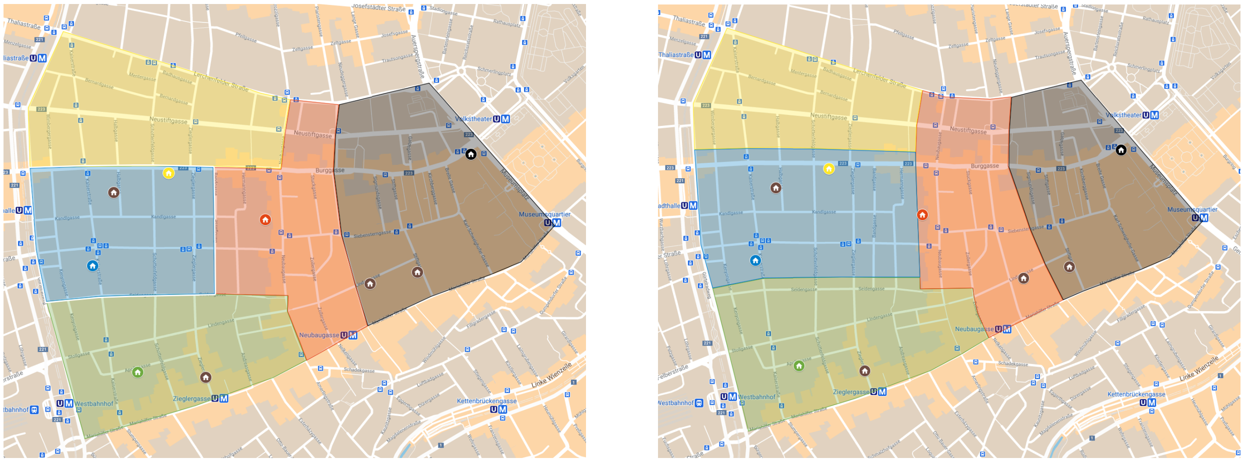
Table 5 exhibits the different workloads of the chosen small hubs throughout the 7 runs. It can be seen that workloads on average vary between 83,43 percent for hub 0 and 75,62 percent for hub 4, which represents a reliable and well-balanced result. Additionally, most results depict a minimum average workload for a single hub of ≥70%, while no hub is ever more than fully occupied.

Table 6: Delivery areas big hubs

Hub	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Average
3	54.60	56.40	60.00	62.40	62.40	55.68	58.80	58.61
4	65.40	63.20	60.00	57.60	57.60	64.20	61.20	61.31

Table 6 points out the different workloads of the chosen big hubs throughout the 7 runs. Workloads on average vary between 58,61 percent for hub 3 and 61,31 percent for hub 4, which represents a very well-balanced result.

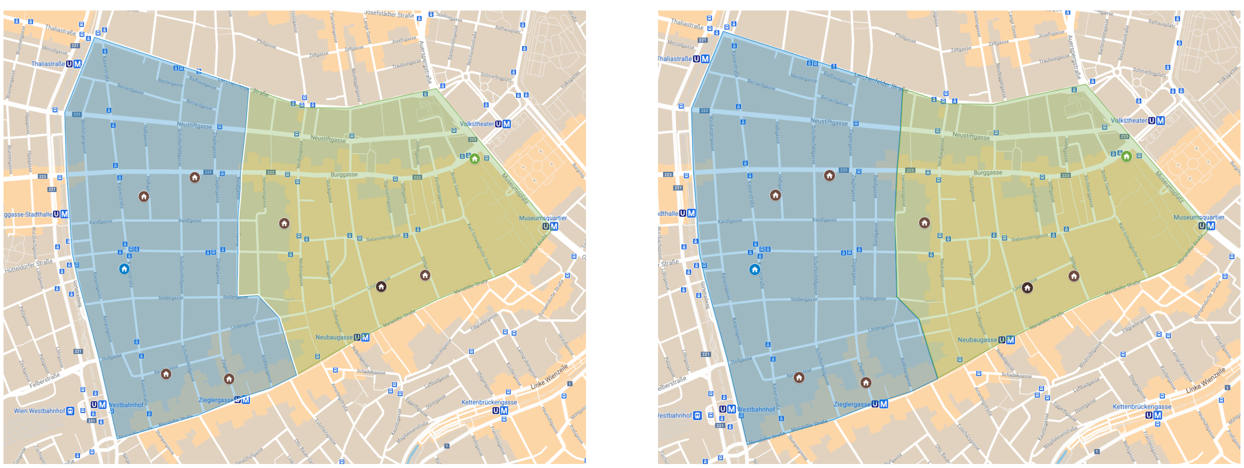
The following tables show the evolvement of hub-partitions as well as "Run 6" and "Run 7" plotted onto a map for both the small and big hub scenario:



(a) First partition (b) Last partition

Figure 4: Evolvement of delivery areas (small hubs) (Google Maps, 2021)

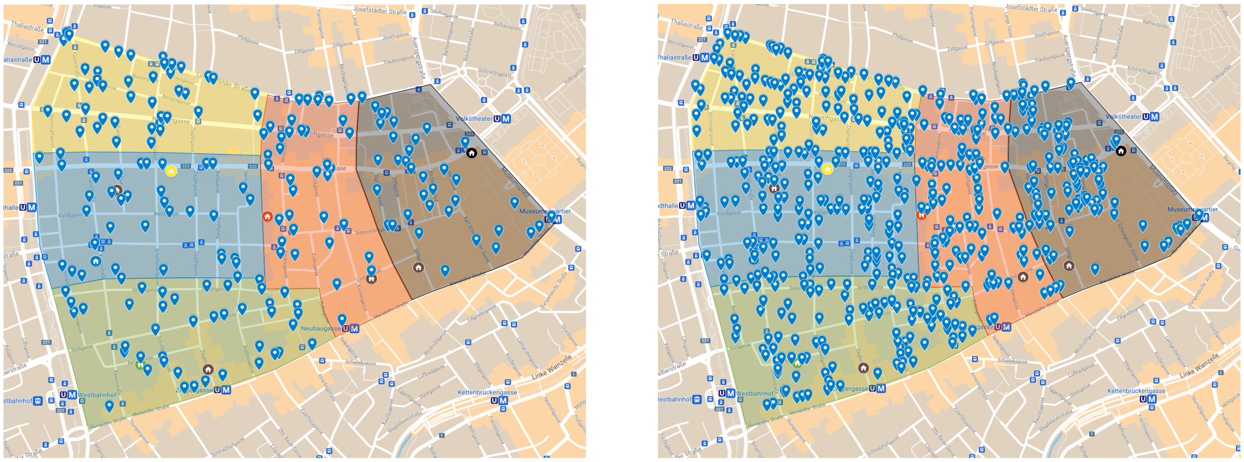
Figure 4 shows the first division of delivery areas after "Run 1" while the fourth and last partition depicts the updated version based on improvements done by plotting a total of a thousand addresses (5x200) to the map and first partition of delivery areas of "Neubau". Selected hubs are represented in the same color-scheme as their respective delivery area.



(a) First partition (b) Last partition

Figure 5: Evolvement of delivery areas (big hubs) (Google Maps, 2021)

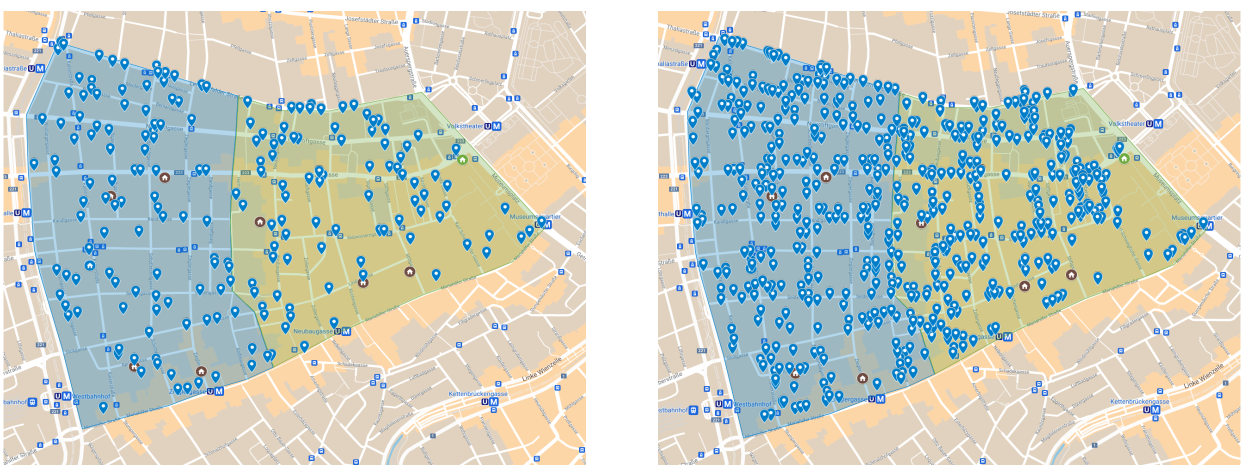
Figure 5 shows the first division of delivery areas after "Run 1" while the second and last partition depicts the updated version based on improvements done by plotting a total of a thousand addresses (5x200) to the map and first partition of "Neubau". Selected hubs 3 and 4 are represented in the same color-scheme as their respective delivery area.



(a) 200 addresses (b) 600 addresses

Figure 6: Delivery areas small hubs (Google Maps, 2021)

Figure 6 shows "Run 6" and "Run 7" plotted onto small hub delivery areas. It can be seen that 600 different addresses with a demand of 1 each cover the area more evenly compared to 200 addresses with a demand of 3 each. The average workloads per hub are very evenly distributed for both runs, indicating that randomly drawing 200 addresses results in reliable partitions of delivery areas.



(a) 200 addresses (b) 600 addresses

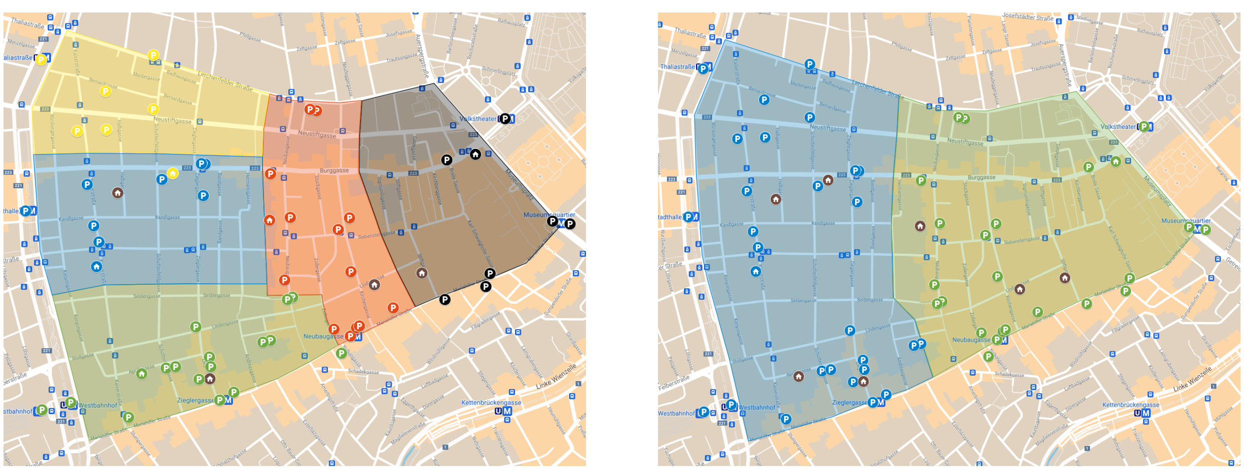
Figure 7: Delivery areas big hubs (Google Maps, 2021)

Figure 7 displays "Run 6" and "Run 7" plotted onto big hub delivery areas. While "Run 7" covers the area in a more balanced fashion, the average workloads per hub are about the same for both runs.

4.3.2 Allocation of customers to lockers

As briefly mentioned in section 4.3.1, 200 randomly drawn addresses ("Run 6") are multiplied by 3 each in order to get 600 individual customer addresses with a respective demand of 1 parcel each. This means that for each address there exist two copies of this address. Out of these 600 addresses, 180 are randomly drawn using a function implemented in Microsoft Excel. This represents a 30% demand probability of a customer for a parcel-locker service. The 420 remaining customers require traditional home delivery. For this, 50 possible parcel-locker locations in and close to the area of "Neubau" are chosen. These locations consist of supermarkets from common chains like Spar, Billa, Hofer etc. as well as some metro-stations, banks and postal offices.

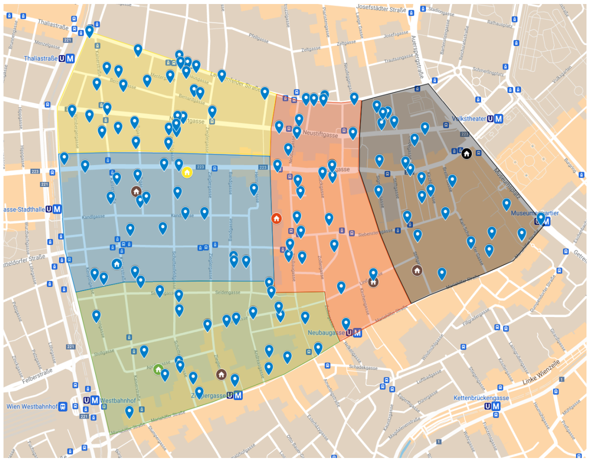
For the testing, different values of $workload_{min}$ of the Integer Program presented in section 3.2 are considered in order to investigate the changes in total distance driven, total number of lockers opened and total number of customers assigned to lockers. $workload_{min}$ is therefore set to either 0.01, 0.50 or 0.70, meaning that a single parcel-locker must be occupied by at least 1,10 or 14 customers (parcels) in order to be opened. $workload_{max}$ is kept at 1.00 for the entire testing.
After completing assignments for every workload scenario and every delivery area of a hub, assignments are included in a Capacitated Vehicle Routing Problem (CVRP) for the second and first tier routing.



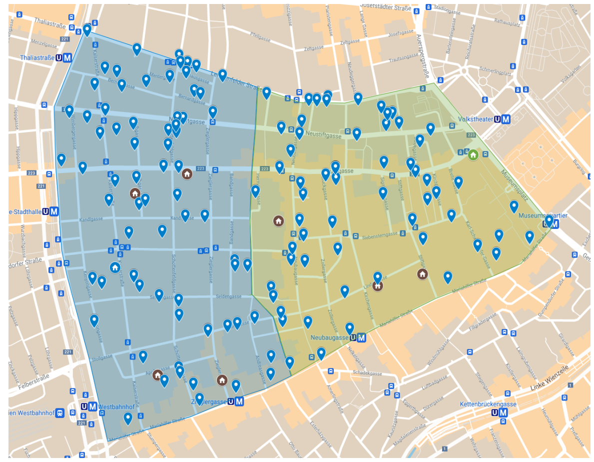
(a) Small hubs (b) Big hubs

Figure 8: Lockers (Google Maps, 2021)

Figure 8 shows the assignment of parcel-lockers to their respective delivery area. Parcel-lockers are colored the same as the delivery area they are assigned to. It can be seen that for both scenarios most of the delivery area is likely to be covered by at least one parcel-locker using a reasonable covering radius.



(a) Small hubs



(b) Big hubs

Figure 9: Locker demands (Google Maps, 2021)

Figure 9 depicts the randomly drawn 180 addresses for the small and big hub scenario drawn from the 200x3 addresses of "Run 6". Locker demands appear to be evenly distributed, indicating that the draw is accurately randomized.

4.3.3 Second tier routing

The routing for the second tier is first done for a home delivery only scenario, where no assignment to parcel-lockers is performed. Following this, scenarios with a combination of home and parcel-locker deliveries are performed according to different minimum workload settings for lockers (see section 4.3.2).

In total, 7 different routings are done for each delivery area for both the small and the big hub scenario, resulting in a total of 63 different vehicle routings for the second tier:

1. Only home deliveries, where all customers are served by cargo-trikes.

2.-4. Home deliveries and parcel-locker service with min. workload of >0%/≥50%/≥70%, where all customers and parcel-lockers are served by cargo-trikes.

5.-7. Home deliveries and parcel-locker service with min. workload of >0%/≥50%/≥70%, but lockers are not served by cargo-trikes, as this is done by first tier vehicles for this instance.

As a Capacitated Vehicle Routing Problem (CVRP) is an NP-Hard problem (Toth & Vigo, 2002), a sample run with 100 customers is performed in order to get an idea of the performance and run-time of the model in Gurobi (see section 3.3). After 1 hour, the gap to an optimal solution is at 8,22% and after 20 hours at 7,30%, showing that solving a problem this size to optimality can take up to several days, which is not suitable for numerous runs that need to be performed for each delivery area.
As small hub scenarios already consist of 120-140 customers and multiple lockers for each hub, it is clear that an IP-Model is not a suitable method for this kind of problem size. For this reason, the VRP Spreadsheet Solver for Excel by Güneş Erdoğan is used to test all the routing scenarios (Erdoğan, 2017).

The VRP Spreadhseet Solver is able to solve problems of up to 200 customers within reasonable amounts of time (under 1 hour for most of the testing done for this work). The solver uses a variant of the Adaptive Large Neighborhood Search (ALNS) Algorithm embedded in the Excel Visual Basic Application (VBA). The Spreadsheet Solver performs very well for up to 100 customers and still relatively well for larger instances, with an average gap of 2,87% to the best known solution with an instance of 199 customers (Erdoğan, 2017).
The Spreadsheet Solver provides a complete vehicle routing interface with the possibility of geocoding addresses, calculating real-world distances and speeds as well as setting time-window and vehicle constraints (Erdoğan, 2017).
As the solver‘s capacity is limited to 200 customers and editing the VBA-code to allow for larger instances is not recommended due to a steady decline in performance, the delivery areas for the big hub scenario have to be divided into 4 smaller areas in order to be solvable:

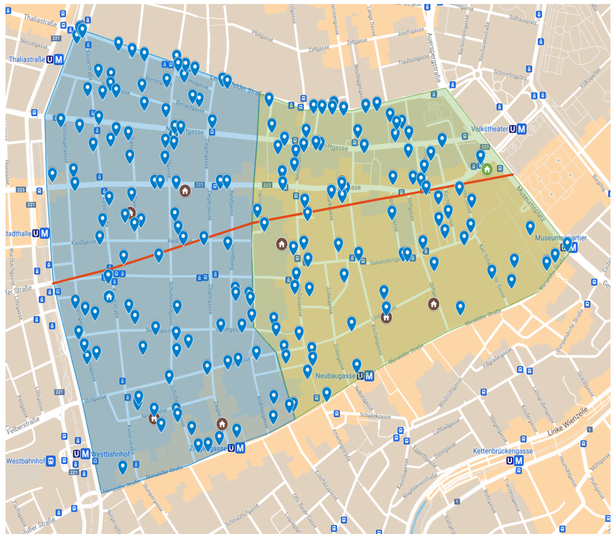


Figure 10: Separation of delivery areas for big hub scenario (Google Maps, 2021)

Figure 10 shows the division of areas of hub 3 and 4 into 2 smaller areas each. The line of division is drawn near the respective micro-hubs 3 and 4 in order to provide similar driving distances from the depot to points located in a respective division.

After performing the routing task for 63 times in total, the following results for the second tier are achieved:

Table 7: Results second tier small hubs

Scenario	**0**	**1**	**2**	**3**	**4**	**$\sum$km**	**$\sum$minutes**	**$\sum$stops**	**$\sum$lockers (customers)**
C only	12.30	10.16	12.42	8.38	10.15	53.41	216	600	0(0)
C + L (≥0)	13.02	8.45	13.87	9.08	10.50	54.92	219	467	27(160)
C + L (>50)	12.06	8.87	11.07	8.40	8.98	49.38	194	473	10(137)
C + L (>70)	12.06	7.97	11.07	8.40	8.98	48.48	191	479	7(128)
C w.o. L (≥0)	9.29	7.27	10.67	7.97	9.00	44.20	174	440	0(0)
C w.o. L (>50)	9.29	7.27	11.04	7.92	9.08	44.60	176	463	0(0)
C w.o. L (>70)	9.50	7.27	12.04	7.92	9.08	45.81	181	472	0(0)

Table 7 depicts the results for the second tier routing for the small hub scenario. The column on the far left shows 7 different routing scenarios for each hub, where C stands for customers (home delivery) and L for parcel-lockers (locker delivery), with their respective minimum workload (%) shown in brackets. The w.o. (without) in the last three scenarios means that cargo-trikes do not deliver to lockers for the second tier routing, as this is later

done by first tier vehicles (see section 4.3.5). Columns with numbers 0 to 4 belong to the respective hub and show the total distance driven within that hub. Furthermore, columns with the total amount of kilometers driven, minutes spent driving and number of stops are shown. The far-right column highlights the total number of parcel-lockers that are opened for each scenario as well as the total number of customers assigned to them. As the minimum workload per locker increases, the total number of lockers and customers assigned decreases.

Table 8: Results second tier big hubs

Scenario	**3**	**4**	**$\sum$km**	**$\sum$minutes**	**$\sum$stops**	**$\sum$lockers (customers)**
Customers only	31.14	27.30	58.44	236	600	0(0)
Customers + locker ≥0	30.98	29.72	60.70	243	470	29(159)
Customers + locker >50	29.99	26.86	56.85	229	472	11(139)
Customers + locker >70	32.99	26.81	59.80	239	482	8(126)
Customers w.o. locker ≥0	28.70	24.32	53.02	212	441	0(0)
Customers w.o. locker >50	28.68	24.94	53.62	214	461	0(0)
Customers w.o. locker >70	31.08	24.94	56.02	226	474	0(0)

Table 8 displays the results for the second tier routing for the big hub scenario. The structure is the same as with the small hub case, but now only two hubs are built. The total number of lockers opened and customers assigned decreases with increasing minimum workloads.

4.3.4 First tier routing

For the first tier routing, the Erdoğan Spreadsheet Solver (Erdoğan, 2017) is used in the same manner as for the second tier with hubs and parcel-lockers now being the customer set. In total, 4 different routing scenarios are done for each the small and big hub scenario, resulting in a total of 8 runs for the first tier:

1. Delivery with trucks to hubs.

2.-4. Delivery with trucks to hubs and parcel-lockers based on results achieved in the second-tier routing process for a minimum locker workload of >0%/≥50%/≥70%.

After performing all 8 routing tasks, the following results are obtained:

Table 9: Results first tier small hubs

Scenario	**$\sum$km**	**$\sum$minutes**	**$\sum$stops**	**$\sum$lockers opened (customers)**
Hubs only	41.29	83	5	0(0)
Hubs + locker >0	49.88	100	32	27(160)
Hubs + locker ≥50	44.82	90	15	10(137)
Hubs + locker ≥70	43.28	87	12	7(128)

Table 9 displays the results obtained for the first tier routing for small hubs showing the total distance driven, time spent driving, number of parcel-lockers opened and customers served. Scenarios 2-4 include the customer to locker assignment done within the second tier routing, where trucks deliver to both hubs and lockers based on different workloads.

Table 10: Results first tier big hubs

Scenario	**$\sum$km**	**$\sum$minutes**	**$\sum$stops**	**$\sum$lockers opened (customers)**
Hubs only	41.25	83	2	0(0)
Hubs + locker >0	50.34	101	31	29(159)
Hubs + locker ≥50	44.41	89	13	11(139)
Hubs + locker ≥70	43.03	86	10	8(126)

Table 10 shows the results obtained for the first tier routing with big hubs with the same structure as *Table 9*.

4.3.5 Overall results

As the first tier routing is the last step of the proposed 4-step process, results of the first and second tier routing are now combined in order to receive complete results.

Table 11: Complete results for small hubs without service costs

Scenario	$\sum$**km**	$\sum$**minutes**	$\sum$**stops**	$\sum$**lockers (customers)**	$\sum$**costs**
(H) + C	94.70	299	605	0(0)	105
(H) + C + L >0	96.21	302	472	27(160)	106
(H) + C + L ≥50	90.67	277	478	10(137)	98
(H) + C + L ≥70	89.77	274	484	7(128)	97
(H + L >0) + C	94.08	274	472	27(160)	99
(H + L ≥50) + C	89.42	266	478	10(137)	96
(H + L ≥70) + C	89.09	268	484	7(128)	96

Table 11 exhibits the overall results for the small hub scenario achieved by the 4-step solution process. In the far-left column, the different routing scenarios are shown with H being an abbreviation for hubs, C for customers (home delivery) and L for parcel-lockers (locker delivery) with an additional indicator of a locker‘s minimum workload in percent. All parts that are bracketed belong to the first tier routing done with delivery trucks departing from a central depot. Everything outside the brackets refers to the second tier routing done by cargo-trikes departing from hubs. The other columns show the total driving distance, the total time spent driving, the total number of stops, lockers opened and customers assigned as well as overall routing costs. The savings achieved between a customer (home delivery) only scenario and the best locker scenario (home delivery and locker delivery combined) are 8,57% in terms of total routing costs and 5,92% regarding total distance driven.

The calculation of total routing costs is done by multiplying the total distances and times for the second and first tier with the respective variable costs for vehicles and workers (see section 4.2.5): $d_{second} * 0,04 + t_{second} * 0,30 + d_{first} * 0,30 + t_{first} * 0,30$

Table 12: Complete results for big hubs without service costs

Scenario	$\sum$**km**	$\sum$**minutes**	$\sum$**stops**	$\sum$**lockers (customers)**	$\sum$ **costs**
(H) + C	99.69	319	602	0(0)	110
(H) + C + L >0	101.95	326	472	29(159)	113
(H) + C +L ≥50	98.10	312	474	11(139)	109
(H) + C + L ≥70	101.05	322	484	8(126)	112
(H + L >0) + C	103.36	313	472	29(159)	112
(H + L ≥50) + C	98.03	303	474	11(139)	107
(H + L ≥70) + C	99.05	312	484	8(126)	109

Table 12 displays the complete results for the big hub scenario. The structure is the same as with *Table 11.* The savings achieved between a customer (home delivery) only scenario and the best locker scenario (home delivery and locker delivery combined) are 2,72% in terms of total routing costs and 1,66% regarding total distance driven.
The routing costs for the best big hub scenario are about 11,46% higher compared to the best small-hub scenario. The total distance driven increased by about 10,03% for the big hubs.

4.3.6 Comparison of total costs

While section 4.3.5 displays and explains costs for the routing (distance- and time- related costs), this section also incorporates a service-time per customer, which is assumed to be 2,5 minutes for a home delivery (Arnold et al., 2018) and 1 minute for a parcel-locker delivery. Times spent loading/unloading at the central depot and hubs are omitted.

Table 13: Comparison of overall costs small hubs

Scenario	$\sum$**routing costs**	$\sum$**service costs**	$\sum$**total costs**
(H) + C	105	450	555
(H) + C + L >0	106	378	484
(H) + C +L $\geq$50	98	388	486
(H) + C + L $\geq$70	97	392	489
(H + L >0) + C	99	378	477
(H + L $\geq$50) + C	96	388	484
(H + L $\geq$70) + C	96	392	488

Table 13 displays the respective scenario, the total routing (distance- and driving time-related) and service costs as well as total overall costs for the small hub scenario. As can be seen, the best overall costs are achieved by serving hubs and parcel-lockers with more than 0% occupation for the first tier and customers at home for the second. This scenario is about 5,71% cheaper in terms of total routing costs compared to the customer (home delivery) only scenario, while respective service costs are reduced by about 16,00%, resulting in a total overall cost decrease of around 14,05%. If the division of savings is observed alone, it can be seen that up to around 92,31% of the savings generated are the result of savings realized by a reduction in service-time.

Table 14: Comparison of overall costs big hubs

Scenario	**$\sum$routing costs**	**$\sum$service costs**	**$\sum$total costs**
(H) + C	111	450	561
(H) + C + L >0	113	378	491
(H) + C +L $\geq$50	109	387	496
(H) + C + L $\geq$70	112	393	505
(H + L >0) + C	112	378	490
(H + L $\geq$50) + C	107	387	494
(H + L $\geq$70) + C	109	393	502

Table 14 depicts the respective scenario, the total routing and service costs as well as total overall costs for the big hub scenario. The best overall costs are achieved by serving hubs and parcel-lockers with more than 0% occupation for the first tier and customers for the second. This scenario is about 0,90% more expensive in terms of total routing costs compared to the customer (home delivery) only scenario, while respective service costs are reduced by about 16,00%, resulting in a total overall cost decrease of around 12,66%. Up to 100% of the total savings generated are the result of savings realized by a reduction in service-time.

5 A measure for parcel-locker efficiency

The best scenario in terms of total costs for both the big and small hub scenario is a first tier delivery via trucks to hubs and parcel-lockers with an average workload of >0% and a second tier delivery via cargo-trikes to customers at home. A best scenario with a second tier delivery via cargo-trikes to parcel-lockers and customers is only about 1-7 Euros more expensive. As the trend of using environmentally friendly delivery methods for the second tier favors the use of cargo-trikes for delivering both to customers at home as well as lockers, a first tier delivery via trucks to hubs and a second tier delivery via cargo-trikes to lockers and customers is selected as a best option. Additionally, time spent searching for parking lots is not considered for this work, which would most likely heighten driving times and costs for a first tier delivery via trucks to lockers to a degree where this option would not even be considered the cheapest.

For this section, costs consisting of variable routing costs and service times are considered. Fixed vehicle costs are assumed to be identical between scenarios as the difference in service time savings does not result in a reduced number of used vehicles for the first and second tier for the underlying case and assumptions.
As section 4.3.6 shows, the major cost-driver for the two-tier delivery process is not the total distance driven nor the total time spent driving. There are only minor changes between different scenarios, which do not feasibly recommend an installment of costly parcel-lockers. It must be stated that the efficiency gains realized by lockers in terms of total routing costs might be considerably higher in more rural areas with larger distances between customers, but for the underlying case concerning a densely populated urban area with short driving distances between addresses, routing costs in general do not appear to influence total costs significantly.
In this context, the major cost-driver that can be identified is the service-time per customer, which makes up between 92,31% and 100% of total savings achieved between a home delivery only and a best scenario of combined delivery to lockers and homes (see section 4.3.6). This service-time can be as high as 2,5 minutes per customer (Arnold et al., 2018), which resembles major increments in total workforce costs when multiplied by 600 customers. Additionally, each customer that is supposed to be delivered to at his/her home represents a potential failed delivery, which means that a parcel cannot be delivered to a customer due to his/her absence and has to be transported to a parcel-locker nearby or back to the depot in order to be delivered on another day. Arnold et al. (2018) assume an 11 percent chance of a failed

delivery occurring for each customer, which, in its simplest form, resembles a delivery to 666 customers instead of 600 in terms of delivery costs. As savings in variable vehicle costs per km for a cargo-trike are only marginal (0,04 Euro/km), they are excluded from the following formula:

$$\frac{\delta_{travel-t.} + \delta_{service-t.} * \sum C_L * (1 + failed_{delivery})}{\sum Locker} \tag{1}$$

Formula (1) first takes into account the savings in total driving time between a home delivery only and a combined scenario. Then, the difference between service-times for a customer and a locker are multiplied by the total amount of customers assigned to lockers plus an additional percentage for saved failed deliveries. It is assumed that a customer that is served by a locker is always able to be served regarding locker-size-mixes. The sum of all terms is then divided by the total number of lockers built in order to receive the total average number of minutes saved per day by installing one locker.

If a service-time per customer that demands a parcel-locker delivery is assumed to be 1 minute, the total savings of a single customer would be 1,665 minutes or 0.4995 Euros ($\frac{(2,5-1,0)*(1*1,11)}{1}$). A service-time of 1 minute per customer served via a parcel-locker seems reasonable, as a locker bank with a capacity of 20 parcels can be expected to be filled within 20 minutes.

If formula (1) is applied to the results of section 4.3.5 for a first tier delivery to hubs and a second tier delivery to parcel-lockers and customers at home, the following savings for the small and big hub scenarios can be achieved:

Table 15: Efficiency of parcel-lockers small hubs

Workload L (%)	**$\sum$ lockers (customers)**	**savings/locker/day (min)**	**$\sum$savings/day (min)**	**$\sum$savings/day (€)**
> 0	27(160)	9.76	263.40	79.02
≥ 50	10(137)	25.01	250.11	75.03
≥ 70	7(128)	34.02	238.12	71.44

Table 15 displays the total amount of parcel-lockers opened and customers assigned as well as total savings per locker per day (time), total savings for all lockers per day (time) and

total savings for all lockers per day (Euros) for each of the three different workload scenarios.

Table 16: Efficiency of parcel-lockers big hubs

Workload L (%)	$\sum$ lockers (customers)	savings/ locker/ day (min)	$\sum$savings/ day (min)	$\sum$savings/day (€)
> 0	29(159)	8.89	257.74	77.32
≥ 50	11(139)	21.68	238.44	71.53
≥ 70	8(126)	25.85	206.79	62.04

Table 16 shows results for the big hub scenario in the same fashion as *Table 15*.

Although formula (1) delivers very interesting results and insights, it does not show overall cost-efficiency of a number of lockers as a total compared to a scenario without lockers installed. For a more wholistic approach, possible acquisition, maintenance and rental costs have to be considered as well as total delivery days per year and total life-span of a locker:

$$\frac{(\delta_{travel-t.} + \delta_{service-t.} * \sum C_L * (1 + failed_{delivery})) * cost_{minute}}{\sum Locker * (\frac{AC+MC*L_{span}+rent*L_{span}}{deliverydays*L_{span}})} > 1 \tag{2}$$

Equation (2) states if a certain number of parcel-lockers is cheaper in terms of total costs compared to a scenario without parcel-lockers implemented. It calculates the total savings in travel and service time in terms of costs and divides it by the number of lockers built multiplied by the total costs of a single locker per delivery day. AC represents acquisition costs, MC maintenance costs, L_{span} the life-span of a locker, $rent$ the total rent per year needed to be paid to owners of locations where parcel-lockers are implemented and $deliverydays$ the total number of delivery days per year. If the quotient is >1, the total number of lockers built under assumption of different costs is beneficial. On the other hand, maximum acquisition, maintenance and rental costs can be calculated for a specific number of lockers in order to still be profitable.

If a certain discount for a locker service is assumed, the formula would look like this:

$$\frac{(\delta_{travel-t.} + \delta_{service-t.} * \sum C_L * (1 + failed_{delivery})) * cost_{minute} + \sum C_L * \delta_{revenue}}{\sum Locker * (\frac{AC+MC*L_{span}+rent*L_{span}}{deliverydays*L_{span}})} > 1 \tag{3}$$

$\delta_{revenue}$ denotes the difference between the revenue per parcel-locker delivery minus revenue per home delivery.

A more general approach could be formulated like this:

$$\frac{(\delta_{travel-t.} + \delta_{service-t.} * \sum_{j \in N} b_j * w_j * (1 + failed_{delivery})) * cost_{minute} + \sum_{j \in N} b_j * w_j * \delta_{revenue}}{\sum Locker * (\frac{AC + MC * L_{span} + rent * L_{span}}{deliverydays * L_{span}})} > 1 \tag{4}$$

$\sum_{j \in N} b_j * w_j$ generalizes the problem by summing over all capacities times workloads of all lockers.

6 Practical implications and recommendations

6.1 Hub sizes

The results of section 4.3.5 show that the efficiency gain in terms of total routing costs for the best locker scenario (home delivery and locker delivery combined) compared to the customer (home delivery) only scenario is slightly larger for the small hub scenario compared to the big hub with the best gain of around 5,92% vs. 1,66%. The reason for this could be that with increasing average driving distances from a hub to the first customer of a tour and from the last customer of the tour back to the hub the efficiency gain regarding total distance and driving time saved by lockers becomes smaller relatively compared to the overall bigger distances and times, at least for the underlying case with 200x3 addresses. The total distance driven for the best big hub scenario is about 10% longer compared to the best small hub scenario. Although a small hub scenario reduces the total routing costs by about 5%-13%, depending on the scenario, the total overall costs including service-times are only reduced by about 1%-3% compared to a big hub scenario.

If 280 delivery days are considered, the best scenario for small hubs in terms of total costs yield total annual savings of around 3640 Euros ((490-477)*280) compared to the best big hub scenario. In the grand scheme of things, these savings are not enough to outweigh the additional costs of installing 3 extra hubs. It must be stated that a hub with a capacity of 500 parcels requires more area and therefore comes at a higher cost, but marginal costs decrease with increasing capacity, as both small and big hubs require some of the same compartments like charging and storage areas as well as room for staff etc. This points at economies of scale to be realized by bigger hubs. This means that five small hubs are not 2,5 times more expensive compared to two big hubs, but the savings realized by small hubs are still not able to outweigh the added costs of installing them.

6.2 Parcel-locker efficiency

As it is pointed out in section 5, parcel-locker efficiency is quite similar between the small and big hub scenario in terms of total savings per day, as deviations are only caused by the pre-assignment of parcel-lockers to different delivery areas for the small and big hub scenario, which can have minor impacts on the respective locker/customer combination at the boundaries of delivery areas (see section 4.3.1). A minimum workload of a locker of >0%

yields the best total overall savings per day. If only the average savings of a single locker are considered, workloads $\geq$50% deliver far larger savings compared to the first scenario. This fact points to a trade-off between maximizing the total amount of customers assigned to lockers and the cost-efficiency of a single locker. With increasing minimum workloads, a single locker yields larger savings, but potential customers are declined due to this restriction, as some lockers are not sufficiently occupied. For the underlying case of "Neubau", the preset maximum covering radius of 600 meters only excluded a few customers from being assigned to a locker, showing that this measure was accurately set and did not affect the total results in a substantial way.

If, for instance, a workload of $\geq$70% per locker is considered for the small hub scenario, a single locker saves about 34 minutes of work per day, resulting in savings of about 10 Euros. If a total of 280 delivery days per year are assumed, this results in savings of about 2800 Euros/year. This sum compared to the acquisition and maintenance costs of a single locker bank shows that only higher workloads for parcel-lockers could yield potential savings for this particular scenario. A parcel-locker with a capacity of 20 parcels comes at about 4300 Euros plus additional installation costs and service and support starting from 900 Euros a year upwards (possibly including multiple lockers). At this price, the control unit is represented as a PIN-Pad, where customers either receive a PIN-Code via an App to unlock their modules or they can scan a respective locker‘s QR-Code to receive their parcels (Cleveron, 2021). Although it is hard to find prices for many locker manufacturers, it is safe to say that more sophisticated and rigid locker banks can easily come at twice the price or more. It must be added that the amounts of savings per locker are greatly influenced by the difference in service times between a home and a parcel-locker delivery. Any potential savings on the parcel-locker side could yield even larger total savings. Additionally, higher failed delivery rates would result in even higher savings achieved per locker. Song et al. (2009) conclude that the percentage of failed first deliveries can be as high as 60%.

For a practical illustration the price of a Cleveron locker bank with 4300 Euros is assumed. Additionally, installation costs (included in aquisition costs) of 200 Euros and maintenance costs of 100 Euros per year per locker bank are assumed. The life-span is set to 10 years (KEBA, 2021) and rental costs for placing a locker inside a supermarket etc. are assumed to be 500 Euros per year. If all variables are put into formula (3) of section 5, the maximum possible discount for a parcel-locker service in order to still be profitable can be calculated for the preferred big hub scenario with a first tier delivery to hubs with trucks and a second tier delivery with cargo-trikes to lockers and customers‘ homes:

Table 17: Possible discount big hubs

Workload L (%)	$\sum$ **lockers (customers)**	**discount (€)**
> 0	29(159)	0.20
≥ 50	11(139)	-0.22
≥ 70	8(126)	-0.25

Table 17 displays the maximum discount per parcel possible for a parcel-locker service compared to an attended home delivery. It can be seen that installing lockers that are occupied by 1 parcel or more does not result in a discount but a surcharge of 0,20 Euro per parcel. As minimum workload requirements per locker increase, possible discounts for a locker service can be granted. The reason for this is that the number of customers lost by raising minimum workloads per locker decreases at a slower rate compared to the number of lockers that are not opened due to workload restrictions.

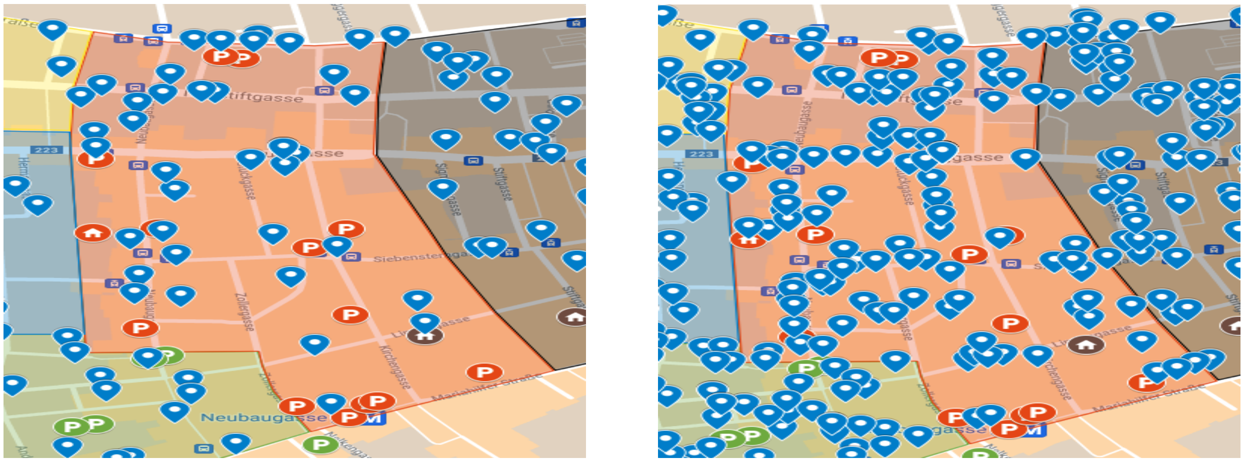
6.3 Another scenario

If, for example, an apportionment potential of 30 percent of the total parcel shipment volume to cargo-bikes would be assumed (Bogdanski & Cailliau, 2020), the number of parcels per address would be reduced to about 1 parcel instead of 3,which equals 1 parcel per household per address (see section 4.2.1). This would result in a random draw of 600 addresses instead of 200 addresses multiplied by 3. It must be mentioned that Bogdanski & Cailliau (2020) consider a cargo-bicycle for their study. The apportionment potential of using cargo-tricycles is likely to be higher. Additionally, it can be expected that with the steadily increasing e-commerce market and its small average parcel dimensions the apportionment potential will grow in the next few years (Bogdanski & Cailliau, 2020).

To test the effect of an exemplary apportionment potential of around 30% of the total parcel shipment volume to cargo-trikes for the case of "Neubau", 600 different addresses with a demand of 1 each ("Run 7") are considered for hub 0 and the small hub scenario in order to give implications on the possible changes if demand per address is decreased. "Run 6" allocated 126 customers (42 different addresses x 3) to hub 0, whereas "Run 7" assigned 123

customers (123 different addresses), which is about the same amount of total customers allocated. Results show that, although less customers were allocated to parcel-lockers for hub 0 in "Run 7" compared to "Run 6" (due to the random draw of parcel-locker customers from the basic population of 200x3 and 600 customers), the efficiency-gain of parcel-lockers in terms of total distance traveled compared to a scenario with no lockers used is still slightly better compared to "Run 6". Additionally, the total distance covered increased between 11,90% and 25,69% for "Run 7", depending on the underlying scenario.
This comes as no surprise, as an increasing number of different addresses is expected to increase the total distance driven, especially as the underlying sample size of 42 different addresses for "Run 6" does not cover the delivery area of hub 0 as evenly as the 123 addresses of "Run 7".The marginal increase in total distance driven for an additional address is therefore assumed to be decreasing with the number of total addresses for the same area. Furthermore, the fact that parcel-locker efficiency regarding total distance driven is higher with "Run 7" compared to "Run 6" can be attributed to the fact that single-customer addresses can be more cost-efficiently assigned to parcel-lockers than multiple customers at one address, as it is unlikely that all customers of one address are assigned to lockers, which therefore does not result in a full allocation of an address to a locker, but in a stop at the respective address and an additional stop at a parcel-locker for most addresses.

It is therefore assumed that with decreasing number of customers per address parcel-locker efficiency increases while total distance driven increases with the total number of different addresses for the same area. Although this realization is very interesting, it is not very decisive when it comes to total parcel-locker efficiency, as the majority of gained efficiency realized by a parcel-locker can be attributed to the savings concerning service-time per customer, which is the same for every customer assigned.



(a) Hub 0 "Run 6" (b) Hub 0 "Run 7"

Figure 11: 200x3 and 600 addresses (Google Maps, 2021)

Figure 11 illustrates the difference in total coverage between 200 and 600 different addresses for the delivery area of hub 0. The total distance driven varies between 12,30 km and 13,02 km for "Run 6" and between 14,19 km and 15,46 km for "Run 7", depending on the scenario.

6.4 Recommendation for "Neubau"

The best combination in terms of minimal total costs is a scenario with less but bigger hubs combined with decently occupied parcel-lockers. It is therefore necessary to reassign some customers from a parcel-locker to a home delivery service due to a maximum convenient covering radius as well as the above mentioned trade-off between total number of customers assigned to lockers and total number of lockers built.

A concrete recommendation (concerning all assumptions made) for the underlying case of "Neubau" would be to install two big hubs and parcel-lockers with an average workload of at least 50 percent. Although the transport of parcels to lockers via trucks instead of cargo-trikes is slightly cheaper for the underlying case, the second tier delivery with cargo-trikes should also include the delivery to parcel-lockers. Reasons for this are that the differences in costs are marginal and from a greenhouse emissions point of view, the exclusive delivery via environmentally friendly delivery methods within "Neubau" does not contribute to further pollution and significant increases in congestion of the inner city of Vienna.

7 Limitations of this work

As the two delivery areas of the big hub scenario had to be divided into a total of 4 delivery areas in order for the problem to be solvable with the Erdoğan VRP-Solver, the results cannot unrestrictedly be compared to the 5-hub scenario.

As parcel-lockers and customers were assigned to a specific hub based on the delivery area that was determined beforehand, meaning that there is no interconnection between parcel-lockers of one delivery area and potentially suitable customers of another area, assignments of customers vary throughout hub scenarios due to the nature of assigning hubs, customers and parcel-lockers to designated delivery areas.

For cargo-trikes as well as trucks, only car-routes are considered using Bing Maps Distance Matrix API (Bing Maps Dev Center, 2021). The reason for this is the lack of a bike-mode within the Bing Maps application. It is possible that with the inclusion of bike-lanes, which are able to shorten distances between customers if running against one-ways, the total distance driven by cargo-tricycles becomes even smaller.

This work does not assume either stochastic demands within certain delivery areas nor does it allocate more than one parcel per household. In reality, a parcel-distribution curve for each customer would resemble the demand in a better way, but is beyond the scope of this work.

As briefly mentioned in section 4.3.1, the division of hubs does not deliver customer/hub allocations that are optimally solved. The reason for this is that delivery areas are assigned and further fixed based on multiple runs in order to guarantee a decent workload for each hub for each random draw. Drawing and optimally assigning customers to hubs for multiple 4-step processes would be an even more accurate measurement, but would result in a lot more testing and no consistent division of delivery areas.

Furthermore, time dependent travel-times due to real-time traffic are omitted for this work, as the distance matrices for all the delivery areas were extracted at different times, which would have distorted the inner consistency between delivery areas and travel-times within.

Failed deliveries are not included for the routing part, as this adds additional complexity to the problem. It is therefore assumed that each customer for a home delivery is able to receive his/her parcel at the time of delivery.

8 Further research on the topic

Future research could focus on the role of different locker-size mixes per locker bank in order to better assess a more realistic allocation of parcels of different sizes to lockers, as it is very likely that not every parcel allocated to a locker can be served by it in reality.

Furthermore, different capacities for lockers as well as different demand probabilities for a locker demand would be an interesting topic for further research. This should also include realistic single customer demand distributions. Additionally, larger problem instances could be considered. Moreover, a scenario for the entire city of Vienna could be investigated by applying findings of this work throughout districts.

Additionally, time-dependent delivery time-windows as well as multiple trips per cargo-trike could be considered in order to factor in specific delivery dates for certain customers or times that are known to reduce failed deliveries.

The general problem could also be stated and solved using different metaheuristic approaches. With added complexity and variables, this problem grows exponentially in size and complexity. Furthermore, a problem of this size and complexity is not likely to be optimally solvable for bigger problem instances for the underlying scenario, meaning that establishing benchmarks via a commercial MIP-Solver for testing a certain metaheuristic approach is limited to date (see section 4.3.3).

9 Conclusion

This thesis investigates the efficiency of parcel-lockers in a two-tier city logistics context for the city of Vienna and its 7th district "Neubau" using trucks as first tier and cargo-trikes as second tier delivery vehicles. Following a 4-step solution approach that defines hub delivery areas, assigns customers to lockers or home delivery and performs the second and first tier routing, the efficiency of lockers in terms of total distance driven as well as total costs is assessed in combination with different hub sizes based on a real-world application for "Neubau" with a sample size of 1 central depot, 9 possible hub areas, 50 possible parcel-locker locations as well as 600 randomly drawn customers. For this purpose, different routing scenarios are analyzed and compared for a small and a big hub scenario. Results show that the implementation of parcel-locker banks is only marginally beneficial in terms of total distance driven when compared to a scenario where all customers are served at their homes (between 1,66% and 5,92%). Parcel-lockers turn out to be very cost-efficient in terms of service-time per customer, which makes up a substantial part of total delivery costs. For the underlying practical case and its assumptions, savings in service-time per customer by implementing parcel-locker banks make up between 92,31% and 100,00% of total savings achieved when total costs are comprised of variable vehicle, time-related and service costs. As a parcel-locker network is very costly to build due to high acquisition, maintenance as well as rental costs, it is recommended that each opened locker bank is decently occupied ($\geq$50%) in order for it to be cost-efficient compared to a scenario where only home deliveries are considered. Additionally, only sufficiently occupied lockers are able to facilitate possible discounts for a parcel-locker delivery, as this service is usually less convenient for the average customer. In terms of hub sizes and capacity, fewer but larger hubs are found to be considerably cheaper compared to a greater number of smaller hubs. The reason for this is that total distances driven do not increase considerably (about 10%), but the number of hubs to be built can be drastically reduced. For "Neubau", a first tier delivery via trucks to micro-hubs and a second tier delivery via cargo-trikes to customers at home and parcel-locker banks is recommended, as trucks are efficient for high delivery volumes combined with low stopping rates, while cargo-trikes are not only cost-efficient if used in densely populated urban areas, but also do not contribute to pollution of inner cities and congestion.

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A Appendix

A.1 Allocation of delivery areas to hubs - Python Code

In this section, a sample implementation of the Single Source Capacitated Plant Location Problem (Jamshidi, 2009) in Python is displayed (see section 3.1). For readability reasons, the distance matrix is not included below:

```
import numpy as np
from gurobipy import *
from first import first
import random
from numpy.random import choice

model = Model("Hub Planning")

rnd = np.random

# set of customers (sample set)
n = [i for i in range(9, 201)]

# set of hubs (sample set)
m = [i for i in range(0,9)]

# number of nodes
N = m+n

# capacity of hubs
b = {j: 150/500 for j in m}

# demand of customers
a = {i: 3.0 for i in n}

# doubling the demand of 8 addresses, as the VRP-Solver is limited
    to 201 locations - see section 4.3.1
```

```
a[rnd.randint(9,201)] = 6
a[rnd.randint(9,201)] = 6
a[rnd.randint(9,201)] = 6
a[rnd.randint(9,201)] = 6
a[rnd.randint(9,201)] = 6
a[rnd.randint(9,201)] = 6
a[rnd.randint(9,201)] = 6
a[rnd.randint(9,201)] = 6

# distance between two points
dist = {(i, j): matrix[i][j] for i in N for j in N}

# big M
M = 100000

workload_max = 1.00
workload_min = 0.00

# binary variables
x = model.addVars(n, m, vtype=GRB.BINARY, name="x")
y = model.addVars(m, vtype=GRB.BINARY, name="y")
w = model.addVars(m, vtype=GRB.CONTINUOUS, name="z")

# Objective function

model.setObjective(quicksum(x[i, j]*dist[i, j] for i in n for j in
    m), GRB.MINIMIZE)

# Constraints

# minimum workload required for a hub to be opened
model.addConstrs(quicksum(a[i]*x[i, j] for i in n) >= b[j]*
    workload_min*y[j] for j in m)
```

```
# capacity of any hub that is built is not allowed to be exceeded
model.addConstrs(quicksum(a[i]*x[i, j] for i in n) <= b[j]*
    workload_max+M*(1-y[j]) for j in m)

# defining w[j]
model.addConstrs(w[j] == (quicksum(a[i]*x[i, j] for i in n)/b[j])
    for j in m)

# setting w[j] to max. 1
model.addConstrs(w[j] <= 1 for j in m)

# strengthen formulation
model.addConstrs(x[i, j]-y[j] <= 0 for i in n for j in m)

# number of hubs to be built
model.addConstr(quicksum(y[j] for j in m) <= 9)

# each customer is served exactly once by a single hub
model.addConstrs(quicksum(x[i, j]for j in m) == 1 for i in n)

# optimize
model.Params.MIPGap = 0.0
model.Params.TimeLimit = 30
model.optimize()

# print solution
EPS = 1.e-6
edges = [(i,j) for (i,j) in x if x[i,j].X > EPS]
nodes = [j for j in y if y[j].X > EPS]

model.printAttr('x')

print()
print ("Optimal value=", model.ObjVal)
```

```
print ("Selected nodes:", nodes)
print ("Edges:", edges)
print ("max distance:", max(dist[i,j] for (i,j) in edges))
print("\nTotal cost for all routes: {}".format(model.ObjVal))
```

A.2 Allocation of customers to lockers - Python Code

In this section, a sample implementation of the Covering Problem (Fallah et al., 2009) in Python is displayed (see section 3.2). For readability reasons, the distance matrices are not included below:

```
import numpy as np
from gurobipy import *
from first import first
import random
from numpy.random import choice

model = Model("Set Covering")

rnd = np.random

# set of customers (from a sample hub delivery area)
n = [i for i in range(14,137)]

# set of parcel-lockers (from a sample hub delivery area)
m = [i for i in range(1, 14)]

# set of nodes
N = m+n

# demand of customers (from a sample hub delivery area)
a = {i: 1 for i in n}

# capacity of parcel-lockers
b = {j: 20 for j in m}

# distance between two points
dist = {(i, j): matrix[i][j] for i in N for j in N}

# maximum covering radius
```

```
r = {j: 0.60 for j in m}

# assignment costs for each customer (ID's of customers that were
   selected to be served via parcel-lockers using a random drawing
    function in Microsoft Excel - here, sample IDs are included)
l = {i: 20 for i in n}
selected =
   [43,90,44,16,67,111,51,84,89,29,120,37,56,52,76,83,14,79,118,32,128,33,41,

        54,26,58,88,74,75,50]

for i in l:
    l[i] = 20
    if selected.__contains__(i):
        l[i]= 1

# workload-coefficient
workload_max = 1.00
workload_min = 0.00

# big M
M = 100000

# Variables

x = model.addVars(n, m, vtype=GRB.BINARY, name="x")
y = model.addVars(m, vtype=GRB.BINARY, name="y")
flow = model.addVars(n,m, vtype=GRB.INTEGER, name="flow")
sum_flow = model.addVars(m,  vtype=GRB.INTEGER, name="sum_flow")
w = model.addVars(m, vtype=GRB.CONTINUOUS, name="z")

# Objective function

model.setObjective(quicksum(w[j]for j in m), GRB.MAXIMIZE)
```

```
# Constraints

# minimum workload required for a locker to be opened
model.addConstrs(quicksum(a[i]*x[i, j] for i in n) >= b[j]*
    workload_min*y[j] for j in m)

# capacity of any parcel-locker that is built is not allowed to be
     exceeded
model.addConstrs(quicksum(a[i]*x[i, j] for i in n) <= b[j]*
    workload_max+M*(1-y[j]) for j in m)

# defining workload of a locker to be the sum of all customer
    demands assigned to it
model.addConstrs(w[j] == (quicksum(a[i]*x[i, j] for i in n)/b[j])
    for j in m)

# setting w[j] to max. 1
model.addConstrs(w[j] <= 1 for j in m)

# strengthen formulation
model.addConstrs(x[i, j]-y[j] <= 0 for i in n for j in m)

# each customer is served at most once by a locker
model.addConstrs(quicksum(x[i, j]for j in m) <= 1 for i in n if l[
    i] <= 2)
model.addConstrs(quicksum(x[i, j]for j in m) == 0 for i in n if l[
    i] >= 2)

# inside covering radius
model.addConstrs(x[i,j]*dist[i,j] <= r[j]* y[j] for i in n for j
    in m)

# optimize
```

```
model.optimize()

# print solution
EPS = 1.e-6
edges = [(i,j) for (i,j) in x if x[i,j].X > EPS]
nodes = [j for j in y if y[j].X > EPS]
model.printAttr('x')
print()
print ("Optimal value=", model.ObjVal)
print ("Selected nodes:", nodes)
print ("Edges:", edges)
print ("max distance:", max(dist[i,j] for (i,j) in edges))
print("\nTotal cost for all routes: {}".format(model.ObjVal))
```

A.3 Second/first tier routing - Python Code

The following code snippets were taken from the Gurobi Support Portal (Towle, 2021) and adapted to this work's needs and only used for determining run-times of a cycled VRP formulated as an Integer Program for larger problem instances (see section 3.3). Distance matrices are not included for readability reasons:

```
import sys
import math
import os
import json
import numpy as np
import random
from itertools import permutations
import gurobipy as gp
from gurobipy import GRB

rnd = np.random
rnd.seed(0)

# number of points (sample range)

where = 1
m = [i for i in range (where,56) ]
n = [0]+m

# number of vehicles (set high enough - cycled VRP)
nv = 100

# demand of a customer
Q = {i: 1 for i in n}

# demand of the hub/ depot
Q[0] = 0
```

```
# capacity of a vehicle (truck/ cargo-trike)
capacities = {i: 400/30 for i in range(nv)}

# capacity is the same for all vehicles
capacity = capacities[0]

# distance between points
dist = {(i, j): distList[i][j] for i in n for j in n}

# cost of vehicle in Euro per km (truck/ cargo-trike)
alpha = 0.30/0.04

# travel time (distList = distance matrix) - speed of either 30 or
    15 km/h
time = {(i, j): (((distList[i][j])/speed)*60) for i in n for j in
   n}

# cost per worker per minute in Euro
beta = 0.30

# Callback - use lazy constraints to eliminate sub-tours

def subtourelim(model, where):
    if where == GRB.Callback.MIPSOL:
        # make a list of edges selected in the solution
        vals = model.cbGetSolution(model._x)
        selected = gp.tuplelist((i, j) for i, j in model._x.keys()
                                if vals[i, j] > 0.5)
        # find the shortest cycle in the selected edge list
        tour = subtour(selected)
        if len(tour) < len(n):
            # add subtour elimination constr. for every pair of
                cities in tour
            model.cbLazy(gp.quicksum(model._x[i, j]
```

```
                                        for i, j in permutations(tour
                                            , 2))
                              <= len(tour)-1)

# Given a tuplelist of edges, find the shortest subtour not
   containing depot
ran = len(n)+1

def subtour(edges):

    unvisited = list(range(where,len(n)))
        cycle = range(ran)  # initial length has 1 more city

    # First, remove all nodes connected to depot

    depot_connected = [j for i, j in edges.select(0, '*') if j !=
       0]
        while depot_connected:
                current = depot_connected.pop()
                unvisited.remove(current)
                neighbors = [j for i, j in edges.select(current,
                   '*')
                                if j in unvisited and j != 0]
        depot_connected += neighbors

    # Now, find subtour

    while unvisited:
                        thiscycle = []
                        neighbors = unvisited

                while neighbors:
                        current = neighbors[0]
                        thiscycle.append(current)
```

```
                    unvisited.remove(current)
                    neighbors = [j for i, j in edges.select(
                       current, '*')
                                     if j in unvisited]

            if len(cycle) > len(thiscycle):
                    cycle = thiscycle
    return cycle

m = gp.Model()

# Create variables
x = m.addVars(dist.keys(),vtype=GRB.BINARY, name='e')
p = m.addVar(vtype=GRB.INTEGER, obj=1.0, name="p", lb=1, ub=K)

# all customers are served
AllNodesVisited={i: gp.quicksum(x[j,i] for j in n if i!=j) for i
   in n if i != 0} # (2.2)
m.addConstrs(AllNodesVisited[i]==1 for i in n if i != 0)

# Track cumulative demand at each node; cannot exceed capacity
u = m.addVars(n, ub=capacity, name='u')

pairs = [(i, j) for i in n for j in n if j != 0 if i != j]
m.addConstrs((u[j] >= Q[j] + u[i] - (1 - x[i, j]) * capacity
             for (i, j) in pairs), 'demand')

# Depot cumulative demand is always 0
u[0].LB = 0
u[0].UB = 0

# Inbound and outbound flow is always 1, except for depot
m.addConstrs(x.sum(i, '*') == 1 for i in n if i != 0)
m.addConstrs(x.sum('*', i) == 1 for i in n if i!= 0)
```

```
# Depot has inbound and outbound flow equal to number of trucks
m.addConstr(x.sum(0, '*') <= K)
m.addConstr(x.sum('*', 0) <= K)

# Set objective function
 totaldist = gp.quicksum(x[i,j]*dist[i,j]*alpha for i in n for j in
     n )
 totaltime = gp.quicksum(x[i,j]*time[i,j]*beta for i in n for j in
    n)

 totalcost = totaldist + totaltime

# Objective function
m.setObjective(totalcost, GRB.MINIMIZE)


# Optimize model
m._x = x
m.Params.LazyConstraints = 1
m.Params.TimeLimit = 1800
#m.Params.MIPFocus = 2
#m.Params.MIPGap = 0.01
#m.Params.ImproveStartTime= 600
m.optimize(subtourelim)
 time_per_neighbor = 1
 time_for_un_load = 5
 neighbor_count = 0
 neighbors = 0
 truck_time_per_vehicle = 0
 total_truck_time = 0

# Print optimal routes
```

```
truck_number = 0
vals = m.getAttr('X', x)
selected = gp.tuplelist((i, j) for i, j in vals.keys() if vals[i,
   j] > 0.5)
for i, tup in enumerate(selected.select(0, '*')):
    neighbor_count = 0
    truck_time_per_vehicle = 0
    print("\nRoute for truck {}:\n 0 Load(0)".format(i+1), end='')
    neighbor = tup[1]
    truck_dist = distList[0][neighbor]
    truck_time = ((distList[0][neighbor])/speed)*60
    truck_load = Q[neighbor]
    truck_number = truck_number+1
    while neighbor:
        print(" -> {} Load({})".format(neighbor, truck_load), end
           ='')
        next_neighbor = selected.select(neighbor, '*')[0][1]
        truck_dist += distList[neighbor][next_neighbor]
        truck_time += ((distList[neighbor][next_neighbor])/speed)
           *60
        truck_load += Q[next_neighbor]
        neighbor = next_neighbor
        neighbor_count = neighbor_count + 1
        truck_time_per_vehicle+=truck_time
    print(" -> 0 Load({})".format(truck_load))
    print("Route distance: {}".format(truck_dist))
    print("Route duration in minutes: {}".format(truck_time))
    print("Route load: {}".format(truck_load))
    print("time spent per customer at site: {}".format(
       neighbor_count*time_per_neighbor))
    neighbors += neighbor_count
    total_truck_time += truck_time_per_vehicle
print("\n")
print("\nOperative costs for all routes: {}".format(m.ObjVal))
```

```
print("\nTotal costs for all routes: {}".format(m.ObjVal+neighbors
    *time_per_neighbor*beta+(truck_number)*time_for_un_load*beta))
print("\nTotal number of trucks used: {}".format(truck_number))
print("\nTotal number of workers/bikes needed: {}".format(math.
    ceil((total_truck_time*beta + neighbors*time_per_neighbor*beta
    + truck_number*time_for_un_load*beta)/480)))
```

A.4 Sample routing results table

The following snippets show the results table of the Erdoğan VRP-Spreadsheet Solver (Erdoğan, 2017) for an exemplary second tier routing for the delivery area of ”Hub 0” (small hub scenario) and delivery to customer‘s homes and parcel-lockers with a workload of $\geq 0\%$. The table highlights the total net profit (total distance driven), the total number of vehicles used with individual stopping times at each customer and locker as well as total driving times and stops per vehicle including the load transported on a tour. The indicator 1,2 or 3 in brackets besides individual customers (C) displays which of the three individual customers per address is selected to be served (see section 4.3.1).
For readability reasons, only a single results table is included. In total, this process was done 63 times for the second and 8 times for the first tier, using allocations of delivery areas (see section 4.3.1) and customer allocations for either service for each delivery area for both the small and big hub scenario (see section 4.3.2):

Total net profit: -13.02

Vehicle: V1 | Stops: 22 | Net profit: -1.53

Stop count	Location Name	Distance travelled	Driving time	Arrival time	Departure time	Working time	Profit collected	Load
0	Depot	0.00	0:00		08:00	0:00	0	30
1	C180(1)	0.12	0:00	08:00	08:00	0:00	0	29
2	C5(3)	0.17	0:00	08:00	08:00	0:00	0	28
3	Locker6	0.31	0:00	08:00	08:00	0:00	0	24
4	C178(1)	0.34	0:01	08:01	08:01	0:01	0	23
5	Locker12	0.40	0:01	08:01	08:01	0:01	0	16
6	C148(2)	0.53	0:01	08:01	08:01	0:01	0	15
7	C17(3)	0.54	0:01	08:01	08:01	0:01	0	14
8	C17(2)	0.54	0:01	08:01	08:01	0:01	0	13
9	C52(1)	0.80	0:02	08:02	08:02	0:02	0	12
10	C199(1)	0.82	0:02	08:02	08:02	0:02	0	11
11	C9(3)	0.85	0:02	08:02	08:02	0:02	0	10
12	C133(3)	0.92	0:02	08:02	08:02	0:02	0	9
13	C63(1)	1.03	0:03	08:03	08:03	0:03	0	8
14	C63(3)	1.03	0:03	08:03	08:03	0:03	0	7
15	C42(1)	1.16	0:03	08:03	08:03	0:03	0	6
16	C42(2)	1.16	0:03	08:03	08:03	0:03	0	5
17	C42(3)	1.16	0:03	08:03	08:03	0:03	0	4
18	C124(2)	1.28	0:03	08:03	08:03	0:03	0	3
19	C65(3)	1.34	0:04	08:04	08:04	0:04	0	2
20	C75(3)	1.34	0:04	08:04	08:04	0:04	0	1
21	C75(2)	1.34	0:04	08:04	08:04	0:04	0	0
22	Depot	1.53	0:04	08:04		0:04	0	0

Vehicle: V2 | Stops: 13 | Net profit: -1.97

Stop count	Location Name	Distance travelled	Driving time	Arrival time	Departure time	Working time	Profit collected	Load
0	Depot	0.00	0:00		08:00	0:00	0	29
1	C180(2)	0.12	0:00	08:00	08:00	0:00	0	28
2	C17(1)	0.55	0:01	08:01	08:01	0:01	0	27
3	C186(1)	0.83	0:02	08:02	08:02	0:02	0	26
4	C186(3)	0.83	0:02	08:02	08:02	0:02	0	25
5	C23(2)	0.87	0:02	08:02	08:02	0:02	0	24
6	C24(3)	0.87	0:02	08:02	08:02	0:02	0	23
7	C24(2)	0.87	0:02	08:02	08:02	0:02	0	22
8	Locker11	0.88	0:02	08:02	08:02	0:02	0	4
9	C23(3)	0.90	0:02	08:02	08:02	0:02	0	3
10	C186(2)	0.93	0:02	08:02	08:02	0:02	0	2
11	C9(2)	1.56	0:04	08:04	08:04	0:04	0	1
12	C25(1)	1.63	0:04	08:04	08:04	0:04	0	0
13	Depot	1.97	0:05	08:05		0:05	0	0
14								
15								
16								
17								
18								
19								
20								
21								
22								

Vehicle:	V3	Stops:	26	Net profit:	-1.93			
Stop count	Location Name	Distance travelled	Driving time	Arrival time	Departure time	Working time	Profit collected	Load
0	Depot	0.00	0:00		08:00	0:00	0	27
1	C43(3)	0.10	0:00	08:00	08:00	0:00	0	26
2	C7(2)	0.20	0:00	08:00	08:00	0:00	0	25
3	C159(2)	0.23	0:00	08:00	08:00	0:00	0	24
4	C76(3)	0.30	0:00	08:00	08:00	0:00	0	23
5	C34(3)	0.67	0:02	08:02	08:02	0:02	0	22
6	C34(2)	0.67	0:02	08:02	08:02	0:02	0	21
7	C165(3)	0.95	0:02	08:02	08:02	0:02	0	20
8	C165(2)	0.95	0:02	08:02	08:02	0:02	0	19
9	C118(3)	1.12	0:03	08:03	08:03	0:03	0	18
10	C118(2)	1.12	0:03	08:03	08:03	0:03	0	17
11	C164(3)	1.20	0:03	08:03	08:03	0:03	0	16
12	C57(3)	1.20	0:03	08:03	08:03	0:03	0	15
13	C143(3)	1.20	0:03	08:03	08:03	0:03	0	14
14	C143(2)	1.20	0:03	08:03	08:03	0:03	0	13
15	C57(2)	1.20	0:03	08:03	08:03	0:03	0	12
16	C172(3)	1.20	0:03	08:03	08:03	0:03	0	11
17	C172(2)	1.20	0:03	08:03	08:03	0:03	0	10
18	C117(3)	1.20	0:03	08:03	08:03	0:03	0	9
19	C52(2)	1.47	0:04	08:04	08:04	0:04	0	8
20	C199(3)	1.49	0:04	08:04	08:04	0:04	0	7
21	C3(3)	1.56	0:04	08:04	08:04	0:04	0	6
22	C25(2)	1.59	0:04	08:04	08:04	0:04	0	5
23	C129(3)	1.63	0:04	08:04	08:04	0:04	0	4
24	C129(2)	1.63	0:04	08:04	08:04	0:04	0	3
25	Locker2	1.82	0:05	08:05	08:05	0:05	0	0
26	Depot	1.93	0:05	08:05		0:05	0	0
27								

Vehicle:	V4	Stops:	27	Net profit:	-4.02			
Stop count	Location Name	Distance travelled	Driving time	Arrival time	Departure time	Working time	Profit collected	Load
0	Depot	0.00	0:00		08:00	0:00	0	29
1	C180(3)	0.12	0:00	08:00	08:00	0:00	0	28
2	C88(3)	0.83	0:02	08:02	08:02	0:02	0	27
3	C38(3)	0.97	0:02	08:02	08:02	0:02	0	26
4	C38(2)	0.97	0:02	08:02	08:02	0:02	0	25
5	C178(2)	1.38	0:04	08:04	08:04	0:04	0	24
6	C178(3)	1.38	0:04	08:04	08:04	0:04	0	23
7	C88(2)	1.87	0:05	08:05	08:05	0:05	0	22
8	C88(1)	1.87	0:05	08:05	08:05	0:05	0	21
9	C12(2)	1.90	0:05	08:05	08:05	0:05	0	20
10	C12(3)	1.90	0:05	08:05	08:05	0:05	0	19
11	Locker1	2.03	0:06	08:06	08:06	0:06	0	18
12	C148(3)	2.33	0:06	08:06	08:06	0:06	0	17
13	C174(3)	2.51	0:07	08:07	08:07	0:07	0	16
14	C174(1)	2.51	0:07	08:07	08:07	0:07	0	15
15	C174(2)	2.51	0:07	08:07	08:07	0:07	0	14
16	C114(3)	2.65	0:07	08:07	08:07	0:07	0	13
17	C114(2)	2.65	0:07	08:07	08:07	0:07	0	12
18	C175(3)	3.27	0:09	08:09	08:09	0:09	0	11
19	C145(1)	3.28	0:09	08:09	08:09	0:09	0	10
20	C145(3)	3.28	0:09	08:09	08:09	0:09	0	9
21	Locker13	3.28	0:09	08:09	08:09	0:09	0	6
22	C199(2)	3.37	0:10	08:10	08:10	0:10	0	5
23	C63(2)	3.57	0:10	08:10	08:10	0:10	0	4
24	Locker4	3.71	0:11	08:11	08:11	0:11	0	2
25	C61(3)	3.71	0:11	08:11	08:11	0:11	0	1
26	C124(3)	3.83	0:11	08:11	08:11	0:11	0	0
27	Depot	4.02	0:12	08:12		0:12	0	0

Vehicle:	V5	Stops:	10	Net profit:	-3.58			
Stop count	Location Name	Distance travelled	Driving time	Arrival time	Departure time	Working time	Profit collected	Load
0	Depot	0.00	0:00		08:00	0:00	0	11
1	C 7(3)	0.20	0:00	08:00	08:00	0:00	0	10
2	C 159(3)	0.23	0:00	08:00	08:00	0:00	0	9
3	Locker5	0.28	0:00	08:00	08:00	0:00	0	6
4	C 167(3)	0.89	0:02	08:02	08:02	0:02	0	5
5	C 167(2)	0.89	0:02	08:02	08:02	0:02	0	4
6	Locker7	0.89	0:02	08:02	08:02	0:02	0	3
7	C 155(3)	2.98	0:08	08:08	08:08	0:08	0	2
8	C 52(3)	3.13	0:09	08:09	08:09	0:09	0	1
9	C 25(3)	3.24	0:09	08:09	08:09	0:09	0	0
10	Depot	3.58	0:10	08:10		0:10	0	0

Abstract

Weltweite Urbanisierung, Klimawandel und die Zunahme des elektronischen Handels als auch stetig steigende Sendungsvolumina haben große Unternehmen im KEP-Markt (Kurier, Paket, Express) dazu gedrängt, kosteneffizientere und umweltfreundlichere Liefermethoden zu implementieren. Ein Konzept, welches hieraus hervorgegangen ist, wird als "zweistufige Stadtlogistik" (two-tier city logistics) bezeichnet. Dieses Lieferkonzept umfasst den Transport von Gütern mit größeren Lieferwägen von einem zentralen Depot außerhalb des Stadtzentrums zu kleineren innerstädtischen Depots (Mikro-Depots) als erste Stufe. In der zweiten Stufe werden diese Güter dann von den Depots mit Hilfe von umweltfreundlichen Liefermethoden wie Lastenfahrrädern, öffentlichen Verkehrsmitteln oder auch Drohnen entweder direkt zu den Kunden nach Hause oder in eine Paketstation (Abholstation) geliefert. Diese Arbeit untersucht die Effizienz von Paketstationen bezüglich einer praktischen Anwendung auf den siebten Bezirk Wiens. Ein 4-stufiger Lösungsansatz dient in weiterer Folge der Erhebung der Effizienz von Paketstationen kombiniert mit verschiedenen Mikro-Depot Standorten und Größen. Am Ende werden ein passendes Maß für die Effizienz von Paketstationen sowie Implikationen für eine praktische Anwendung dargelegt.