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1. Introduction

Over the past decades, e-commerce has shown a remarkable growth worldwide and has shifted the focus from the business-to-business segment to a direct business-to-customer commerce. In mature markets such as the U.S. and Germany, annual growth rates are between 7 percent and 10 percent and in developing markets such as India, growth rates reach almost 300 percent (Joeress, et al., 2016). The ongoing boom in e-commerce attracts more and more companies to enter the online retailing market. In Austria, the parcel volume has shown an increase of 35 percent within three years pre-pandemic and is expected to increase even more due to COVID-19 (WKO Wien, 2020). This trend imposes great challenges on the logistics' system behind e-commerce. In a business-to-customer delivery, customers must be supplied to their home addresses individually which results in a high number of delivery locations with low yields per delivery. At the same time, customer expectations regarding lead time, delivery costs and convenience are particularly high in e-commerce (Mangiaracina, et al., 2019). This leads to last-mile becoming the most inefficient and expensive part along the entire supply chain in e-fulfilment (Ehmke & Campbell, 2014).

To cope with this growth and to increase efficiency and reduce costs, researchers increasingly focus on introducing new solutions for the last-mile delivery. Innovative systems include new technologies such as drones or robots to the delivery systems. In 2013, Amazon's CEO Jeff Bezos proposed his plan to use drones to deliver light-weight parcels to customers and several companies such as DHL, Google X and Walmart consider drone delivery to be the next promising technology in consumer retail (Rose, 2013; French, 2015). However, the implementation of drones is limited by the low carrying capacity and flight endurance of drones which considerably limits the area of application.

Murray and Chu (2015) are among the first researchers to address this limitation by introducing a model where truck and drone perform a combined and synchronised delivery, called a Truck-and-Drone delivery. The features of both vehicles have the potential to complement each other and hereby outweigh the respective disadvantages of the other: Trucks have relatively high capacities and a long driving range but since they are dependent on the road network, especially in dense urban areas they may travel in low speed. Drones, on the other hand, have very low carrying capacities of only one up to a maximum of a few parcels and a low flying range. However, they may be able to fly in high speeds even in urban areas since they are independent of traffic and can fly in any direction (Agatz, et al., 2018).

Concluding, a Truck-and-Drone delivery may increase efficiency and reduce costs due to lower operating costs of drones. In recent years, this topic has attracted the interest of many researchers who have published new Truck-and-Drone models (Otto, et al., 2018). As a result, several companies have adopted the idea of Truck-and-Drone delivery and started developing their own delivery drones. The service provider DPD, for instance, made several test runs of a delivery system including drones that launch from and land

on the roof of a truck. In cooperation with the drone developer Matternet, Mercedes Benz invented a truck with two drones that are able to autonomously land on the truck's roof using nets (Stewart, 2017). The topic of this thesis is related to delivery planning and is specialized in e-fulfilment for urban delivery areas. The relevance of drones in a truck-combined delivery for future delivery planning shall be detected. Precisely, the research question is as follows:

What is the state of the art for Truck-and-Drone delivery, and which is the best suited model for urban delivery in e-commerce?

This thesis is the first to analyse, compare and categorise Truck-and-Drone models with a focus on e-commerce delivery. Otto et al. (2018) and Chung et al. (2020) offer a broad review on Truck-and-Drone models. However, they do not specify the application area and serve as a general overview on the topic. To the knowledge of the author, this thesis is the first to apply two Truck-and-Drone models to real-life data and to compare them in order to find the best-suited model for a specific delivery area. In general, the minority of papers offer an application using real-life data none of which compare and evaluate the solutions of applying different delivery models. Concluding, it becomes clear which model attributes are especially relevant for the application of Truck-and-Drone delivery in an urban e-commerce environment. This may serve as a guideline for service providers that consider including drones for the last-mile delivery. Furthermore, the question whether the application of drones for last-mile delivery may reduce costs will be pursued.

Several parties are involved in the introduction of drones in last-mile and thus there are many perspectives from which the topic can be viewed. Customers may want to agree on small reliable delivery windows and fast, free delivery. City governments may aim to reduce traffic and exhaust gas pollution and may have security concerns regarding possible drone accidents. The public may have privacy concerns towards drones that are equipped with cameras and service providers want to reduce costs to increase profit margins. The interests of all parties involved may be contradictory and therefore, this thesis focuses on the goal of one party only: Due to the high cost pressure in the last-mile, the focus is set on reducing costs from the perspective of the logistics provider.

The research question will be answered using a strategic literature review on recently published scientific papers that propose Truck-and-Drone models. The theoretic approach follows a case study to validate the analysis using real-life data for the delivery in Vienna's 9th district.

This thesis is structured as follows: The chapter two serves as a foundation for the later analysis. The process of e-commerce as well as characteristics and challenges for e-commerce and e-fulfilment in the last-mile delivery will be detected. This will be important for the subsequent narrowing down of models to answer the research question. Moreover, the second chapter introduces the basics of mathematical models for delivery planning and offers fundamental information on drone technologies. In the third chapter, the research question will be answered. In order to find the state of the art in Truck-

and-Drone models, an extensive literature review is performed. Hereby the most important recent papers will be ascertained and compared using various attributes. By analysing the models those that best fulfil the conditions and prerequisites for an urban e-commerce delivery will be detected. After a short introduction to the most relevant papers for urban e-commerce delivery, the two most promising papers will be analysed in detail and compared to find out similarities and differences. This will be important for the subsequent part of the thesis, where these models will be applied.

In the fourth chapter, the theoretical analysis will be substantiated by a case study using real-life data. Two models that are identified as the best suited Truck-and-Drone models in the previous part will be applied. This will be done by implementing the linear models to CPLEX, a solver for linear programming. On the one hand, the goal of this section is to find out whether the introduction of drones into last-mile delivery reduces costs compared to the conventional truck only delivery. On the other hand, the models will be compared to find out which Truck-and-Drone model delivers best results for the delivery in Vienna's 9th district in terms of cost reduction. In a sensitivity analysis, the influence of changing certain parameters will be discovered in order to obtain results as realistic as possible under varying assumptions. In the fifth chapter, the results of the previous research will be analysed, discussed, and limitations to the study will be emphasised. The conclusion summarises the findings of this thesis.

2. Terminologies of Delivery Planning

2.1 Trends and Characteristics of Electronic Purchase

The term e-commerce describes the electronic retailing of goods and services of which the transaction is performed via internet. The entire process until the sales closure is completed online, including the initiation, conclusion and settlement of the purchase. In order to characterize a purchase as e-commerce sale, it is not sufficient that the entire transaction process is performed electronically. If physical products are purchased, they must be delivered using regular transportation systems. However, the conclusion of trade must take place online on a virtual marketplace. These virtual spaces may be addressed to end-customers directly (B2C) or to business customers (B2B) (Deges, 2020, p. 2). In this thesis, the focus lies on B2C e-commerce, since here, the challenge for the logistics system is especially high.

Internet Pure Player are companies that sell their products exclusively online. These single channel retailers are often small companies that operate in highly specialized industries. Internet Pure Players benefit from being able to reach many customers at the same time via internet without having to pay high staffing and rental costs for static branches. In contrast, stationary retail trade operates only physical via stores without using the internet for the distribution of their products. However, most retailers operate on multiple distribution channels. In recent years, Internet Pure Players have increasingly started to step into conventional retailing by opening stores. Companies expect a positive interaction for the online business through the offline presence and offer the customer the opportunity to experience their brand in a more tangible way. For instance, Zalando started as an Internet Pure Player but expanded their online channel by opening Concept Stores in selected locations. Furniture online retailers such as Home24 or SofaCompany opened show rooms at reputable locations in several countries to provide a real-life experience of their furniture. At the same time, former stationary retailers increasingly use e-commerce to reach customers online more efficiently. By this, both online and offline shopper may be skimmed (Deges, 2020, pp. 88-90).

In the past two centuries, e-commerce has recorded a constant boom worldwide. In Austria, the percentage of online buyers increased from 2003 to 2020 by over 20 percent. In 2020, two out of three Austrian residents used online shopping. Not only the number of customers in e-commerce records a significant increase, also e-commerce sales in Austria have grown around 40 percent since 2015. The most popular segments among Austrians are clothing and textiles, followed by electrical appliances and books (WKO Wien, 2020).

With its growing relevance and an increased volume of online purchases, e-commerce contributes to an increasing transportation traffic, CO₂ emissions and climate change. Since conventionally, delivery takes place on the road, e-commerce has a significant influence on the traffic system. Especially in urban areas,

where a high demand in e-commerce meets limited urban infrastructure capacities, e-commerce contributes to increasing traffic congestion, declining air quality and increased noise levels (Boysen, et al., 2020). As many cities such as Vienna follow strategies to reduce the inner city traffic, logistics service providers are under pressure to find better solutions for urban delivery. Innovative solutions may include the use of low-emission vehicles such as electric cars, cargo bikes – and more recently drones (WKO Wien, 2020). Another challenge for firms operating in e-commerce are the high expectation levels of customers regarding the entire process of ordering. Websites must be designed well-structured and functional, the products on offer should be broadly diversified, well described and well rated by previous buyers. Customers should be able to decide between several payment methods and the real-time availability of products should be displayed. Furthermore, the service should include the possibility to get expert answers to individual questions which may include direct personal communication with a service employee (Deges, 2020, pp. 175-180).

The expected services relating to logistics put the entire fulfilment under pressure. Fulfilment is located at the step between retailer and customer after the purchase has taken place. It includes the process of logistical order processing including the delivery to the customer. In the warehouse, items are selected and packaged, and orders are prepared for the delivery. According to several aspects, orders are bundled together for the pick-up by the delivery vehicle. Further processes include quality control, data management and return management. The process is called E-fulfilment if the retailer operates online. Customers' expectations relating to e-fulfilment include several services, such as the opportunity to choose between express or standard shipping, the selection of a time window and a certain service provider for the delivery. Customers usually expect free standard delivery without a minimum order value. The shipping itself should be insured and the return shipment is expected to be uncomplicated and free (Deges, 2020, p. 191f).

One of the major challenges in e-fulfilment is a high return rate. Since customers cannot physically observe the product before buying, the chance of returning the article increases. On the customer side, an accommodating and simple solution for the return process is expected. On the company side, the return of articles is a major cost driver. Often, the costs for the return shipment are covered by the company since a free return shipping is a decision criterion for consumers. This is especially relevant for the shoe and fashion industry. Here, return rates in Austria lie at around 54 percent. The most common reason for a return is that the item does not fit. In Germany, up to 80 percent of goods are being returned (Zapfl, 2019). For online retailers, high return rates are one of the most critical aspects for their business. The warehouse or fulfilment centre must have an efficient return management so that as many return articles may be resold as possible. Additional personnel are needed for the return process, which can mean a financial burden especially for small businesses. However, even with an efficient return management some returned items may not be resalable and must be destroyed or donated. Therefore, retailers try to

reduce return rates through providing detailed product information, size calculators and customer reviews (Zapfl, 2019).

The huge number of retailers on the internet makes it particularly important to use a good search engine placement. Since the majority of information research takes place via Internet search engines, online retailers have to show up in the search for relevant search terms in order to generate high visitor frequency and attract new customers (Deges, 2020, p. 165).

In summary, e-commerce is the electronic retailing of goods and services and covers all processes from ordering to the delivery. E-fulfilment includes all logistics related processes of an electronic purchase from the order entry in the warehouse to the delivery to the customer. Main challenges are the high expectations of customers especially in the logistical parts of the retail. Therefore, efficient and inexpensive logistics processes are necessary for online retailers. Even though, e-commerce is possible both for B2B and B2C, in this thesis the focus lies on e-commerce in the field of B2C.

2.2 Process and Challenges of last-mile Delivery

Last-mile is defined as the final part of delivery along the supply chain and is part of the fulfilment process. Namely, it is the process of transporting the ordered good to the buyer. In a B2C e-commerce, the delivery locations are the private residence of the end-customers. Each order is delivered to an individual customer location which means that a bundled delivery of several orders is not possible. This results in a high number of delivery locations with a low parcel volume per location. The entire process starts as soon as the customer places an order either online or via other order systems. In response to the order, the good will be shipped from the manufacturer or suppliers at the transportation hub close to the customer location. Here, the last-mile process begins:

Delivery vehicles are available at the hub to transport the goods to the end-customer. Orders are scheduled and assigned to vehicles. Routes are built according to the drop-off locations, good characteristics, vehicle capacities and time restrictions. In the next step, items are scanned and loaded on the corresponding vehicle. The driver then delivers the items to the customers (Boysen, et al., 2020).

Driven by the constant e-commerce boom, the volume of shipments has grown massively in Austria in recent years. In 2019, it amounted to almost 250 Mio. parcels, which is an increase of 35 percent in only three years. However, the logistics companies' turnover cannot keep pace with the development of volumes. In 2019 the generated turnover for a standard parcel in Austria was 4 Euros. Due to necessary investments in vehicles, infrastructure and digitalization as well as rising costs for rent and personnel, transportation costs are expected to increase in the next few years (WKO Wien, 2020).

In order to hold costs minimal and find optimal routes, the allocation of orders is typically generated by using optimization problems such as the Vehicle Routing Problem or the Traveling Salesman Problem

(Cleophas & Ehmke, 2014). However, last-mile delivery is considered as one of the most expensive and least efficient parts along the supply chain. Up to half of the total logistics costs are spent here (Mangiaracina, et al., 2019). The reasons are diverse: Due to the direct delivery to individual customers, quantity and value of the goods per drop-off location are relatively low. In rural areas, delivery locations may be several kilometres apart. Resulting, long distances must be covered while the value for the delivering company is relatively low. In urban areas, distances between locations may be smaller. However, congestion may influence the travel times so that delivery vehicles may travel with low average speed. Moreover, the traffic situation varies throughout the day so that travel times differ strongly dependent on the daytime. As a result, last-mile delivery both in rural and urban areas is often highly inefficient (Dolan, 2018).

Due to the strongly increased parcel volume especially in urban areas, delivery vans increasingly add to congestion and CO₂ emissions in city centres. Resulting, the pressure for service providers to intensify sustainability efforts and to reduce negative impacts of deliveries in urban areas rises. Both customer acceptance and governmental legislations force the companies to find ecologically better solutions for the last-mile (Boysen, et al., 2020).

On the customer side, high expectations add to the challenges in last-mile delivery. They demand short lead times and precise order tracking. Ordered goods shall be insured so that in the case of lost or damaged items, no additional costs appear to the customer. Another important aspect for customers is convenience. Delivery time should be predictable and precise, so that they do not have to wait at home for the delivery. Customer satisfaction may be increased by agreeing on certain time windows. However, time windows increase delivery costs significantly (Ehmke & Campbell, 2014). On the other hand, customers are usually not willing to pay for the logistical service, so that these costs must be covered by the retailers (Mangiaracina, et al., 2019). Furthermore, it is important to notice, that the delivery is the only physical contact between company and customer since the purchase is relocated to the internet. This means, that an effective and for the customer satisfying delivery procedure plays an important role in the customer satisfaction for the e-commerce company even if the logistics processes are outsourced (Boysen, et al., 2020).

Failed delivery is another major cost factor in the last-mile delivery process. It occurs if the customer is not available for receiving the parcel during the delivery attempt. As the delivery according to time windows is very costly, it is not common in the delivery of small parcels. In many cases it is not possible for the retailer to fixate time windows already during the order placing. In the case of a failed delivery attempt, the provider must return to the customer at a later point in time or drop off the parcel at a pick-up station. Both options significantly increase delivery costs for the provider. Moreover, failed delivery attempts decrease customers' satisfaction, as they must wait longer for their parcels or must pick up their parcels at the pick-up location. Failed delivery becomes even more critical, if the delivered goods are

perishable and must be stored in the refrigerator immediately. In this case, a failed delivery may mean that the goods are no longer usable and must be destroyed (Florio, et al., 2018).

Another major challenge in last-mile delivery is time pressure from retailers. Since the competition online is very high, e-commerce companies offer fast deliveries as basic service promises to the customers. This results in narrow time frames for the last-mile deliveries and time pressure to realize the retailers' promise. In addition, e-commerce activities vary strongly within the week but also seasonally. Service providers, therefore, face strongly varying workloads, which is a challenge especially with regard to personnel planning (Boysen, et al., 2020). Workforce is not only a challenge for the industry regarding varying demands but also due to an aging workforce in many industrialized countries. Finding less personnel intense solutions for the last-mile may be an answer to rising personnel costs and a lack of personnel in the future. Self-driving cars, autonomous delivery robots or the integration of drones are some of the recent ideas for the last-mile (Mangiaracina, et al., 2019).

Mangiaracina et al. (2019) narrowed the costs factors of last-mile delivery down to three main contributors: The transport mean cost, the driver cost and the opportunity cost. Transport mean cost include semi-fixed and variable costs for the transport mean per kilometre, such as maintenance costs and fuel. Moreover, it considers the average travelled distance of the vehicle to finish a delivery tour. The second cost factor, driver cost, includes all costs that relate to the driver of the vehicle, such as the salary and the time that is needed to perform all activities related to the whole process. This includes for example the physical delivery to the customer's door and the time that is needed for additional activities in the case of a failed delivery. Opportunity costs are such costs that occur to the company through customer dissatisfaction on the delivery service. For instance, in the case of a failed delivery attempt that results in a longer wait for the parcel or requires effort of the customer (by collecting the parcel from a pick-up station). This thesis focusses on the transport cost as one of the main contributors of last-mile delivery costs. Introducing drones into the process may have the potential to influence transport cost positively.

Last-mile delivery is a very critical part along the supply chain in e-fulfilment. The major challenges are high costs, time pressure and high customer expectations. The strong increase in demand in the e-commerce sector intensifies these challenges and demands for innovative solutions in the last-mile.

2.3 Mathematical Models for last-mile Routing

In the last-mile of B2C fulfilment orders must be scheduled and delivered to the end-customers. Either a single vehicle or a fleet of available vehicles must be assigned to the orders and must then be sequenced in the most cost-efficient way. Due to the high number of delivery locations with a low parcel volume per delivery, each truck may supply several customers during one trip. The optimization problems for this scenario are either the Traveling Salesman Problem (TSP) for a single vehicle or the Vehicle Routing Problem (VRP) for multiple vehicles (Cleophas & Ehmke, 2014). Both problems are classical transportation

optimization problem that deal with minimizing total travel costs while visiting several locations. Here, each location is equal to one customer who ordered an item online.

Traveling Salesman Problem

The TSP is an optimization problem that has been intensively studied in the context of transportation logistics and vehicle routing. It aims to find the shortest path among several nodes. In order to illustrate the problem, it can be presented by the example of a salesman that must visit several cities: The salesman must visit all cities exactly once and in the minimal distance. The problem is NP-hard; however, there exist several exact methods and heuristics that can solve the problem to optimality. The TSP can be modelled as a complete directed graph such that the cities and the depot are the graph's vertices and the paths between the cities are the graph's edges. The TSP can be formulated as an integer linear program (ILP) (Applegate, et al., 2011). There exist several formulations of the problem as an ILP, which differ mainly in the way subtours are avoided. The subtour elimination constraint ensures that the solution consists of one tour visiting all nodes instead of several small tours. In Figure 1, the Dantzig–Fulkerson–Johnson formulation can be seen (Padberg & Sung, 1991).

$$\min \sum_{i=1}^n \sum_{j \neq i, j=1}^n c_{ij} x_{ij} : \quad (1)$$

$$\sum_{i=1, i \neq j}^n x_{ij} = 1 \quad j = 1, \dots, n; \quad (2)$$

$$\sum_{j=1, j \neq i}^n x_{ij} = 1 \quad i = 1, \dots, n; \quad (3)$$

$$\sum_{i \in Q} \sum_{j \neq i, j \in Q} x_{ij} \leq |Q| - 1 \quad \forall Q \subsetneq \{1, \dots, n\}, |Q| \geq 2 \quad (4)$$

Figure 1: Traveling Salesman Problem (Padberg & Sung, 1991)

The binary decision variable x_{ij} is one if the arc (i,j) is part of the solution and zero otherwise. The variable c_{ij} represents the costs to travel along the arc (i,j) . The objective (1) is to minimize the sum of travel costs of all arcs that are part of the solution. Constraint (2) and (3) ensure that each vertex is visited exactly once and left exactly once. Constraint (4) prevents the formation of subtours. The decision variable x_{ij} is binary (Padberg & Sung, 1991).

Application areas are due to the simplicity of the problem's statement widely spread such as postal deliveries or school bus routing. However, particularly in the last decades, the TSP became extensively studied in the field of e-fulfilment as it is easily applicable to last-mile delivery. Here, a truck (salesman) delivers parcels to a set of customers (vertices) while minimizing the distance. The model is usually extended by a depot from where the driver picks up the parcels and at which he/she must return after finishing his/her route. In e-commerce, due to the large number of individual customers who must be delivered from the depot, the delivery planning gains in complexity compared to a bundled business-to-business delivery and

demands for an optimization. Many variations of the standard TSP have been developed in literature, such as the TSP with time windows, in which customers can only be serviced within individual time slots or the TSP with pickup-and-delivery, in which items are not only delivered but also collected from customer locations (Gromicho & Vigo, 2017; Yao, et al., 2017). Furthermore, the TSP is the fundament for other optimization problems such as the VRP (Dantzig & Ramser, 1959).

Vehicle Routing Problem

The Vehicle Routing Problem (VRP), first introduced in 1959 by Dantzig and Ramser, is a generalization of the TSP and a central problem in the physical delivery of goods and services. Instead of considering one single vehicle, the VRP seeks to find the optimal routes for a fleet of vehicles to service a set of customers starting and ending at a depot node. The objective is to minimize overall transportation costs, while costs can be defined either as travel time or travel distance.

The simplest adaption is the Capacitated VRP (CVRP), in which the capacity of vehicles is restricted by an additional constraint. The CVRP is especially relevant if the transported goods are relatively large or the vehicle capacity is relatively low and therefore an exceeding of the capacity is very likely (Gromicho & Vigo, 2017).

$$(VRP1) \quad \min \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij} \quad (1)$$

$$\text{s.t.} \quad \sum_{i \in V} x_{ij} = 1 \quad \text{for all } j \in V \setminus \{0\} \quad (2)$$

$$\sum_{j \in V} x_{ij} = 1 \quad \text{for all } i \in V \setminus \{0\} \quad (3)$$

$$\sum_{i \in V} x_{i0} = K \quad (4)$$

$$\sum_{j \in V} x_{0j} = K \quad (5)$$

$$\sum_{i \notin S} \sum_{j \in S} x_{ij} \geq \gamma(S) \quad \text{for all } S \subseteq V \setminus \{0\}, S \neq \emptyset \quad (6)$$

$$x_{ij} \in \{0, 1\} \quad \text{for all } i, j \in V. \quad (7)$$

Figure 2: The Capacitated Vehicle Routing Problem (Toth & Vigo, 2002)

The vehicle flow formulation of the CVRP is shown in Figure 2. The set of nodes is described as V , with node i and j as customers and node zero as the depot ($i, j \in V$). K is the set of vehicles available. The transportation costs of moving from i to j are denoted by c_{ij} . The binary decision variable x_{ij} is equal to one if the arc (i, j) is traversed by a vehicle in the solution and zero otherwise. The objective (1) function minimizes the sum of transportation costs. Constraints (2) and (3) ensure that each customer node is entered and left exactly once. Constraint (4) and (5) state that the depot must be entered by the same number of vehicles as it has been left, which is the number of available vehicles. The capacity restriction of each

vehicle is ensured and subtours of the vehicle are eliminated from the solution in constraint (6). The decision variable x_{ij} is binary (Toth & Vigo, 2002).

The similarity to the TSP can be observed: Constraint (2) and (3) correspond to the TSP, as well as the binarity constraint for the decision variable. Moreover, both models forbid subtours, as the models intend only one single tour (per vehicle) to serve the nodes. However, unlike the TSP, the CVRP considers a depot as start and end node of the tour, as well as a capacity constraint of the vehicle (Toth & Vigo, 2002).

The VRP is from large theoretical and practical interest. In e-fulfilment, the VRP plays an important role in the last-mile delivery for the routing of delivery trucks to the end customer. The advantage compared to the TSP is, that the tours of multiple trucks can be calculated, which is practical for high demands. There exist numerous variants and extensions of the VRP, according to the type of service, the delivered good or the required quality of service (Mangiaracina, et al., 2019). A widely discussed extension is the VRP with time windows (VRPTW): In this model customers may only be served within a time window that is set either by the service provider or the customer him/herself. Especially in e-commerce the VRPTW is from large relevance, as the delivery often requires physical attendance of the customer. However, most customers are not at home during the entire day and may require an individual fixed time window for the delivery (Yao, et al., 2017).

2.4 Drone Technologies for Delivery Processes

One of the innovative solutions for the last-mile include the use of unmanned aerial vehicles (UAV). UAVs are also referred to as drones which will be the preferred term in this thesis. In general, drones are flying devices that fly autonomously without an on-board pilot. However, this broad definition may include ballistic and cruise missiles which are commonly not referred to as UAVs. Therefore, in this thesis drones are defined as “(...) an airborne powered vehicle without a human operator capable of operating autonomously, semi-autonomously, or piloted remotely, capable of producing aerodynamic lift and may or may not carry a payload” (Barrera, 2021, p. 3). Drones may be driven by different types of propulsive power such as electric batteries, solar cells or internal combustion engines. They may be remote controlled by a pilot or may operate fully autonomous using algorithms and sensors to make decisions without human interaction (Otto, et al., 2018).

Compared to human-piloted aircrafts, drones have some significant advantages: Since no human is on-board, there is no necessity for life-critical systems. Hereby the construction is less complicated and less expensive. Moreover, no control interface, cockpit, or windows are required which has a positive impact on the weight and size of the vehicle. Due to the smaller size, less resources are needed for the construction and less power is needed to keep the drone in the air. Furthermore, the small size makes them manoeuvrable in areas that may not be approachable by a human-piloted aircraft (Barrera, 2021, p. 8). Compared to trucks, drones emit less CO₂ and can travel independently of road networks and traffic. They

operate on a lower cost per mile compared to trucks and may decrease labour costs due to the saving of a driver (Otto, et al., 2018). In general, drones are useful for a wide range of operations that are a potential risk for humans.

Drones can be divided into fixed-wing and rotary-wing UAVs. Fixed-wing drones are comparable to airplanes, while rotary-wing drones are analogous to helicopters which can have one or multiple propellers. However, in several application areas rotary-wing drones are dominating the market. This is due to their ability to produce uplift without the need to move. Fixed-wing drones on the other hand must continuously move in order to stay in the air and are therefore less manoeuvrable and their movements are less controllable. The vertical landing and launching of rotary-drones allows for a precise landing without the need of a large landing or launching area (Barrera, 2021, p. 9). This makes them especially attractive in narrow spaces such as dense urban areas (Otto, et al., 2018).

Nowadays, drones are applied to many different areas including military operations, disaster operations and in a wide range of civil operations. They are expected to be a promising device in agriculture where they can be used to track crop growth in large terrains, spray fertilizer or supervise cattle. Agriculture is predicted to become the largest application area for drones in the U.S. in the following years. Furthermore, drones can be used for physical infrastructure as supporting advice by generating aerial views that may help to track progress at construction sites or analyse areas for planned construction sites (Otto, et al., 2018). However, especially the application of drones for delivery operations has caught the media's interest in the past years. The application of drones may include package deliveries for the last-mile in urban or suburban areas as well as deliveries to remote regions that are difficult to reach by road. Drones can, moreover, be used to fast, inexpensively and efficiently transport medical supplies such as vaccines or blood which may be especially relevant in countries with a poor road infrastructure. For last-mile delivery, the introduction of drones may have the potential to decrease transport costs, labour costs and decrease delivery time (Otto, et al., 2018). Drones may further be used for security operations and in the media branch to film and take pictures as well as for private use. The potential market value for infrastructure and construction applications is estimated around 45 billion Dollar, for transport the estimation lies at around 12 billion Dollar. Even though the market of drones for commercial and private use has shown a remarkable growth in the past two centuries, the market share of drones for military purposes in the U.S. is at around 70 percent. Drones are used for reconnaissance and surveillance, or they drop bombs or fire missiles (Otto, et al., 2018).

Legal regulations play a fundamental role when it comes to the application of drones. Currently, there are no uniform rules across countries or continents. Regulations for the use of UAVs vary widely between countries and make the development of new regions more difficult for companies (Zapfl, 2019). Generally, three aspects are of concern when deciding about drone regulations: The congestion of airspace is especially in densely populated areas of concern. Here the airspace is often already overcrowded with

airplanes and helicopters with which the drones would need to share airspace. Collisions with manned aircraft are cause of concern as well as an aggravated air traffic control. In addition, technical problems are feared that could lead to drones falling from the sky and hitting pedestrians. A public concern towards drones is the misuse of data generated by drones that are equipped with cameras or sensors and may violate the privacy of people (Heutger & Kückelhaus, 2021).

In the U.S., drones are allowed to fly up to 122 m. For flights at higher altitude or close to military areas or airports prior permission is sufficient. Each drone that is used for commercial purposes must be officially registered (Heutger & Kückelhaus, 2021). Regulations are similar in Austria. Drones flying higher than 120 m are subject to approval or certification, they must be registered and for drones with a weight higher than 250 g an online licence must be acquired (ÖAMTC, 2021).

Since this thesis deals with the usage of drones in the last-mile delivery process, the following characteristics refer to drones that are used for the delivery of goods. The payload of a delivery drone usually does not exceed 3 kg. Payload and size of the drone are in a trade-off which means that a higher payload requires more energy storage. Moreover, a heavier drone consumes more energy which may be reflected in higher transportation costs (Otto, et al., 2018). Especially for the application in cities the size of drones is restricted as they must fly and land in dense areas. Usually, a drone carries a single item only. However, there are also drone models that consider the carriage of several packages in one flight. The Chinese e-commerce company JD proposes several drone prototypes for the delivery of e-commerce goods in remote rural areas in China with payload capacities of 5 up to 30 kg. Since here, drones must not launch and land in densely built-up areas, they are not restricted in size as much as in urban areas and may therefore have a higher payload capacity (JD, 2016). Drones have a limited flight range which is dependent on different factors such as weather conditions, payload or the type of drone. Usually, delivery drones are powered by electric batteries that must be either swapped or recharged after a flight. For the recharging process, the assistance of a human may be required. A trade-off exists between flight endurance and transportation costs since a larger battery increases weight and by that, energy consumption per distance flown (Otto, et al., 2018). In general, delivery drones are expected to have a maximum endurance between 20 and 40 mins (Dell'Amico, et al., 2019; Wang & Sheu, 2019; Sacramento, et al., 2019).

Due to the advantage of a precise movement and the possibility to launch and land without runway airstrips, in urban areas rotary-wing UAVs are the preferred type of drones (Otto, et al., 2018).

For delivery purposes drones are expected to launch, navigate, and land autonomously without the need of a human ground pilot. Since truck and drone usually travel simultaneously, the truck driver cannot navigate one or multiple drones at the same time. Therefore, a delivery drone must be equipped with a self-navigation software. In several countries there exist regulations that require a human navigator for drone operations which must be considered when introducing drone delivery in a country (Otto, et al., 2018).

The speed assumptions for drones differ strongly between sources. Drones may travel with a speed up to 120 km/h. UPS, for example, tested delivery drones with a maximum flight speed of 72 km/h (Boysen, et al., 2018). However, the actual speed may be strongly dependent on the payload and the delivery area. In a densely populated area, it may not be realistic for a drone to reach such a high speed due to security reasons. For the delivery in different US-American cities researchers expect average drone speeds between 36 km/h and 80 km/h (Kitjacharoenchai & Lee, 2019; Moshref-Javadi, et al., 2020a; Raj & Murray, 2020).

One central aspect for the use of delivery drones is the way the parcels are being dropped off at the customer location. Most companies introduce drones that use a landing delivery, such as DHL, DPD and JD.com (JD, 2016; DPD, 2019; Heutger & Kückelhaus, 2021). This means, that the parcels are attached to the bottom of the drone and the drone must land in order to release them at the referring customer location. The Chinese company JD.com allows their drones to land only at a designated drop-off point from where the parcels are taken by a promoter (JD, 2016). The DHL Paketcopter can land at any customer location and may release the parcel automatically without the need for human interaction (Heutger & Kückelhaus, 2021). Another possible way to deliver parcels is the parachute airdrop. Here, the parcel is equipped with a small parachute. The drone stays in the air while the parcel will be released and glide to the ground (Wang & Sheu, 2019). Google, for instance, has introduced a prototype for a drone using parachute drop. However, this type of delivery may be more practicable in rural areas without obstacles like buildings and where an exact drop-off is not necessary (Heutger & Kückelhaus, 2021).

In summary, it can be said that drone technology is a current topic that has the potential to capture many different areas such as agriculture, logistics and entertainment. Limitations in size, flight endurance and carrying capacity of drones are challenges that must be managed in upcoming years. Moreover, in order to make delivery by drones a viable option, regulations must be standardised across countries and continents.

3. Overview on Truck-and-Drone Models

In the following section, the first part of the research question will be answered: A detailed literature review is to be carried out to explore the state of the art in Truck-and-Drone models. The results of the research will be categorised and analysed in detail. Subsequent, the aim is to find the best suited model for an urban e-commerce delivery by filtering the models according to the most important criteria. In the end of this chapter, two Truck-and-Drone models will be found that are ideal for an urban e-commerce delivery.

3.1 Strategic Approach for the Literature Review

For the search a strategic approach for finding relevant papers was used. The aim was to find recent published Truck-and-Drone delivery models for the application in e-commerce. The results of the search were then extensively analysed and categorised in order to find a suitable model to apply in the following part of this thesis. Figure 3 shows the research process. It can be roughly divided into four parts:

1. **Search:** An overview on the general literature in the field of Truck-and-Drone models could be generated by inserting key words in different combinations on several well-known platforms. The results can be seen in Table 1. However, they include several duplicates and need to be pre-selected for the further analysis. Furthermore, backwards search was being used to ensure a complete search result. The references of papers that include large literature reviews (such as Otto et al. 2018 and Chung et al. 2020) were studied for more relevant papers.
2. **Pre-Selection:** In the next step, the search results were analysed according to the title and the abstract. The inclusion and exclusion criteria will be explained in the further proceeding.
3. **Final-Selection:** After selecting all papers that appear relevant, the full-text analysis could further limit the number of papers that are relevant for the hereafter literature review of Truck-and-Drone models.
4. **Analysis:** In the final step, the selected papers were analysed extensively according to various categories. The results of the analysis can be found in the following chapter.

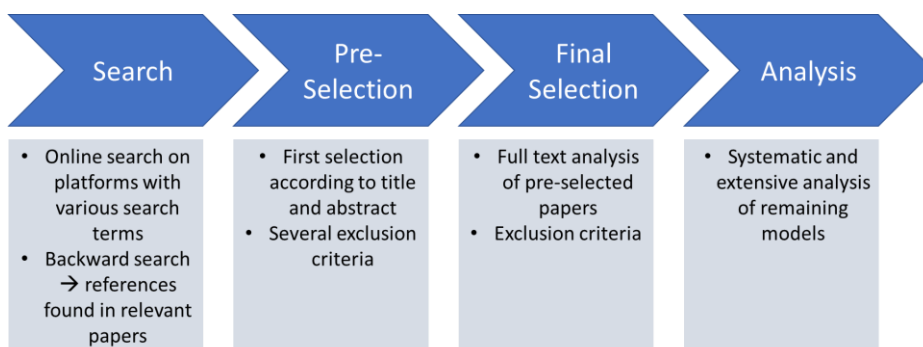


Figure 3: Systematic Literature Review in four Steps

In the first three steps of the search, several inclusion and exclusion criteria were applied to specify the results. The more specific a criterion is, the later it can be applied in the search process.

- **Language:** Only results in English language were included, which is due to the language skill limits of the author.
- **Publication year:** The search is specified to research that was published from 2018 up until January 2021 (last search: 02.02.21). As the aim is to find the state of the art in Truck-and-Drone models, the author wants to focus on the most recent work.
- **Application area:** The results were filtered according to the application area at which the referring paper is addressed. The research focusses on papers that are related to e-commerce or parcel delivery or that could be applied to this area. If other application areas were explicitly mentioned in the title or abstract of papers, they were excluded from the results (for example models that address disaster management or medication supply).
- **Contribution:** The following analysis focusses on mathematical delivery models and referring solution methods. Therefore, only papers that either formulate an optimization problem, adapt an existing model or develop a new solution method to solve a delivery model are relevant.
- **Transportation Mode:** The model must include the usage of both trucks and drones for the delivery and cannot include other vehicle types such as robots. However, it is not relevant which vehicle type is responsible for the delivery to the end customer.

Search Terms	Platforms & Results			TOTAL
	Springer Link	Science Direct	Scopus	
"truck-and-drone"	27	72	23	122
"drones" AND "last-mile"	248	245	87	332
"truck and drone" "last-mile"	18	52	12	82
"vehicle routing problem" "drone"	109	155	56	320
"traveling salesman problem" "drone"	118	149	65	332
"truck" "drone" AND "last-mile"	110	149	38	297
TOTAL	382	822	281	1485

Table 1: Search Results

Table 1 shows the results in the first step of the search. Three reputable platforms were used for the search. Starting with the most obvious search term "truck-and-drone", the search was broadened by combining several terms. The term "drone" can be found in each search as drones are the stand-out aspect and innovative element of the delivery models. In total, 1,485 search results were obtained of which several papers are duplicates. The search shows limitations in the amount of search terms and the platforms accessed. Moreover, it must be considered that the platforms' data bases are not complete at the end of

the research. Finally, 43 models could be detected. The full result of the literature review can be found in attachment 1.

3.2 Results of the Literature Review

Objectives

Regarding their objectives, the models can be roughly divided into three categories, namely time related, cost related, and customer focussed models.

Time related Objectives

The most often applied objective among papers that focus on the travel time is to minimize the completion time, which is the time the last vehicle will arrive at the depot (Dell'Amico, et al., 2019; Freitas & Penna, 2018; Poikonen, et al., 2019; Schermer, et al., 2019b). In the highly competitive market of e-commerce companies aim to improve their customer service by reducing the delivery time. Integrating drones into the delivery process allows for parallel operations that will naturally reduce the total delivery time. Therefore, selecting the minimal makespan or completion time as objective is a consequent decision (Chung, et al., 2020). In the case of multiple trucks the objective has the additional effect to balance the tour length across all drivers, which is useful for the scheduling of drivers' shifts.

Other papers aim to minimize the time to service all customers, which is equal to the minimization of delivery time without considering the travel time from the last customer to the depot (Schermer, et al., 2019a; Schermer, et al., 2019b; Jeong, et al., 2019). Kitjacharoenchai et al. (2019) minimize the maximal tour length while Jeong et al. (2019) reduce the earliest departure time. Overall, more than half of the surveyed papers have a time related focus.

Cost related Objectives

Considerably less paper aim for minimizing the overall costs (Wang & Sheu, 2019; Ha, et al., 2018; Tu, et al., 2018; Karak & Abdelghany, 2019). Only 7 out of the 43 analysed papers have a cost related objective. Sacramento et al. (2019) justify their change from reducing the completion time to cost minimization with an operational argument. They assume, that usually, drivers have contracts with fixed working-hours that must be met. By setting a fixed maximum time for the duration of all tours, this aspect is considered while costs can be held minimal. In the cost intense last-mile delivery, minimizing costs can have a significant impact on the overall logistics costs.

Besides costs that are associated with the travel time, overall costs can include several other cost factors such as parking fees for the truck, maintenance cost or labour cost (Chung, et al., 2020). Ha (2018) includes not only travel costs but also the costs of waiting for the other vehicle. While most paper consider only the variable costs of traveling to customers by truck and drone, Wang and Sheu (2019) include also fixed costs of employing trucks.

Customer focussed Objectives

Dayarian et al. (2020) and Moshref-Javadi et al. (2020a) take a more service-oriented approach: The former aim to maximize the percentage of delivered orders among all orders received while the latter focuses on minimizing the total customer waiting time. Das et al. (2020) developed a multi-objective problem that aims to minimize travel distance on the one hand and maximize customer satisfaction on the other hand by scheduling the delivery according to customer time windows. Focussing on customer satisfaction and following a service-oriented approach may be a competitive advantage when considering the high customer expectations regarding delivery time.

Other Objectives

Only a few papers follow differing goals such as Wikarek et al. (2019) who aim to minimize the distance covered by the drone for their model in which only drones are allowed to deliver parcels to the customer.

Mathematical Models

Most Truck-and-Drone models are adaptations of well-known mathematical models such as the TSP and the VRP which have been explained in chapter 2.3. The models are extended by implementing drones to the delivery process. In the following, it will be discussed how the basic transportation problems were adapted.

Traveling Salesman Problem with Drones

In the context of Truck-and-Drone deliveries the TSP is an often used optimization problem including a single truck for the delivery only. The most common adaption found in the literature research is the TSP-D (TSP with Drone) (Agatz, et al., 2018; Poikonen, et al., 2019; Es Yurek & Ozmutlu, 2018). Ha et al. (2018) differentiate between a truck and a drone delivery depending on which vehicle delivered the parcel to the customer. Drone deliveries are represented as a 3-node tuple which includes the launching node, from where the drone starts from the truck, the drone node, which is the location of delivery, and the rendezvous node, where drone and truck meet again. Launching and rendezvous node cannot be the same so that cyclic tours of the drone are not allowed. The TSP-mD allows for a set of drones that operate with a single truck instead of one drone only (Tu, et al., 2018). Apart from that, the model is similar to other TSP-D models. Kitjacharoenchai et al. (2019) designed a mTSPD with multiple drones and multiple trucks. The model formulation is an extension of the Multiple Traveling Salesman Problem (mTSP) with the addition of drones. It includes constraints from the mTSP as well as from the Flying Sidekick Traveling Salesman Problem (FSTSP), which is originated by Murray and Chu (2015) (see below). At any customer node, only one drone can launch or start from a truck and again, no cyclic drone tours are allowed. There is no drone-truck assignment. Moshref-Javadi et al. (2020a, 2020b) use an extension of the Traveling Repairman which

is an extension of the TSP itself and a basic routing problem aiming to minimize the sum of waiting times of all customers.

Flying Sidekick Traveling Salesman Problem

The Flying Sidekick Traveling Salesman Problem (FSTSP) is a generalization of the TSP and the VRP and was designed by Murray and Chu (2015). They were the first to introduce a model, in which a single truck and a single drone operate parallel to serve a set of customers starting and ending from a single depot. The makespan is to be minimized while all customers are being serviced exactly once either by a truck or a drone. During the truck tour the drone may make multiple trips to serve one customer per trip. The drone trips are - corresponding to the TSP-D model – characterized by three nodes: the launch node, the customer node and the rendezvous node. Drones may start a trip either from the depot or from a customer location, where the truck driver loads the drone with a parcel. Murray and Chu (2015) formulate the problem as a mixed integer linear problem (MILP). An additional binary decision variable y_{ijk} is required which is equal to one if the drone travels along the arcs (i,j) and (j,k) , and becomes zero otherwise. Furthermore, two auxiliary decision variables p_{ij} and u_i are required: p_{ij} synchronises the order sequence of truck and drone while u_i prevents truck subtours.

Corresponding to the TSP model, the FSTSP includes constraints to ensure that each customer is visited and left exactly once and to eliminate truck subtours. Moreover, the model includes several constraints for the synchronization of drone trips and the truck tour. The objective seeks to minimize the latest time at which either the truck or the drone arrives back at the depot. In fact, due to a constraint linking the arrival times of truck and drone at the depot, the objective can be viewed as a min-max objective which aims to minimize the maximal time at the depot among truck and drone (Murray & Chu, 2015).

Following the idea of Murray and Chu, other researchers developed extensions of the problem (Dell'Amico, et al., 2019; Freitas & Penna, 2018; Raj & Murray, 2020; Murray & Raj, 2020; Gonzalez-R, et al., 2020). Jeong et al. (2019) extended the model to the FSTSP with energy consumption and no-fly zones. The model provides a response to practical limitations that other models did not consider so far. They assume that the use of drones may not be allowed in all areas due to security reasons, for instance at airports, or due to nature conservation in national parks. In the model circular and non-overlapping areas can be included as no-fly zones. The second extension considers the load weight in regard to the drone's flight range. Murray and Raj (2020) modified the FSTSP by allowing multiple drones instead of one single drone and Gonzalez-R et al. (2020) extended the model allowing the drone to visit several customers in one trip without meeting the truck in between.

Vehicle Routing Problem with Drones

In the context of Truck-and-Drone models, the VRP with drones (VRP-D) is the most common extension of the VRP (Sacramento, et al., 2019; Schermer, et al., 2018; Schermer, et al., 2019b; Wang & Sheu, 2019).

Thirteen out of the 43 models are formulated as an extension of the VRP. Multiple trucks operate in synchronization with multiple drones to serve a set of customers. The VRP-D and the FSTSPD correspond in the most characteristics. However, one major difference is that in the VRP-D drones are allowed to return to the truck to the same location of which they departed from. This allows for cyclic drone trips and may increase the number of drone deliveries in the case of delivery locations being very remote: If cyclic trips are not allowed, traveling from one customer, supplying one customer, and flying to the next customer to land back at the truck may exceed the flying endurance of the drone (Nguyen, et al., 2020). Usually, trucks and drones are dedicated to each other which means that drones always come back to the truck from which they launched. The model formulation is extended by multiple tour and time synchronization constraints to ensure that the drone trips and the truck tour are coordinated with each other in time and place (Sacramento, et al., 2019).

The Vehicle Routing Problem with Drone Resupply (VRP-DR) considers a home delivery problem where customers constantly place orders while the trucks are traversing their tours. The drones move back and forth between trucks and depot and supply the recently received orders from the depot while only the trucks deliver the orders to the customers (Dayarian, et al., 2020). Similar to the model of Kitjacharoenchai and Lee (2019), Bakir and Tiniç (2020) designed the VRP with flexible drones (VRPFD), in which drones can swap between trucks. That means, that drones may be retrieved by any truck not only the one from which they started. Schermer et al. (2019a) extended the VRP by allowing en route operations (VRPERO). That means, that drones may be launched not only at customer locations or the depot but also at some points along the route. This allows for multiple drone operations during a single truck delivery.

Other Formulations

While the majority of papers extend one of the previous mentioned transportation problems, some researchers propose new formulations such as the k-Multi-visit Drone Routing Problem (k-MVDRP) that is designed as a MILP and seeks to minimize completion time using a single truck and a set of drones (Poikonen & Golden, 2020). Ulmer and Thomas (2018) address a same-day delivery problem in which customers' orders arrive dynamically. In contrast to the VRP, TSP and FSTSP, the model allows several truck tours to the depot from where the truck can resupply the recently ordered goods. Due to the dynamic and stochastic nature of the problem, it is formulated as a Markov decision process. Peng et al. (2019) developed the joint routing and scheduling problem for wide-area vehicle-drone cooperative inspection which can be compared to a Two-Echelon VRP that uses trucks as mobile intermediate depots. The problem is a combination of a Facility Location Problem (for the parking spot allocation), a VRP (for the routing of both truck and drones), and a Bin Packing Problem (for the assignment of parcels to drones). The Synchronised Truck and Drone Routing is a multi-objective MIP combining a VRPTW for the routing of both trucks and drones and a job-scheduling problem in order to meet the customer time windows

(Das, et al., 2020). Among all surveyed papers, it is the only paper including time windows, which play an important role in e-commerce due to the customers' high expectations and demands for a precise planning of the delivery.

Drone Trip Characteristics

The surveyed papers differ in characteristics that affect the drone flight. The most important differences are described below.

Cyclic Drone Trips

Drone trips are usually denoted by a launching node, one or several drone nodes and a rendezvous node (Ha, et al., 2018). Cyclic drone trips occur if the truck does not move during a drone delivery. The drone starts from the truck from a launching node, serves one or several customers and moves back to meet the truck at a rendezvous node which is the same as the launching node. Due to different model formulations, cyclic drone trips are either allowed or forbidden. In the latter case, drones can only meet the truck at a node which they haven't visited yet which means that the truck must move to the next customer location during the drone operation. Furthermore, there are models that only allow cyclic drone operations: In the Multi Trip Traveling Repairman with Drones model (MTRPD) the truck stops at a discrete set of customer locations from where it launches one or multiple drones to serve customers. During the drone operations, the truck waits for the drones to return and only travels to the next customer location carrying all drones once they have returned. This model only allows cyclic drone tours as a result of the model's design (Moshref-Javadi, et al., 2020a).

Customers per Drone Trip

Due to the small payload capacity and endurance of drones, the majority of models allow only one customer delivery per drone trip. After serving one customer, the drone must fly back either to the depot or the truck to change the battery and pick up the next parcel (Freitas & Penna, 2018; Jeong, et al., 2019; Murray & Raj, 2020). Only a few models consider multiple customer visits during one trip. In the k-MVDRP, the drone can serve a variable number of customers if the operation is energy feasible. Energy feasibility depends on the weight of packages delivered and the distance of customer locations (Poikonen, et al., 2019). Similarly, Wang and Sheu (2019) allow several customer deliveries per drone trip as long as the payload capacity is not exceeded.

Consideration of non-dronable Customers

Due to the small load capacity of a drone, it may not be possible, that all parcels can be delivered by a drone. Some items may be too large or too heavy and must therefore be delivered by the truck. Several papers do consider this aspect and introduce a subset among all customers, that may be drone eligible

(Dell'Amico, et al., 2019; Freitas & Penna, 2018; Kitjacharoenchai, et al., 2019). Customers with a demand weight lower than the drone's carrying capacity will be addresses as dronable customers in the following. In an earlier process, customers are divided into those that can be delivered only by truck and those that can be serviced both by drone and truck. However, there are also models that allow the supply of customers by drones only: Chang and Lee (2018) designed a Truck-and-Drone model, in which the truck simply serves as a mothership that carries the drones from one customer cluster to the next. The truck stops at a centre of cluster, releases the drones for the delivery, and waits until all drones have returned before it moves on to the next cluster. They assume that all parcels are sufficiently small and light enough to be delivered by a drone. This may be relatable for types of goods that are generally small such as mailings.

Roles of Vehicles

Models differ according to the role the respective vehicle plays within the delivery process: In some models, the truck has a supporting role only. Chang and Lee (2018), as above explained, created a model, in which the truck functions as a moving depot and charging station without delivering parcels itself. Here, the drones play the primary role while the truck only supports them. Contrary, Sacramento et al. (2019) designed a drone-supporting-truck model. Both vehicles service customers. However, the drones cannot deliver all parcels due to load capacity or weight constraints. That means, that the tour can be completed by the truck without using drones, but not vice versa. Ergo, trucks play a primary role in the delivery process. However, around half of the surveyed papers are designed such that both vehicle types are on an equal level: Both vehicle types are involved in the customer delivering and each parcel can be delivered by both vehicle types (Schermer, et al., 2018; Es Yurek & Ozmutlu, 2018; Tu, et al., 2018).

Contribution

The surveyed papers differ in terms of what they contribute to the research field. Some researchers propose new model formulations, while others introduce novel solution methods for existing problems. Moreover, they differ in the type of problem set on which the models and methods are being tested.

Problem Formulation

The majority of models are formulated as linear models: Mixed Integer Linear Programs are the most common formulations (Bakir & Tiniç, 2020; Dell'Amico, et al., 2019; Poikonen, et al., 2019). Moreover, there is one Binary Integer Linear Program and one Integer Linear Program (Wikarek, et al., 2019; Poikonen & Golden, 2020). Only a few of the surveyed papers provide non-linear models: In the multiple Flying Traveling Salesman Problem with Variable Drone Speeds (mFSTSP-VDS), Raj and Murray (2020) do not set the drone's speed as constant but introduce it as a decision variable to the model. Due to the

drone speed variable, the model cannot be formulated as linear problem. Chang and Lee (2018) include the calculation of distance between the centre of a cluster from which drones will be launched from the truck, and each delivery location within the cluster to the objective. Due to the Euclidian distance calculation, the model is non-linear. Ulmer and Thomas (2018) followed a different approach: The Same Day Delivery Routing Problem with Heterogeneous Fleets of Drones and Vehicles (SDDPHF) is designed as a Markov Decision Process. Customer requests arrive during the truck's tour and are unknown before the tour start. The model allows for a continuous adaption of the tour with each new customer request.

Mathematical Models

Most paper introduce a novel model formulation, that is typically an adapted version of an already existing transportation model. Here the contribution lies within the extension of certain constraints or relaxations, that make the model more realistic or that focus on different aspects. For example, both Agatz et al. (2018) and Ha (2018) deal with the TSP-D. However, each model is adapted in specific details, such that one model has a time related focus, while the other aims for cost minimization. Moreover, they differ in the allowance of cyclic drone tours. Other papers introduce diverse versions of the VRP-D that have different objectives, a varying number of drones per truck and the number of customers that can be served within one drone trip (Sacramento, et al., 2019; Schermer, et al., 2018; Wang & Sheu, 2019).

Solution Methods

Some papers' contribution lies within the creation of new heuristics for an already existing problem. For instance, Dell' Amico et al. (2019) provide a new heuristic combining a greedy constructive algorithm and local search for the FSTSP model, which was introduced by Murray and Chu (2015). Their proposed solution method outperforms other existing ones and leads to close to optimal solutions in a short computing time.

Due to the complexity of the models, an exact solution for the linear problems is only computable for around eight to twelve customers in reasonable run time with state-of-the-art linear solvers such as CPLEX (Es Yurek & Ozmutlu, 2018). In order to solve larger instances, researchers focus on proposing new heuristics or the implementation of metaheuristics.

Freitas and Penna (2018) introduce a hybrid heuristic consisting of an exact solution of the MILP and a metaheuristic. The exact solution serves as initial solution that will be improved by the General Variable Neighbourhood Search (GVNS). In the first step, a regular TSP is solved, in which the truck serves all customers. Following, the solution will be improved by iteratively replacing truck deliveries by drone deliveries if savings can be generated and the total delivery time is decreased. Then, the GVNS is applied to optimize the solution using local search and best improvement. The presented solution method is able to generate improvements for the solutions of several benchmark instances. Wang and Sheu (2019) follow a different approach: They propose a branch-and-price algorithm to solve a path-based model for the

VRP-D. For the initial solution, customers are divided into those that can be reached by drones starting from the depot and the rest. The solutions for both subsets are then combined to one initial solution. Thereafter, the pricing sub-problem is solved. As soon as the obtained solution is integral, it will be returned. The algorithm is able to find good solutions for problem instances, that are too large to be solved by a linear solver.

Test Instances

Most papers test their models and proposed solution methods on randomly generated problem instances or benchmark instances that were proposed by other researchers. Only a few researchers use actual street maps to examine their models for real-life settings. Moshref-Javadi et al. (2020b) apply the Simultaneous Traveling Repairman Problem with Drones (STRPD) model to a fictive set of customers in the City of Sao Paolo. The problem set is solved with the proposed Truck and Drone Routing Algorithm (TDRA) which is a metaheuristic solution method that is inspired by the Adaptive Large Neighbourhood Search (ALNS). Customers range from 28 to 101 per problem instance. While the truck follows the road network calculated using the Google Distance Matrix service, drones move in Euclidian distance between the truck and customer locations. Compared to the TRP model without drones, savings in customer waiting time of 48.8 percent and maximum savings of up to 51.2 percent could be generated.

All Truck-and-Drone models could generate significant savings in costs or time (depending on the referring objective) compared to a solution that involves trucks only. Furthermore, delivery times of each customers can be improved which implies that a combined delivery system using trucks and drones as synchronised units can bring valuable benefits in the last-mile delivery process (Wang & Sheu, 2019; Moshref-Javadi, et al., 2020b; Sacramento, et al., 2019).

3.3 Requirements for urban Delivery in e-Commerce

The 43 previous analysed models are all applicable for an e-commerce delivery in general. In order to preselect models out of the pool of models that were found during the literature review, it is important to identify essential requirements that result from the type of delivery. By that, models can be eliminated from the list of possible models that are not suitable for the specific scenario. Therefore, it must be found out, which of these models are specifically suitable for a delivery in an urban environment on the one hand and an e-commerce delivery on the other hand.

Urban Delivery

The demand in e-commerce is particularly high in densely populated areas. In several European countries it is evident that metropolitan areas show concentrations in the shipment volume compared to the average population. In Austria, for instance, around 39 parcels are delivered per household per year while Vienna accounts for 74 parcels per household and year. This means that a Viennese household is delivered

nearly twice the number of parcels compared to the total population. In 2020, 130 Mio. parcels were delivered in Vienna (WKO Wien, 2020). On average, this accounts for 400,000 parcels delivered per day and means a great challenge for service providers in urban areas.

However, there are also major differences within a city, which can cause additional challenges for delivery companies. Proceeding with the example of Vienna, it can be seen in the inner districts 1 to 9 and the 20th district that around one third of all shipments are concentrated here, even though these districts only account for 10 percent of Vienna's size (WKO Wien, 2020). On the one hand, this poses challenges for parcel delivery companies due to the high demand within a very small area. On the other hand, the small area and short distances between stops enable the use of alternative means of transport that only operate on shorter distances, such as drones. In the perspective of Truck-and-Drone models, the high parcel volume in urban areas implies that the models must include multiple trucks. Since one truck is packed with up to 270 parcels, per day at least 1,500 trucks are required for the delivery in Vienna (WKO Wien, 2020). With an assumption of 10 service providers operating in the Viennese market, this accounts on average for 150 trucks per day for each service provider. A single truck model is therefore not useful for the application in e-commerce in Vienna. Compared to other central European countries, Austria has average numbers in shipments per inhabitant per year (Statista, 2015). Therefore, it can be assumed that this conclusion applies to urban areas in general. Accordingly, all single truck models are eliminated from the pool of Truck-and-Drone models.

E-commerce Delivery

Since e-commerce is popular in most branches from electrical goods to fashion and furniture, the parcels differ strongly in weight and size. Small items that are lighter than one kilogram as well as heavy goods such as TVs must be delivered by a service provider. DHL, for instance, delivers parcels with up to 31.5 kg weight in Austria (DHL, 2021). Resulting, the last-mile delivery system must be flexible enough to handle all kinds of items regarding size and weight. Since most drones are only able to carry up to 3 kg, a Truck-and-Drone model must consider the parcels' weight and ensure that drones only deliver such parcels that they can carry (Sacramento, et al., 2019). It also implies that both vehicle types are included in the delivery of customers. In the first place, the parcel's weight must be declared for each individual customer. Customers must then be assigned to the referring vehicle such that customers with a parcel weight higher than the drone's carrying capacity are delivered by the truck only, while the rest may be delivered either by truck or drone.

Two restrictions for the models could be found: First, only multiple truck models are relevant in the further proceeding. Second, the parcels weight must be considered which results in the distinction between dronable and non-dronable customers.

3.4 Short Introduction in Truck-and-Drone Models for urban e-Fulfilment

After filtering the models according to the above explained characteristics, only five models remain in the pool. In the following, these models will be introduced shortly. The two models that will be used for the application scenario will be explained in detail. Reasons for picking these models and a detailed comparison follow afterwards. Table 2 gives an overview on the remaining models with all twelve attributes examined. All models are formulated as a MILP and are extensions of the VRP. All delivery systems are designed as such that the drones are supporting the trucks. This results from the fact that drones can only supply a subset of customers due to capacity restrictions while the trucks can supply all customers. However, they differ in several aspects such as the objective and the number of customers that can be supplied during one drone trip.

Reference	mathematical Model	Objective	Amount of Vehicles		Roles of Vehicles							Solution Method				
			Trucks	Drones	cyclic Drone Trips	Customer Trips per Drone	all Parcels can be delivered by Drone	Truck supporting Drone	Drone supporting Truck	same-level both Vehicles deliver	proposing mathematical Model	Problem Formulation	exact Solution	Heuristic	Meta-heuristic	Road Map Testing
(Kitjacharoenchai, et al., 2020)	2EVRPD (2-Echelon VRPD)	minimizes total arrival time	multiple	multiple	no	several	no		x	yes	x	MILP	x	x	x	no
(Sacramento, et al., 2019)	VRPD	minimize costs	multiple	single (one per truck)	no	single	no		x	yes	x	MILP	x		x	no
(Schermer, et al., 2019b)	VRPD	minimize time to service all customers	multiple	multiple	yes	single	no		x	yes	x	MILP			x	no
(Tamke & Buscher, 2021)	VRPD	minimize max. (total) completion time of all vehicles	multiple	multiple	no	single	no		x	yes	x	MILP	x	x		no
(Wang & Sheu, 2019)	VRPD	minimize costs	multiple	multiple	no	several	no		x	yes	x	MILP	x	x		yes

Table 2: Overview of the surveyed Models relevant for urban e-Commerce Delivery

Two Echelon Vehicle Routing Problem with Drones in last-Mile Delivery (Kitjacharoenchai, et al., 2020)

The two echelon vehicle routing problem with drones (2EVRP-D) is a variant of the Vehicle Routing Problem that includes drones into the routing and a generalization of the mTSPD. The trucks, the first level, serve as intermediate movable hubs from where drones, which are on the second routing level, can start and land. Drones are retrieved from the truck at customer locations only. At that location, the truck delivers the parcel to the customer while the retrieved drone supplies other customers in the meantime. The proposed MILP model seeks to minimize the total arrival time of trucks at the depot. Each truck may carry multiple drones. At each node, only one drone can be launched or retrieved at the same time. Launching and landing times of trucks and drones are synchronised so that by minimizing the total arrival times of trucks the arrival times of drones are minimized at the same time. Drones can merge with a truck at customer nodes only. As long as the carrying capacity limit and battery endurance is not violated, drones can serve multiple customers within one flight. Two binary decision variables are assigned for traveling along an arc by a truck and drone respectively.

In order to solve large size problems, the authors propose two heuristics for the 2EVRP-D, the Drone Route Construction (DTRC) and a metaheuristic that is based on Large Neighbourhood Search (LNS).

A Metaheuristic for the Vehicle Routing Problem with Drones and its Variants (Schermer, et al., 2019b)

The VRP-D proposed by Schermer et al. (2019b) minimizes the makespan by which the tour length of all vehicles is balanced in order to find the shortest total tour time. The model, which is formulated as an MILP, supposes a fleet of homogenous trucks and drones and a set of customers with equal demand. However, although the model anticipates uniform demand across all customers, a subset of nodes is created, that includes drone-serviceable customers only. Per operation, the drone can serve a single customer before it must return to the truck for a battery recharge. Trucks and drones are assigned to each other which means, that drones must return to the same truck from which they departed. Drones and trucks can only merge on customer locations or at the depot. Different to most models, the proposed VRP-D allows for cyclic drone trips. By this, the drone can make several operations during a single truck delivery. This may be especially relevant if the drone travels significantly faster than the truck. Drone operations include a required time for launching and retrieving the drone. Trucks can launch and retrieve multiple drones at the same time. Compared to other models, the VRP-D by Schermer et al. (2019b) is relatively complex. The model has eleven decision variables of which five are binary, one is integer and five are continuous. The continuous variables are used for the synchronization of trucks and drones and to minimize the makespan. The paper proposes both a two- and a three-index formulation for the problem. In the three-index model, the drone operation is defined as tuple with three indices (i, w, j) . Hereby, the number of decision variables and constraints decreases, while the total number of variables increases. The authors develop a Drone Assignment and Scheduling Problem metaheuristic that can solve large instances in a short run time.

A branch-and-cut Algorithm for the Vehicle Routing Problem with Drones (Tamke & Buscher, 2021)

Tamke and Buscher (2021) propose a VRP-D variant with two different time-related objectives. The min-sum approach minimizes the total completion time of all vehicles and is focussed on efficiency. A maximum route duration is added in order to ensure that all vehicles are used. The min-max approach aims to balance the tour length among all vehicles of the fleet by minimizing the maximum tour length and is focussed on the optimal capacity utilization. Drones are assigned to a certain truck which means that drones must return to the truck from which they departed. While drones can wait at customer location for the truck, trucks cannot wait vice versa. During a drone operation, a single customer can be serviced only. The MILP model considers service times for the delivery process for truck and drone delivery respectively. Due to capacity limits, only a subset of all customers can be serviced by a drone. Moreover, customers can only be delivered by drone as long as the maximum flight endurance is not exceeded. A capacity limit for the truck is not assumed as in small parcel delivery the capacity is rarely reached and therefore is not expected to be a restrictive element for the model.

Five binary and one continuous variable are used to construct the path of trucks and drones. Five further variables are used for the synchronization of arrival and departure time of the vehicles. The paper provides valid inequalities for the problem, of which follows a branch-and-cut algorithm for the VRP-D in order to find exact solutions for the VRP-D for up to 30 customers.

Vehicle Routing Problem with Drones (Wang & Sheu, 2019)

Wang and Sheu (2019) introduce a version of the VRP-D with a focus on transportation costs contrary to the majority of Truck-and-Drone models that focus on minimizing travel time. At the beginning of the delivery, trucks are located at the depot. Drones are initially located at the depot and on docking hub nodes. They can be carried by a truck and can start from the depot and customer locations but cannot land back at customer locations. Docking hubs are introduced for the landing of drones as the authors claim that this is the preferred approach in the delivery industry. These hubs are additional nodes that serve as a transfer station between drones and trucks. Docking hubs are equipped with a storage space for drones and include backup drones as well as battery changing equipment. Only here, drone and truck can meet again after a launch. More precisely, drones can only land at docking hub nodes or the depot. When supplying a customer, drones drop the parcel at a customer location by parachute airdrop. This approach differs significantly from the models proposed by other researchers.

Drones can serve several customers during one operation as long as the carrying capacity and the maximum flying duration are not exceeded. Drones are allowed to switch truck, which means that they can be picked up by a different truck at a docking station than from which they departed. Similarly, trucks do not have to wait at a docking hub for a specific drone to arrive but can pick up another drone that is already available at the hub. The weight of each customer demand must be set beforehand. The “dronability” of customers is defined by a constraint that forbids drone flights for which the cumulated weight of parcels exceeds the carrying capacity. In the model, a maximum of drones on each truck and a maximum of drones per hub are set for capacity reasons. The model does not consider launching and recovery time for the drone as well as service time for both vehicles. The authors claim that these times are so small in relation to the whole operation that they can be neglected.

Objective and Decision Variables

The objective consists of three parts: The fixed costs for employing a truck, the transportation cost of the trucks and the transportation costs of the drones. Four binary decision variables are defined for the travel of vehicles. x_{ijk} equals one if the k th truck travels the arc (i,j) independently, which means without carrying a drone. y_{ijd} is the referring variable for the drone delivery. z_{ijkd} and u_{ijk} are added to define the combined travel of truck and drone, which means that the truck carries a drone along the arc (i,j) . Moreover, the model has two decision variables for the cumulative weight units of customer parcels that the truck (w_{ik}^T) and respectively the drone (w_{id}^D) has delivered at node i . These variables are used to ensure that the

carrying capacity of truck and drone are not exceeded. v_{id} cumulates the flying time at node i for the d th drone after it left from either the depot or a docking hub and ensures that the drone maximum flying time duration is met.

Constraints

Constraint (3) and (4) restrict that all vehicles that leave the depot must return to the depot at the end of the tour. Constraints (5) and (6) ensure that each customer is visited exactly once, either independently by a truck, a drone or by a truck carrying on or more drones. The flow conservation at each customer and hub node is ensured in constraints (7) and (8). Each truck can only carry a specified number of drones (9). Constraint (10) ensures that the maximum number of drones per hub is not exceeded. The variable v_{id} for the cumulative flying duration is defined in constraint (12) and (13). Drones can serve several customers in one operation but are not allowed to land on a customer location (12). They can only land at a docking hub node or the depot in which case the cumulative flying duration is set to zero as the battery can be swapped here (13). Constraint (15) defines the variable w_{id}^D for the cumulative dropped weight of drones and constraint (14) ensures the drone's maximum carrying capacity feasibility. The variable w_{ik}^T for the cumulative dropped weight of trucks is set such that it guarantees the truck capacity feasibility and such that it allows the drop-off of several customer parcels at a docking hub (15-17). The following constraints define the relationships of decision variables (19-21). Finally, constraint (22) ensures that drones cannot land at customer nodes.

The authors propose a branch-and-price algorithm to solve the path-based formulation of the model which can obtain solutions in a significantly lower run time compared to a linear solver.

An adaptive large Neighborhood Search Metaheuristic for the vehicle Routing Problem with Drones (Sacramento, et al., 2019)

The proposed version of the VRP-D aims to find the route for a set of trucks and drones to deliver customers with the lowest transportation costs. Each truck can carry exactly one drone and each drone is assigned to one truck. This means that drones must always land at the same truck from which they launched. At the beginning of the route, trucks and drones start at the depot. In the end, they must return to the depot either independently or the truck carries the drone. The travel times of trucks and drones are synchronised such that both vehicles wait for each other at customer locations. Drones can start and land from the depot, or at customer locations, and can meet their dedicated truck at each customer location. Within one flight, a drone can serve one customer only. The model includes fixed drone launch and recovery times, as well as service time for delivering the parcel to the customer. Trucks and drones have different service times which may vary between customers according to the accessibility of the customer location. Trucks have a limited carrying capacity which must not be exceeded and a maximum duration of the tour. The latter corresponds to employment contracts that include a specific standard for working

hours. A drone operation is limited by a maximum flying duration. A maximum drone capacity is not included by a constraint. However, drones are only allowed to service customers from a subset of dronable customers. The subset may be pre-defined such that it only contains customers with a demand smaller than the maximum drone carrying capacity. As drones can only serve one customer before returning to the truck or depot, a drone operation always consists of three nodes. Wang and Sheu (2019) define such an operation by using a tuple consisting of three nodes: the launch node, the delivery node - which corresponds to all dronable customers - and the rendezvous node where drone and truck meet again. Only those tuples are allowed where the travel time plus service time of the customer plus launch and recovery times are smaller than the flight endurance. All three-node sorties that hold mentioned conditions belong to the set P and are defined as s .

Objective and Decision Variables

The objective function minimizes the variable travel costs of trucks and drones. Hereby, the fuel consumption is the only cost factor for the truck movement which does not cover all costs involved in the distribution process. The VRP-D makes use of three binary and three continuous decision variables. The binary variables x_{ijv} and y_{sv} are defined for the truck and drone travel respectively. As each truck can only carry one drone and trucks and drones are assigned to each other, the model does not require an extra set of drones. x_{ijv} is equal to one if a truck v travels along the arc (i,j) . Respectively, y_{sv} is equal to one if a drone assigned to truck v travels along the tuple (i,j,k) , which is defined as s . The third binary variable p_{ijv} indicates if a customer j is visited after a location i . The relative position of visiting node i is defined by the continuous variable u_{iv} . The variables t_{iv} and t'_{iv} indicate the arrival time at node i of trucks and drones respectively. These time related variables are used to synchronise the arrival time of both vehicles.

Constraints

Constraint (2) ensures that each customer is visited exactly once either by truck or drone. Each truck may leave and return to the depot at most once which means that not all available trucks must be used for the solution (3,4). Traveling directly from depot to depot is prohibited by constraint (5). The flow conservation is ensured by constraint (6). Constraint (7) and (8) eliminate subtours for the trucks in the solution. Customer demand that is delivered by the truck plus the demand that will be delivered by the assigned drone must not exceed the maximum carrying capacity of a truck (9). Drones can launch and land at most once at each node which means that a drone cannot make several operations during one truck operation (10,11). Constraint (12) ensures that the routes of truck and drone meet at the launching and recovery node of a drone's sortie. Trucks must visit both nodes as drones can only launch from and land on a truck (except for the depot) (12). The variables for the arrival time of truck and drone are set to zero at the beginning of the tour (13,14). Constraints (15) and (16) ensure that the maximum tour duration is not exceeded. The truck movement is defined in constraint (17) including the launch and recovery times of

the drone as well as the service time for the delivery. Correspondingly, constraint (18) and (19) define the drone movement dependent on the truck's position including travel time, launch and recovery time, and service time. In constraints (20-23), the travel times of trucks and drones are synchronised such that the vehicles must wait for each other. One exception arises for the case that truck and drone return independently to the depot. The flight endurance must not be exceeded (24). Constraint (25) and (26) set the value for the variable p_{ijv} which defines the order of visits of truck. If the position of the truck at location j is larger than the position at location i , the variable p_{ijv} is set to one. For the case that the truck visits neither node i nor j , constraint (26) ensures that p_{ijv} is equal to zero. Constraint (27) prohibits new launches while the drone is already flying along the route.

The authors propose an adaptive large neighbourhood search metaheuristic for solving the VRP-D. For the initial solution, a construction heuristic, a local search algorithm and a drone addition algorithm are applied. Then, several destroy and repair mechanisms modify the solution in each iteration.

3.5 Comparing Sacramento et al. (2019) and Wang and Sheu (2019)

As indicated above, the two models that were chosen to fit the most to an urban e-commerce delivery using truck and drones are the VRP-D by Sacramento, Pisinger and Ropke (2019) and the VRP-D by Wang and Sheu (2019). Reasons for this choice are given in the following text. Since, without further examination, none of the five preselected models appear to fit particularly best, the author chose the two models stated due to the following conditions:

Given that the aim of this thesis is to find the best Truck-and-Drone model in regards of costs, it might appear obvious to select those models that have a focus on minimizing costs. While this element was an important factor in the decision process, it was not the only one. Both, Sacramento et al. (2019) and Wang and Sheu (2019), propose a VRP-D formulation with a cost minimizing objective. However, by analysing the models in detail, it became obvious that they differ in several important elements: The synchronization of both vehicle types and the idea behind the delivery systems differ strongly between the two models. The author finds it particularly interesting to compare two entirely different approaches so that advantages and disadvantages become apparent. In Figure 4, the delivery processes are modelled on a six customer example.

Hereby the main differences can be observed: Wang and Sheu (2019) allow multiple customer deliveries within one sortie while in Sacramento et al. (2019), drones can only visit one customer before they must return the truck. Wang and Sheu (2019) introduce additional docking hubs that are used for the launch, landing, and recovery of drones. Drones can land at these hubs only and are not allowed to land at customer nodes. These docking hub nodes require for a certain infrastructure and the need to invest in the rent of a location. These locations must be easily accessible by both truck and drone and must be maintained regularly. In the VRP-D proposed by Sacramento et al. (2019), drones may start and land at

customer locations, where they meet back with the truck. Here, the trucks must have a launch and landing station as well as battery changing equipment, and no further infrastructure is required.

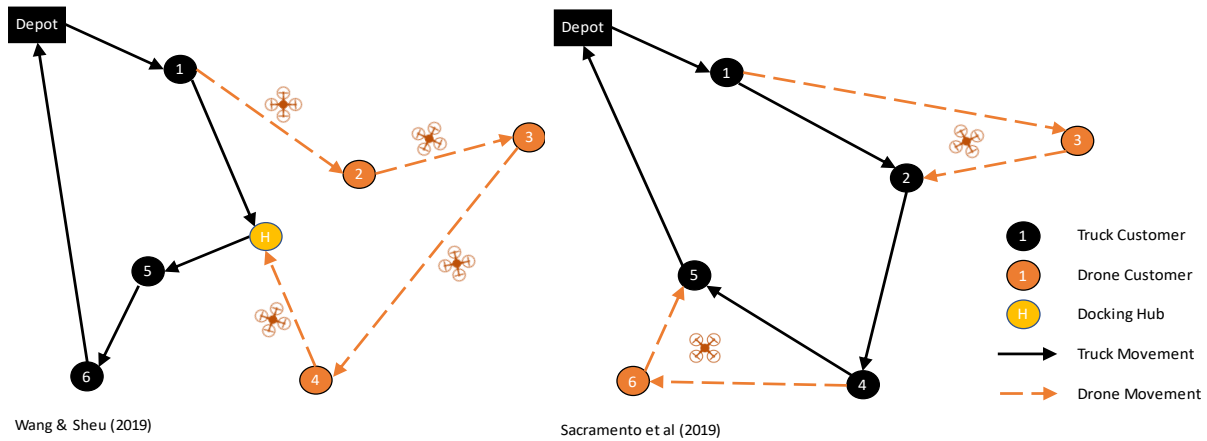


Figure 4: Graphic Illustration of the Delivery Systems by Wang and Sheu (2019) and Sacramento et al. (2019)

Besides the differences in the delivery process, the models differ in important aspects regarding the mathematical formulation. Sacramento et al. (2019) do not introduce a drone set, but rather assign one drone to each truck. Resulting, each truck can carry exactly one drone and drones are not allowed to switch trucks. In contrast, Wang and Sheu (2019) include a set of drones and a maximum number of drones per truck and hub that can be set arbitrarily. From this follows, that drones can be picked up and carried by a different truck than of which they were brought to the docking hub or of which they launched before. Moreover, the models differ in the mathematical formulation of the drone movement. Sacramento et al. (2019) define a drone movement by using a tuple consisting of a launching node, a delivery node and a rendezvous node. In contrast, the drone movement in Wang and Sheu (2019) consists of multiple arcs. This results from the fact that drones may serve multiple customers within one flight. Start and landing nodes are either a docking hub node or the depot. The VRP-D by Sacramento et al. (2019) includes variables for the time travelled by each vehicle which makes an exact time synchronization of the vehicles possible. Wang and Sheu (2019) do not introduce such decision variables so that an exact travel time schedule or an overall tour duration is not measurable. The objective function of both models aims to minimize the logistics costs by multiplying the transportation costs of truck and drone with the travelled time of each vehicle respectively. Wang and Sheu (2019) add the fixed costs for employing a truck for each truck that is used in the solution. The dronability of customers is dependent on the endurance and the drone carrying capacity in both models. Dronable customers are defined by a subset of customers whose demand weight is smaller than the maximum carrying capacity of a drone in Sacramento et al. (2019). Moreover, only those drone sorties are defined which do not exceed the endurance of a drone. On the other hand, Wang and Sheu (2019) add a constraint to ensure that the maximum carrying capacity is never exceeded as well as constraints to ensure the feasibility of the drone flying duration.

The model by Wang and Sheu allows drones only to land at docking hub nodes and the depot but not at customer locations. Therefore, the drone must drop the parcel from the air using a parachute. Wang and Sheu claim, that parachute landing is the preferred delivery since the landing operation requires a large area and a special docking device which is not available at all customer locations.

Contrary, in the VRP-D by Sacramento et al., the drone lands at a customer location, releases the parcel and launches again to meet the truck. While the landing delivery is the more common method, both systems have their advantages and disadvantages: When landing at the ground in a dense area, the drone is exposed to various hazards, such as passing pedestrians, bikes or pets. Moreover, landing at locations that do not offer a spacious area requires the drone to navigate through obstacles like trees or streetlights. This not only increases delivery time but also is a potential risk to the longevity of drones and may in the long run increase costs. However, a landing delivery enables a secured and controlled delivery of the parcel at the exact location required. Moreover, is the delivery at locations possible, that cannot be reached by a drop delivery, such as balconies.

Parachute drop delivery saves time since the drone does not operate a complex landing and launching. It secures the drone from various risks that it may face on the ground. However, wind may mislead the delivery and may hinder an exact delivery. Moreover, parcels could only be delivered to free spaces without obstacles between drone and ground such as trees which may minimize the potential delivery locations. Especially in urban areas with narrow sidewalks, it may be difficult to navigate the parcel precisely to the desired landing point without interfering with road traffic.

Neither of the two models consider a realistic scenario of how the parcel will find its way to the customer after the parcel drop-off.

Strengths and Weaknesses of both Models

By the introduction of docking hub stations in the VRP-D by Wang and Sheu (2019), additional challenges await the service providers. The locations for the station must be chosen carefully considering the reachability by truck and drone both and the delivery area's demand. The stations must be built, maintained, and rented. In the case of a shift in demands, the delivery system may not be able to react instantly since docking hub stations must be developed first. Docking hub stations salvage significant costs that add to last-mile delivery costs. However, a well located docking hub station ensures an uncomplicated and safe landing for the drone and decreases the risk of accidents. Moreover, the parachute airdrop delivery secures the drone from potential risks on the ground. Therefore, the model by Wang and Sheu (2019) ensures a long life cycle for the drone which may save costs in the long-term.

Since here drones and trucks are not assigned to each other, trucks do not have to wait for the drone to arrive back at the docking hub but can immediately pick up a back-up drone from the hub and continue

its tour without waiting time. The benefit is a fast delivery and a shorter truck tour duration which may decrease labour costs for the driver since working hours may be reduced.

Drones are not allowed to land at customer locations but can only land at the docking hub. The authors argue that customer locations may not have enough space for the landing of the drone. This may be true. However, launching is allowed from any customer node without any consideration of space. If the truck's roof is already equipped for a drone launch and the authors assume there is sufficient space for the drone to launch, why would the landing be problematic? This is an aspect that is not mentioned in the paper, and it is questionable if this assumption is realistic. Another detail in the model that may be discussed is the parachute drop-off delivery. Evidently, this delivery method has advantages. However, it does not appear to be the preferable way for companies in the drone delivery industry. Amazon claims a patent for a drone with parachute drop-off delivery but has not been introducing this technology (Shields, 2017).

The Sacramento et al. (2019) model is very flexible in terms of the delivery area since no additional infrastructure is necessary. This means that the delivery area may be extended or reduced immediately in the case of changes in the demand. Since the model includes variables that indicate the time at which trucks and drones are located at each customer, delivery companies can exactly plan their tours regarding the time at which they visit each customer and can inform them about the delivery time.

In the model drones can launch and land at any customer location regardless of the available space. Especially in urban areas with narrow streets intense traffic and highly frequented pedestrian routes a landing and launching operation may be difficult. Since the drone uses a landing delivery, the drone is exposed to hazards of different kinds. It may not be possible for the drone to land and deliver parcels at any given location due to space restrictions which should be considered in the model. The condition for the subset of dronable customers may therefore be extended by a landing and launching space requirement for each customer which, for instance, may be computed using Google Maps Street View. In a delivery according to the Sacramento et al. (2019) model, at most half of the customers can be delivered by drone since the truck travels simultaneously and the drone must return to the truck after supplying one customer. Ergo, for each drone customer, there is a truck customer. Since traveling by drone is both cheaper and faster, it is beneficial to increase the number of drone customers to the highest possible. Due to the architecture of the delivery process, the maximum is already reached at 50 percent of all customers. Resulting, the model has a limited potential for cost reduction.

4. Case Study: Truck-and-Drone Delivery in the 9th District of Vienna

In the proceeding part of this thesis, the VRP-D by Wang and Sheu (2019) and the VRP-D by Sacramento et al. (2019) will be compared using real life data of an urban e-commerce delivery. After the theoretical comparison and evaluation of the models, they will be tested on actual data to find the model that is more cost efficient. The delivery will take place in the 9th district of Vienna (also referred to as Wien Alsergrund) and actual travel data will be used. Following questions will be answered: Which model delivers the lowest transportation costs for the delivery in Wien Alsergrund? Can the introduction of drones into the last-mile delivery decrease logistics costs compared to a truck-only scenario? Which model is most realistic to implement for e-commerce delivery in Alsergrund?

4.1 Defining the Application Scenario

In the first step, the real-world application will be defined according to the area and the industry's characteristics. This will be important for the setting of parameters and general assumptions such as the location of docking hub nodes. In the scenario, it is assumed that all customer locations are in the 9th district. No further deliveries in nearby districts are considered. All customers must be supplied during the tour.

Delivery Area and Traffic Situation

The 9th district borders the inner city to the north-west and belongs to Vienna's inner districts. Alsergrund is one of the smallest districts of Vienna with an area of 2.99 square kilometre and a population density of 14,000 population per square meter. It is home to Vienna's largest hospital and several locations of Universität Wien (Stadt Wien, 2021). The street network is highly developed. The two most important through roads along the district are the Gürtel and Rossauer and Spittelauer Lände along the Danube Canal. Several embassies are located in the 9th district, such as the U.S. embassy which is highly secured. Alsergrund is a predominantly residential area with no large industry areas (Stadt Wien, 2021).

Vienna is one of Austria's cities with the most traffic congestion. In 2017, for a one hour ride, around 31 percent additional time must be considered per day (ORF, 2017). During the peak hours in the morning and afternoon, the Gürtel and the Rossauer and Spittelauer Lände are mostly affected, as well as the main connection roads that cross Alsergrund such as Alserbachstraße and Nussdorferstraße.

In the perspective of e-commerce delivery, the 9th district's street network offers good conditions for the delivery by truck. However, during peak hours, additional travel times must be considered. The delivery area is relatively small, which is ideal for drone delivery considering the low battery endurance. By calculating a drone flight with the VRP Spreadsheet Solver by Erdogan it could be found out that drones can easily reach every location within the 9th district. With an endurance of 30 minutes and a speed of 40

km/h, a drone can complete a delivery and return to the truck even along the longest possible arc within a single battery life (Erdoğan, 2017).

Since Alsergrund is not characterized by much vegetation in the streets, this aspect may not be considered as a critical factor. However, streets and sidewalks are often narrow in Alsergrund which may require an exact drone delivery which is only possible by landing delivery. In 2020, around 120 Mio. parcels were delivered in Vienna (WKO Wien, 2020). This is an amount of 400,000 parcels per workday in Vienna. For the 9th districts, this counts to a demand of 8,800 parcels per workday.

State of Service Providers in Vienna

The scenario created considers the delivery of e-commerce goods which can be anything from electronic goods to fashion and can be transported by a service provider such as DHL, DPD or the Austrian Post. The type of goods is not determined beforehand so that the transportation system must be flexible enough to carry goods of diverse size and weight. DHL, for example, delivers goods up to 31.5 kg and a size of 100 x 60 x 60cm (DHL, 2021). There are several distribution centres around Vienna: DHL supplies Vienna from a location in the second district, DPD from a distribution centre in Leopoldsdorf which is south to Vienna (Google Maps, 2021). As same-day delivery is not a common service in Austria (excluding recently emerged grocery delivery services), it is not part of the scenario. Ergo, all parcels and customer locations are known at the start of the tour. There is no resupply of parcels possible once the truck leaves the depot.

4.2 Setting the Parameter Values

In the next step, the parameter values for the implementation of both models are set. The goal is to find values that are as close to reality as possible. Since the models differ in the mathematical formulation and in the definition of parameters, some parameters must be set to zero in order to ensure an exact comparison between the models. For instance, does the VRP-D by Sacramento et al. (2019) include parameters for the launching and recovery time of a drone as well as the service time for both vehicles respectively. Since these parameters do not appear in the compared model, they are set to zero. Instead, times for launching and recovery may be calculated in the average travel speed. The truck costs per kilometre are calculated by multiplying fuel price by the consumption rate. The fuel price is set at 1.196 €/l which refers to the petrol price on 8.3.2021 for Austria (Global Petrol Prices, 2021). The consumption rate is dependent on the actual vehicle model and the travel speed as well as the congestion level. Transporters consume in average 11 l/100 km (Webfleet, 2020). However, due to the density of area and the many stops as well as high congestion rate the consumption rate is set to 13 l/100 km. Resulting, the costs per kilometre are set to 0.15548 €/km. Since the objective focusses on the travel time instead of distance, the costs must be multiplied by the truck speed, under the assumption that the vehicle travels 30 km/h in average so that the travel costs per hour result in 4.66 €/h. The general city speed limit in Vienna is 50 km/h. However,

the truck speed is set to 30 km/h due to high congestion, traffic lights, and the additional time to park the vehicle. The drone costs are set to 1.3 €/h for a drone speed of 50 km/h. This refers to a cost assumption of 0.05 \$/mile (Wang & Sheu, 2019). Drones may reach speeds of up to 75 mph (120 km/h) (Moshref-Javadi, et al., 2020b) and Amazon and Workhorse state that their drones can fly up to 50 mph (80 km/h) (Sacramento, et al., 2019). However, due to the dense urban environment of the 9th Viennese district, the drone speed is set to an average of 50 km/h. The drone endurance is set to 30 mins and is similar to the values of the majority of papers (Wang & Sheu, 2019; Sacramento, et al., 2019; Moshref-Javadi, et al., 2020b). The carrying capacity of a drone is set to 3 kg which corresponds to the characteristics of common drones used by Amazon or Workhorse (Sacramento, et al., 2019; Otto, et al., 2018). However, as technology is constantly evolving, drones will possibly be able to carry considerably higher loads in the future.

Choosing the number of customers for the main testing is a trade-off between two factors. On the one side, as many as possible customers should be considered in order to create a realistic application of demand in the 9th district of Vienna since an estimated 8,800 parcels are delivered per day (see chapter 4.1). On the other side, the computational complexity of the problem increases exponentially with an increased customer number and complicates finding a feasible solution within a reasonable run time. Due to the NP hardness of the problems, linear programming solvers are not able to solve large instances. After testing several customer sets with different sizes, 20 customers were chosen as compromise between the computational complexity and a realistic delivery scenario. It is not guaranteed that the globally optimal solution is found, however, a good feasible solution can be found by the solver. The program used is IBM ILOG CPLEX Optimization Studio 20.1.0. The program is a linear solver for linear programming, mixed-integer programming and quadratic programming, uses constraint programming, and supports Optimization Programming Language (IBM, 2021).

The number of dronable customers – the number of customers with a demand of 3 kg or smaller – is set to 15 which equals 75 percent of all customers. The remaining 25 percent customers may only be supplied by truck. Since there exists no reliable data regarding the weight distribution of parcels in e-commerce to the best knowledge of the author, the values for the customer demand are an estimate only. Amazon, for instance, states that 86 percent of its deliveries includes parcels with a weight less than 5 lb (2.27 kg) (Sacramento, et al., 2019). The parcel weights used for the main testing correspond roughly Amazon's statement and are rounded to full kilograms between 1 kg and 13 kg. Among the 20 customers, eight parcels have a demand of 1 kg, and five parcels have a demand of 2 kg. This is relevant for the VRP-D by Wang and Sheu (2019) since here drones can carry several drones during one operation.

For the delivery, two trucks and two drones are available. Usually, one delivery person delivers between 130 and 150 parcels per day which means that for the set-up scenario one truck would be sufficient (WKO Wien, 2020). However, since the possibility to include multiple trucks was set as a requirement earlier (see chapter 3.3), it should be utilized for the application scenario. Due to the drone-truck ratio of one in

the VRP-D by Sacramento et al. (2019), only two drones are allowed. In order to have a comparable setting, a set of two drones was chosen for the Wang and Sheu model.

Since only two drones are included in the scenario, it is expected that both truck and hub station have sufficient capacities to handle all drones at the same time. Therefore, the values for the maximum drones per hub and drones per truck are set such that they are not restricting.

The maximum tour duration for the Sacramento et al. model is 8 hours. On the one hand, this corresponds to a normal working day. On the other hand, since the model by Wang and Sheu does not include such a parameter, it is set such that it does not restrict the model. The delivery of only 20 customers in the small area of the 9th district is not expected to come close to 8 hours. Similarly, the truck capacity was chosen. Since only the Sacramento model considers a capacity limit for the truck, it was set such that it is not restricting to the model. With only 20 customers in the testing and customer demands between 1 kg and 13 kg, the capacity limit of a standard delivery vehicle, which lies at around 1,400 kg, will not be reached (Sacramento, et al., 2019). For simplicity reasons it was set to 1,000 kg for the main tests. The weight limit of trucks is not expected to be an important factor in last-mile delivery in e-commerce. The size of packages, as only private customers are serviced, is relatively small, so that the capacity of the vehicle may not be a strongly restricting element to the routing. Tour duration and travel time, on the other hand, may be a more limiting factor in the last-mile delivery in general.

For the VRP-D proposed by Wang and Sheu, the number of docking hubs is set to two. The locations for the nodes were chosen so that they are located centrally within the delivery area and well connected at main connection roads. The first hub is placed at Nussdorfer Straße which is the largest street crossing the district from north to south. In the north, the street connects to the Döblinger Gürtel and in the south, it continues as Spitaler Straße to the 8th district. Thus, an ideal connection within the district but also to the Gürtel is possible. The location functions as a drone hub for the northern part of the district. The southern hub is located at Währinger Straße which is one of the largest streets in the district. It runs from the first district (south) to the Währinger Gürtel (west) and crosses the Nussdorfer Straße. Thus, the hub at Nussdorfer Straße can be reached easily by truck.

For the depot location the Amazon distribution centre in Wien Liesing was chosen. As one of two centres in the metropolitan area, it acts as a hub for Vienna's south and west and is therefore responsible for deliveries to Wien Alsergrund (Vienna.at, 2020). The Open Data Österreich platform was used as a source for the addresses (Open Data Österreich, 2017). A data set containing all access addresses was filtered for all addresses with the postcode 1090. Access addresses represent the actual entrance to the building or building complex and thus, are a subset of addresses (Open Data Österreich, 2017). All locations from different hospital station of Allgemeines Krankenhaus Wien were removed from the pool as no end-customers are expected here. Furthermore, all subway stations were excluded for the same reason. Finally,

the data sets were generated randomly from a pool of 3023 addresses in the 9th district. The full list of customer addresses of the 15 instances can be found in attachment 2.

4.3 Parameter and Model Implementation

Calculation of Travel Times

In the next step, the travel times were calculated. The Erdogan VRP solver was used for the calculation of travel times (Erdoğan, 2017). For the truck data the solver console was filled with the number of customers plus one and one depot, the travel speed of the vehicle and the computation method for both distance and duration (see Figure 5, upper part). The remaining parameters were not changed since they are not relevant for the computation of travel times. Bing Maps driving durations and distances were chosen in order to obtain real-life travel times along the road network. For the drone travel the distance was computed according to bird flight distances since the drone can move in three dimensions and in Euclidean Distance between two locations (see Figure 5, lower part). The duration is computed by using the average vehicle speed. The drone can move independently of traffic which means that it can fly in constant speed. By default, the travel duration for the truck is rounded to full minutes while the travel duration for the drone is computed exactly. This is due to the choice of different computation method.

Sequence	Parameter	Value
0.Optional - GIS License	Bing Maps Key	AnRqx3IFHRhRFY8c-POFlkaiOsOqX7F8jd-IVDOFEV1rAsB4rTmntkw6YBlSZ5H
1.Locations	Number of depots	1
	Number of customers	21
2.Distances	Distance computation method	Bing Maps driving distances (km)
	Duration computation method	Bing Maps driving durations
	Bing Maps route type	Fastest
	Average vehicle speed	30
3.Vehicles	Number of vehicle types	1

Sequence	Parameter	Value
0.Optional - GIS License	Bing Maps Key	AnRqx3IFHRhRFY8c-POFlkaiOsOqX7F8jd-IVDOFEV1rAsB4rTmntkw6YBlSZ5H
1.Locations	Number of depots	1
	Number of customers	21
2.Distances	Distance computation method	Bird flight distances (km)
	Duration computation method	Average vehicle speed
	Bing Maps route type	Fastest
	Average vehicle speed	50
3.Vehicles	Number of vehicle types	1

Figure 5: Solver Console Set-up for generating Vehicle Travel Times (Erdoğan, 2017)

In the location sheet all locations were filled in in the form “street name - house number, postcode city” using the addresses that were randomly chosen in the previous step. The depot location was entered in the depot section and additionally as the last customer. This means that for a 20 customer instance 21 was filled in in the solver console in the customer field.

Location ID	Name	Address	Latitude (y)	Longitude (x)
0	Depot	Perfektastraße 71, 1230 Wien	48,1415500	16,3043300
1	Customer 1	Lustkandlgasse 44, 1090 Wien	48,2292994	16,3517962
2	Customer 2	Galileigasse 3(SCHULE), 1090 Wien	48,2255600	16,3537500
3	Customer 3	Höfergasse 1A/2, 1090 Wien	48,2156600	16,3418200
4	Customer 4	Alser Straße 24, 1090 Wien	48,2154500	16,3477800
5	Customer 5	Schwarzspanierstraße 8, 1090 Wien	48,2216800	16,3512400
6	Customer 6	Sobieskigasse 4, 1090 Wien	48,2260800	16,3534300
7	Customer 7	Badgasse 6/3, 1090 Wien	48,2272200	16,3595500
8	Customer 8	Gilgegasse 12(SCHULE), 1090 Wien	48,2169800	16,3464400
9	Customer 9	Währinger Straße 40-42, 1090 Wien	48,2204880	16,3560238
10	Customer 10	Währinger Straße 27, 1090 Wien	48,2199651	16,3565042
11	Customer 11	Viriotgasse 4/1, 1090 Wien	48,2303800	16,3551400
12	Customer 12	Rooseveltplatz 8(PFARRE VOTIVKIRCHE), 1090 Wien	48,2156900	16,3576100
13	Customer 13	Wilhelm-Exner-Gasse 1, 1090 Wien	48,2210000	16,3506100
14	Customer 14	Seegasse 32, 1090 Wien	48,2233515	16,3669323
15	Customer 15	Nordbergstraße 18/7, 1090 Wien	48,2228600	16,3519800
16	Customer 16	Grünentorgasse 30, 1090 Wien	48,2083400	16,3709200
17	Customer 17	Lichtentaler Gasse 4/1, 1090 Wien	48,2270100	16,3573600
18	Customer 18	Sobieskigasse 33, 1090 Wien	48,2304084	16,3533743
19	Customer 19	Badgasse 25/2, 1090 Wien	48,2281200	16,3584400
20	Customer 20	Van-Swieten-Gasse 16, 1090 Wien	48,2190995	16,3572199
21	Customer 21	Perfektastraße 71, 1230 Wien	48,1415500	16,3043300

Figure 6: Location Sheet for Instance 1 (Erdoğan, 2017)

Since the node sets for both VRP-D models were defined as such that the first and the last node are the depot, the depot address must be the first and last entry. The latitudes and longitudes were then calculated by the server using the addresses that were filled in (see Figure 6). Then, the addresses were checked for the right allocation on the map in order to avoid incorrect calculation of coordinates by the Erdogan VRP solver. After creating the distance sheet, the distances and durations between locations must be brought into the form of the travel time variable in the model. Sacramento et al. (2019) define the truck and drone travel (i,j) such that i is element of the set N_0 and j is element of N_+ . This means, that such arcs must be eliminated from the distance sheet, where i is the last depot node (customer 21 in the 20 customer example) and j is the first depot node (depot node). Moreover, all durations will be filtered out for which holds i is equal j , since the durations from one node to itself are always zero and not relevant for the tour calculation.

Wang and Sheu (2019) define the truck and drone travel along all arcs. The set of arcs (i,j) is defined by all paths between locations for which i is not equal j . The distance table was then filtered respectively. Finally, for each model and each vehicle type, the travel durations were prepared for the implementation.

Besides the travel durations, the excel sheet also includes all relevant parameter values such as vehicle speed, customers' parcel weight and transportation costs of each vehicle. Using the SheetConnection function in the CPLEX data set, all values could be directly read from the Excel sheet. By that, the CPLEX model and data set must not be changed when changing parameter values for later testing. Additionally, the code is kept as short and clear as possible.

Implementing the Models in CPLEX

For the implementation of the VRP-D models IBM ILOG CPLEX Optimization Studio IDE 20.1.0 was used. All computational work was performed on an Intel core i7-6700 processor with 4 GB RAM running Windows 10 Home in 64-bit mode. Since both VRP-D models are NP-hard, the solver is not able to find the exact solution for large instances (Sacramento, et al., 2019; Wang & Sheu, 2019). For smaller instances in the low double-digit range the solver takes around 8 hours to find the exact solution.

The run time is set to 1,800 seconds. The longer the program runs the better the solution it may find. There are several reasons for setting a relatively low run time of 30 mins: It is not practical to run the program to optimality for many instances when considering that it may take 8 hours or more to find the optimal solution. Second, the computer often stopped the process after around 5 hours without finding a solution. This may be due to the high computational effort that may overwhelm the processing ability of the computer. Moreover, it could be found that solutions during significant longer run times do not differ strongly from the solutions found when setting a shorter run time. After comparing the solutions for four instances obtained by running the program 10,800 and 1,800 seconds it could be found out that the solutions did not deviate greatly: For two data sets, a decrease of costs in the single-digit range could be observed when increasing the run time to 10,800 seconds. One testing shows an increase in the objective of 4 percent and one testing shows no difference between the run times. These inconsistent results do not justify a six-fold increase in run time. Therefore, the decision was made in favour of the shorter run time and the run time was chosen to 1,800 seconds for the following testing. Table 3 shows the parameter settings and the references for the main test instances briefly.

Parameter	Value	Reference
customer number	20	
dronable customers	15	
docking hubs	2	
drone capacity	3 kg	(Sacramento et al, 2019)
drone endurance	30 min	(Wang & Sheu, 2019)
drone costs per km	0,026 €/km	(Kim, 2016)
drone speed	50 km/h	(Trop, 2016)
truck costs per km	0,15548 €/km	(Sacramento et al, 2019)
truck speed	30 km/h	
depot location	Amazon Distribution Center, 1230 Wien	
docking hub 1	Nußdorfer Straße 25, 1090 Wien	
docking hub 2	Währinger Straße 28, 1090 Wien	

Table 3: Parameter Setting for the main Testing

4.4 Delivery Planning using the VRP-D by Wang and Sheu

Model Implementation in linear Solver

In the following, selected sections of the programming code are shown and discussed. The entire code can be found in attachment 3. In order to keep the actual code clean, all parameters were set in the data set. The code is structured as follows: At first, all sets and parameters are defined, as well as the decision variables. In the second part, the actual model follows: The objective function is defined and proceeding all constraints. The third part is the printout in which the output will be defined for the documentation. In Figure 7, the most relevant fractions of the code implemented in CPLEX can be seen.

Lines 11 to 17 show the set definitions and for the sets relevant parameters. Since the testing includes 20 customers, in line 11 *c* is set to 20. Line 12 shows the number of arcs *n* which is 23. In line 13-15, it is defined that the set of all nodes *N* include the start node *OS* which is equal to the depot, the two docking hubs, the 20 customer locations, and the end node *OT* which again is equal to the depot ($N = \{OS, \text{docking hub station 1, docking hub station 2, customer nodes 1...20, OT}\}$). The set of customers *C* is a subset of the set *N* and includes all customer nodes (line 16). In line 17, the set of hub nodes *O* is defined as a subset of the set *N* and includes node 1 and 2. The arcs for traveling between nodes is defined in line 18 and line 19 as a tuple. The set of arcs are defined for all nodes in the set *N* except for those combinations of *i* and *j* where *i* is equal *j*.

```
11 int c = ...; // number of customers (w/o docking hub nodes)
12 int n = ...; // number of arcs
13 int OS = ...; // start node
14 int OT = ...; // end node
15 {int} N = ...; // set of all nodes
16 {int} C = {i | i in N: 2 < i < n+1}; // customer nodes: nodes from 3 to n+1
17 {int} O = {i | i in N: 0 < i < 3}; // hub nodes: node 1 and 2
18
19 tuple arc {int i; int j;} // arcs
20 setof(arc) Arc = {<i,j> | i,j in N: i!=j}; // set of arcs

59 minimize
60 CT*(sum(<i,j> in Arc, k in K) tT[<i,j>]*(x[<i,j>,k] + u[<i,j>,k]))
61 + CD*(sum(<i,j> in Arc, d in D) tD[<i,j>]*y[<i,j>,d]); // w/o fixed costs of employing a truck

80 forall(j in O) // (5.1)
81 sum(<i,j> in Arc, k in K) x[<i,j>,k] + sum(<i,j> in Arc, k in K) u[<i,j>,k] == 1;
82
83 forall(i in O) // (6.1)
84 sum(<i,j> in Arc, k in K) x[<i,j>,k] + sum(<i,j> in Arc, k in K) u[<i,j>,k] == 1;
```

Figure 7: Relevant Code Fractions of Wang and Sheu (2019) in CPLEX

In order to save memory, the data type *int* was preferred if possible. All parameters were defined as *int* for which decimal places were not specifically relevant. For example, all parcel weights are defined as whole number since the weights are based on assumptions and a gram exact specification is not decisive for the testing. The same applies to the vehicles' speeds and the truck capacity. The variable vehicle costs, on the other hand, were defined as *float* since here differences in the decimal spaces will affect the solution strongly. Deviating from the model proposed by Wang and Sheu, the objective function minimizes

the variable transportation costs of truck and drone respectively only (line 59-61). The fixed costs of employing a truck were removed since the focus in this thesis lies on the comparison of the variable transportation costs and especially the cost reduction through the application of drones.

Wang and Sheu (2019) do not allow drones to land at customer locations or to reunite with the truck while the truck parks close to a customer location. The argument is that the landing of a drone requires a spacious area and a special docking device. Contrary, are drones allowed to launch from any customer location. This appears to be illogical since the launching of a drone is a critical operation that needs a spacious area as much as the landing process. If there was enough space and a device installed at the top of the truck that makes the launching from any node possible, the landing should supposedly be possible as well. However, since the 9th district is a densely populated area it may indeed be the case that drones cannot land at any location. Therefore, following the above argumentation, the model was changed such that both landing and launching is only allowed at docking hub stations. These stations have sufficient space and a docking station so that a safe launching and landing can be secured.

In order to implement this element, two constraints were added to ensure that each docking hub station is visited once by a truck. While visiting the hub, those parcels will be dropped off at the station that are designated drone deliveries. After the truck visit, the drones can begin with their deliveries. After the delivery, the drone will return to the docking hub station to pick up the next parcels. In the meantime, the truck can continue its tour. In the model, these additional constraints are denoted as 5.1 and 6.1. Constraint 5.1 ensures that each docking hub is left exactly once, while 6.1 ensures that each hub is visited exactly once. The added constraints can be viewed in Figure 7 from line 80 to line 84. By enforcing drones to launch and land only on docking hubs, constraint 10 becomes obsolete and is therefore eliminated.

Results for the Delivery Planning

The parameters for the main testing can be found in chapter 4.2. Fifteen randomly generated test instances with 20 customers and two centrally located hubs were solved using CPLEX Optimization Studio. The solutions of the objective and the number of customers served by drone are summarised in Table 4.

Test Instance	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Standard		
																Average	Deviation	Correlation
Costs	5,35	5,66	5,40	5,38	5,47	5,14	5,98	5,34	5,62	5,66	4,98	5,90	5,53	5,50	5,69	5,51	0,26	
Drone Deliveries	12	12	14	13	14	10	9	10	13	13	10	6	10	13	11	11,33	2,19	-0,25

Table 4: Results for the main Testing of Wang and Sheu (2019)

In average, the overall transportation costs are 5.51 Euro for supplying all 20 customers and return to the depot. The results show low deviations. The standard deviation is 0.26. The number of drone deliveries on the other hand shows strong deviations between 6 and 14 deliveries by drone. Among the 15 dronable customers in average 11.33 customers are served by a drone. This accounts for more than 50 percent of all customers. Since the costs for operating a drone are significantly lower than the costs of operating a

truck, it may be assumed that a higher number of drone customers may lead to lower transportation costs. However, for this model the assumption seems not valid. There is only a very low negative correlation of -0.25 between drone deliveries and costs. This suggests that other factors are relevant, such as the location of docking hubs and customers. However, the low number of instances may be a reason for the low correlation as well.

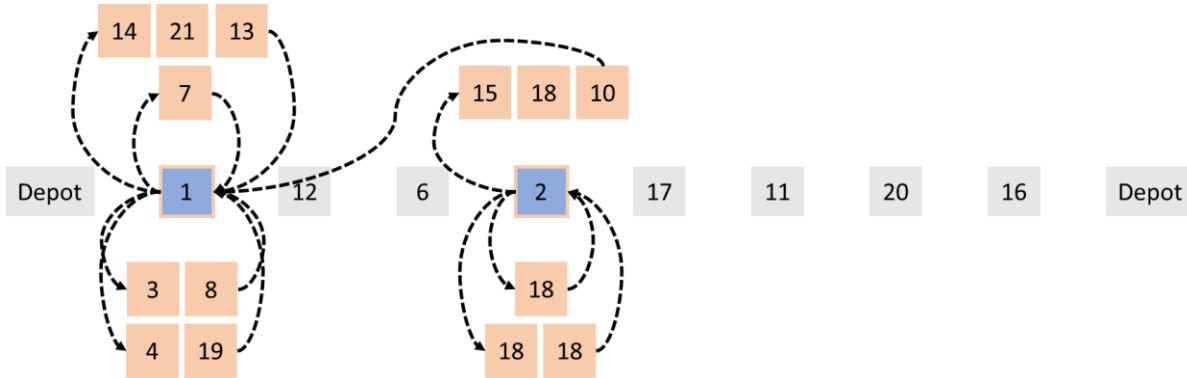


Figure 8: Solution of Instance 3 using the VRP-D by Wang and Sheu (2019)

For a better understanding of the delivery system, the result for test instance 3 will be explained in detail and an illustration of the result can be seen in Figure 8. The objective function is 5.40 and there are 14 drone customers and 6 customers serviced by a truck. In the solution, only one truck is used. Since the model does not force the use of all available trucks for the delivery, only those trucks are used that are needed. The truck starts from the depot and arrives at location 1 which is defined as docking hub node 1 (Nußdorferstraße 25, 1090 Wien). Now, those parcels will be dropped off at the docking station that are assigned for a drone delivery from this hub. From docking hub node 1 eight customers will be served on four different drone flights. Meanwhile, the truck continues its tour to customer 12 and 6, which are the first truck deliveries, before it arrives at the second docking hub node (Währinger Straße 28, 1090 Wien). Here, those parcels are dropped off that will be supplied from hub 2. At each docking hub station, the truck does not have to wait for the drone to finish its tours but can either continue without a drone or pick up a drone that is deposited at this station. The drone serves six customers in three drone flights. Both docking hub stations are used for drone deliveries almost equally. In sum, 14 customers are served in 7 drone flights. It is noticeable that one flight starts from docking hub station 2 but returns to docking hub station 1. At the end of the entire tour, two drones are at docking hub 1 and zero drones are at docking hub 2. It follows, that after each delivery tour, it should be checked, how many drones are at each docking hub station. The next truck should be equipped with drones accordingly to ensure that each docking hub station has sufficient drones.

4.5 Delivery Planning using the VRP-D by Sacramento, Pisinger and Ropke

Model Implementation in linear Solver

The code for the Sacramento et al. model is structured in the same way as the Wang and Sheu code. In the following, important parts of the code will be described. The full code can be found attachment 4.

```
8 int c = ...; // number of customers
9 {int} N = ...; // set of all nodes
10 {int} C = {i | i in N: 0 < i < c+1}; // subset of all customers
11 {int} N0 = {i | i in N: i < c+1}; // subset of outgoing nodes
12 {int} Nplus = {i | i in N: i > 0}; // subset of ingoing nodes
13 {int} deltaplus = {i | i in Nplus};
14 {int} deltaminus = {i | i in N0};
15 {int} V = ...; // set of trucks
16
17 int Dcap = ...; // added! max. capacity of a drone
18 int q[C] = ...; // customer demand
19 {int} Cdrone = {i | i in C: q[i] <= Dcap}; // subset of dronable customers
20
21 tuple arc {int i; int j;}; // arcs
22 setof(arc) Arc = {<i,j> | i in N0, j in deltaplus : i != j};
23
45 tuple p {int i; int j; int k;};
46 setof(p) P = {<i,j,k> | i in N0, j in Cdrone : i != j, k in Nplus :
47 k != i && k != j && SL+SR + tD[<i,j>] + tD[<j,k>] + SeD <= e};
48
63 minimize CT*(sum(<i,j> in Arc, v in V) tT[<i,j>]*x[<i,j>,v])
64 + CD*(sum(<i,j,k> in P, v in V) (tD[<i,j>] + tD[<j,k>])*y[<i,j,k>,v]));
--
```

Figure 9: Relevant Code Fractions of Sacramento et al. (2019) in CPLEX

In Figure 9 the definition of sets and the most important code fractions can be observed. In line 8 the number of customers c is set to 20 in the main testing. The set of all nodes N is defined in line 9 such that it includes all customers and the depot ($N = \{0, \dots, 21\}$). The depot is defined as node 0 as start node and node $c+1$ as end node of the tour. The subset of customers C includes all customers, which are all nodes between 1 and 20 (line 10). The subset of outgoing nodes N_0 is defined in line 11 as all nodes except for node $c+1$ since the last depot node cannot be left. The subset of ingoing nodes N_{plus} is defined in line 12 as all nodes without node 0 since the first depot node can only be left but not entered. The subsets $deltaplus$ and $deltaminus$ are similar to N_0 and N_{plus} but are defined in line 13 and line 14 as the set of nodes that can be used to reach node i (as part of N_0 or N_{plus}). This means that the set excludes node i since a vehicle cannot travel from one node to the same node. The referring node will be excluded in the constraints in the forall statements. The subset of all dronable customers is defined in line 16 to line 19. For that, the maximum carrying capacity of a drone $Dcap$ must be set, and the weight of customers' demand q must be defined. All nodes are part of the subset $Cdrone$ for which applies that the customer demand is smaller or equal to the maximum carrying capacity. By this, it is ensured that drones only supply customers with a parcel weight that does not exceed the drones' carrying capacity.

The set of arcs is defined in line 21 and line 22 in the same way as in the Wang and Sheu model. Since the drone travel is defined as a tuple of three nodes including starting node, customer node and landing node,

an additional definition is required. The tuple p consists of three nodes $\langle i, j, k \rangle$ where i is the launching node from the truck, j is the delivery node and k is the rendezvous node (line 45). The set P is defined in line 46 and line 47 for all combinations of i, j and k that do not exceed the flying endurance of the drone. The objective was adapted such that the variable travel costs were separated into its elements travel duration and travel costs per time. The parameters drone costs per time unit CD and truck costs per time unit CT were added to the model and refer to the Wang and Sheu model. The truck costs and drone costs are then multiplied with the travel duration of the referring vehicle type. In the last part of the code the most important parameters and solutions are printed to the scripting protocol for the documentation. This includes the travel time of vehicles and the number of dronable customers among all customers. Moreover, all nodes that are serviced by a truck will be printed out. However, since the scripting for the truck customers does not always appear to be correct, it is additionally checked by analysing the solutions of each variable. The correct number of drone and customers are then noted in the documentation.

Results for the Delivery Planning

Table 5 shows the results for the testing of the 15 main test instances in CPLEX Optimization Studio. The parameter setting is presented in chapter 4.2.

Test Instance	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Average	Standard Deviation	Correlation
Costs	6,63	6,74	6,46	5,81	6,73	5,74	6,39	5,81	6,22	5,90	5,85	5,87	7,96	6,81	5,64	6,30	0,62	
Drone Deliveries	8	8	8	9	9	8	8	8	9	6	8	6	5	8	8	7,73	1,16	-0,34

Table 5: Results for the main Testing of Sacramento et al. (2019)

In average the transportation costs for delivering 20 customers in Wien Alsergrund using the VRP-D by Sacramento et al. are 6.29. The standard deviation for the costs is 0.62. The number of drone deliveries lies between 5 and 9 and is in average 7.8. A small negative correlation of -0.34 between transportation costs and the number of drone deliveries can be seen. This means that higher costs correlate weakly with a lower number of customers delivered by drone. Increasing the drone deliveries may have a positive impact on transportation costs. However, due to the low number of instances, the correlation may not be representative.

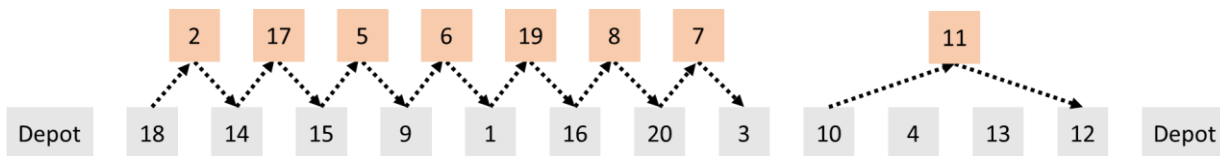


Figure 10: Solution of Instance 3 using the VRP-D by Sacramento et al. (2019)

For a better understanding of the delivery system of the VRP-D by Sacramento and to show the process of a delivery for the application in Wien Alsergrund, the solution for test instance 3 will be described in detail. In the solution, only one truck is used for the delivery of all 20 customers. Since each truck can carry a single drone, only one drone is included. The truck starts the tour carrying the drone from the

depot and delivers to customer 18. Here, the drone launches from the truck and delivers a parcel to customer 2. In the meantime, the truck proceeds to customer 14. After its delivery, truck and drone meet again at customer 14. The same procedure repeats six times. The drone launches, delivers a parcel, and lands back on the truck at the next customer location. Both vehicles move simultaneously and synchronise their movements in order to meet at the designated rendezvous location. At customer 10, the drone launches one more time and delivers customer 11. This time truck and drone do not meet at the next truck delivery. Instead, the truck fulfils two more deliveries before both vehicles meet again. This may lead to a waiting time for the drone at the rendezvous customer. At the end of the tour, the truck carries the drone and both vehicles arrive at the depot together.

4.6 Delivery Planning using a VRP without Drones

Model Implementation in linear Solver

The simulation of a conventional delivery without drones is intended to show whether and to what extent the use of drones can reduce costs. Therefore, a standard VRP was applied to the 15 test instances for the delivery in Wien Alsergrund as well. The formulation is based on the Miller-Tucker-Zemlin formula and is similar to the Sacramento et al. (2019) model without the drone related constraints. It includes a maximum load capacity for the truck and is therefore a CVRP.

```

8  int c=...;      // number of customers
9  int OS=...;    // depot = start node
10 int OT=...;    // depot = end node
11 {int} N=...;   // set of nodes
12 {int} C={i|i in N: 0<i<c+1}; // set of customers
13 {int} N0={i|i in N: i<c+1}; // set of nodes from which a vehicle may depart
14 {int} Nplus={i|i in N: 0<i}; // set of nodes to which a vehicle may arrive
15
16 tuple arc {int i; int j;}
17 setof (arc) Arc={<i,j> | i in N0, j in Nplus: i!=j}; // set of arcs
18
41 forall(j in C) // (2) all customers must be left once
42   sum(<i,j> in Arc, k in K)x[<i,j>,k]==1;
43
44 forall(k in K) // (3) depot can be left at most once, not all vehicles must be used
45   sum(j in Nplus)x[<0,j>,k]<=1;
46
47 forall(k in K) // (4) depot can be reached at most once
48   sum(i in N0)x[<i,c+1>,k]<=1;
49
50 forall(k in K) // (5) no direct travel between depot nodes
51   x[<OS,OT>,k]==0;
52
53 forall(k in K) // (6) truck capacity constraint
54   sum(j in C, i in C: i!=j)d[j]*x[<i,j>,k]<= LT;
55
56 forall(k in K, i in C) // (7) flow conservation
57   sum(j in Nplus:i!=j)x[<i,j>,k]==sum(j in N0:i!=j)x[<j,i>,k];
58
59 forall(<i,j> in Arc, k in K) // (8) subtour elimination constraint (Miller-Tucker-Zemlin)
60   u[i,k]-u[j,k]+(c-1)*x[<i,j>,k] <= c-2;

```

Figure 11: Relevant Code Fractions of the VRP in CPLEX

The parameters equal the parameter settings for the Sacramento et al. VRP-D. An explanation can be found in Chapter 4.5 above. The full code can be found in attachment 5. The objective minimizes the sum of transportation costs. Constraint (3) and (4) allow that the depot can be left and arrived at most once. Thereby, not all available vehicles must be used for the solution, similar to the Wang and Sheu and the Sacramento et al. models. Constraint (5) forbids direct travel between the depot nodes. The vehicle capacity constraint (6) ensures that the maximum load of each truck is not exceeded. Constraint (7) ensures the flow conservation between nodes and constraint (8) is the subtour elimination constraint based on the Miller-Tucker-Zemlin formulation. By using an additional decision variable u for the sequence of visits, subtours are restricted. The last part includes the statements for the scripting protocol. In the same way as for the other models the parameters are read from an excel document. All parameters are equal to the parameters for the main test instances for the VRP-D models.

Results for the Delivery Planning without Drones

Table 6 shows the results for the 15 main test instances for the truck only delivery in Wien Alsergrund. In average the transportation costs are 9.95.

Test Instance	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Average	Standard Deviation
Costs	9,95	10,42	10,42	9,72	10,73	9,95	10,03	9,87	10,18	9,41	9,48	10,03	9,80	10,18	9,17	9,96	0,41

Table 6: Results for the Truck-only Delivery

The result for test instance 3 will be explained shortly. In the solution both vehicles are used. Truck 1 starts from the depot and serves five customers while truck 2 serves 15 customers. Both vehicles return to the depot after finishing their tour.

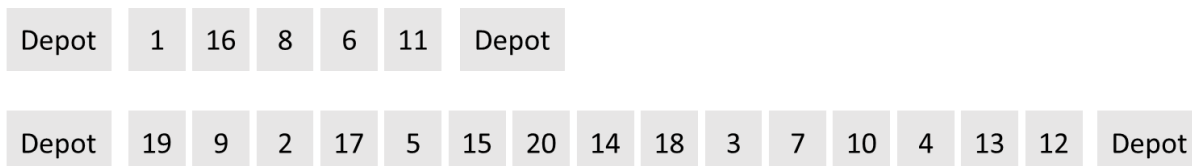


Figure 12: Solution of Instance 3 using the VRP without Drone

4.7 Comparing the Delivery Systems for the Application in Vienna's 9th District

When comparing the results of the VRP-D models with the conventional routing without drones, it becomes clear that the application of drones may save costs significantly. For all 15 test instances, the VRP without drones has higher costs than the Truck-and-Drone models (see Table 7).

	VRP-D by Sacramento et al.		VRP-D by Wang & Sheu		VRP by Miller Tucker Zemlin	
Test Instance	Costs	Drone Deliveries	Costs	Drone Deliveries	Costs	Drone Deliveries
1	6,63	8	5,35	12	9,95	0
2	6,74	8	5,66	12	10,42	0
3	6,46	8	5,40	14	10,42	0
4	5,81	9	5,38	13	9,72	0
5	6,73	9	5,47	14	10,73	0
6	5,74	8	5,14	10	9,95	0
7	6,39	8	5,98	9	10,03	0
8	5,81	8	5,34	10	9,87	0
9	6,22	9	5,62	13	10,18	0
10	5,90	6	5,66	13	9,41	0
11	5,85	8	4,98	10	9,48	0
12	5,87	6	5,90	6	10,03	0
13	7,96	5	5,53	10	9,80	0
14	6,81	8	5,50	13	10,18	0
15	5,64	8	5,69	11	9,17	0
Average	6,30	7,73	5,51	11,33	9,96	0

Table 7: Overview on the main Testing Results

In average, transportation costs for the delivery in Wien Alsergrund could be reduced by 44.7 percent when using the Wang and Sheu model. For the Sacramento model, a cost reduction of 36.8 percent could be realized.

The delivery computed using the Wang and Sheu model shows lower transportation costs for 13 out of 15 test instances compared to the Sacramento model. The average costs for the Wang and Sheu model are significantly lower than the costs for the Sacramento VRP-D. When comparing the number of drone deliveries, it becomes clear that the delivery computed with the Wang and Sheu VRP-D includes considerably more drone deliveries. In average 11.33 customers out of the 20 customers are being delivered by drone which are more than half of all customers. When using the Sacramento model, only 7.73 customers are drone customers.

In a direct comparison of the solution of test instance 3, the Wang and Sheu models delivers the lowest transportation costs. Conventional delivery without drones has by far the highest transportation costs for the delivery of the 20 customers in Wien Alsergrund. The Wang and Sheu model uses 47 percent more drone deliveries compared to the other VRP-D. Both Truck-and-Drone models use one truck for the delivery, while the truck only solution includes both vehicles available at the depot. If the fixed costs for employing a truck were to be included, the truck only solution would be even worse off in terms of costs. Since each truck can only carry one drone in the Sacramento model, only one drone is used for the solution. The VRP-D by Wang and Sheu does not have an assignment of trucks and drones. Here, both drones are part of the delivery.

4.8 Experiments with different Parameter Settings

In the following, the impact of different parameters on the systems' performance will be examined. The parameters for the main setup are based on assumptions and according to data used by other studies. The goal is to create a scenario that is as realistic as possible. Since there exist no real-life parameters for Truck-and-Drone delivery so far, it is interesting to examine the relative importance of different parameters on the models' output. This is especially interesting for those parameters that are based on assumptions made by the author such as the drone speed or the weight of customer parcels. By this, the probability of a realistic simulation becomes more likely and a comparison of both VRP-D models under changing parameters can be made. In the previous part it could already be proven that both Truck-and-Drone models deliver lower transportation costs for the delivery in Wien Alsergrund compared to the truck only solution. Therefore, in the sensitivity analysis the truck only solution will not be relevant. Only the VRP-D models will be compared in the following. For each sensitivity analysis, the value of a certain parameter will be changed while the rest is fixed in the settings of the main testing. In the following part, only the average results will be discussed. For the full results see attachment 6.

Changing the Drone Speed

One assumption made by the author concerns the drone speed. While drones may be technically able to reach speeds up to 120 km/h, for the application in the urban and dense area of Wien Alsergrund a significantly lower speed appears more realistic (see 4.2). However, even the in the main setup estimated speed of 50 km/h may be too high when considering narrow roads, pedestrians and obstacles such as trees or traffic lights. Therefore, in the following the drone speed will be reduced to 40 km/h and 30 km/h respectively.

Reference	30 km/h		40 km/h		50 km/h	
	Objective	Drone Deliveries	Objective	Drone Deliveries	Objective	Drone Deliveries
Sacramento et al.	6,11	8	6,18	8,13	6,30	7,73
Wang & Sheu	5,49	11	5,49	12,07	5,51	11,33

Table 8: Average Results for changing the Drone Speed

The average transportation costs for the Sacramento VRP-D with a drone speed of 40 km/h are 6.18 and slightly decrease compared to the solutions of the main setup (6.30). When reducing the speed to 30 km/h the average objective function decreases even more to 6.1. This amounts to a cost reduction of 3.1 percent for the delivery in Wien Alsergrund for reducing the drone speed to 30 km/h.

For the Wang and Sheu model, a similar but smaller effect can be observed. When reducing the drone speed, the average transportation costs for the delivery in Wien Alsergrund slightly decrease. Compared to the main testing with 50 km/h, reducing the speed to 30 km/h results in an average cost reduction of 0.38 percent. The Wang and Sheu model shows a stronger robustness for changing the drone speed.

It may seem counterintuitive that the transportation costs decrease when reducing the drone speed since the delivery time increases. However, this is due to the focus on travel durations rather than travel distance for both models. It follows that the variable vehicle costs are defined as costs per time unit and concludingly they include the vehicle's speed. This means, that the variable costs decrease when decreasing the vehicle speed. Even if the travel duration rises with lower drone speed, the lower variable costs compensate this effect. For the application in Wien Alsergrund, this may mean that a lower drone speed of 30 km/h may not only be favourable in terms of safety aspects but also may decrease transportation costs and may therefore be preferred.

Reducing the Number of Docking Hub Stations

In the main data set, two centrally located docking hub stations were used for the application of the Wang and Sheu model for Wien Alsergrund. As two docking hub stations might be too much in relation to the size of the delivery area, in the following it will be tested how the solutions change when testing with one station only. For this, the search strategy for the station will be changed. Instead of choosing a centrally located and well connected location within Wien Alsergrund, this time a gas station is the chosen. Amazon and DHL already make use of the optimal conditions at gas stations by using them as parcel pick up stations (Shell, 2021; DHL, 2021). There are several advantages: Gas stations have sufficient parking spaces at their disposal even for larger vehicles such as delivery trucks. Renting a part of the outside area of a gas station may be significantly cheaper than renting a retail space. Moreover, gas stations are well accessible by car and often strategically well located. They may also have enough space to launch and land drones since gas stations are often built generously in terms of space. In sum, they may be optimal locations for drone hub stations.

Wien Alsergrund has only two gas stations of which one is relatively small and closely located in between residential houses. The other gas station, an Eni gas station, is in the north of Alsergrund and has sufficient space for a docking hub station.

Reference	Objective	Drone Delivery
Sacramento et al.	6,30	7,73
Wang & Sheu	5,51	11,33
Wang & Sheu one Hub	5,67	11,87

Table 9: Average Results for reducing the Number of Docking Hubs

Table 9 shows the average results for the testing with one hub station and with two hub stations. In average the objective function increases slightly when using only one docking hub station. Since the docking hub station is in the north of Alsergrund while the depot is in the south of Vienna delivery trucks must drive up until the northern end of the district which increases the traveling distance of the truck. Moreover, drones may make longer routes from the less centrally located docking hub station at the gas station,

which increases travel costs of the drones. However, the cost increase in average is only small (2.9 percent) and transportation costs are still lower than the solutions of the Sacramento model. Interesting is the number of drone deliveries that is in average higher in the model with one docking hub station (4.8 percent higher than with two hubs). This may be due to the northern location of the station that makes the travel distances for both vehicles longer. Since the travel costs of the drone as well as the durations are significantly lower than the truck travel durations and costs, more deliveries may be shifted to the drones. However, the differences between the two and one hub testing are rather small and may not have high information value.

Overall, though, it can be said that the Wang and Sheu model with one hub shows lower transportation costs for the delivery in Wien Alsergrund compared to the Sacramento model. Reducing the number of docking hubs may have a significant positive impact on the overall costs due to savings in renting, maintaining and setting up of docking stations.

Increasing the Parcel Weight

An advantage of the delivery model introduced by Wang and Sheu is the possibility to deliver several customers during one drone trip as long as the capacity restriction of drones are not exceeded. Instead of returning back to the docking hub or the truck after each delivery, the VRPD by Wang and Sheu allows the drone to directly fly to the next customer. This may reduce the travel distance and durations significantly compared to the Sacramento model. While this may be an advantage in terms of transportation costs, it is not certain that drones are capable of carrying several parcels and releasing only one parcel at a time while keeping the others. Moreover, are the parcels' weights based on assumptions only which may not reflect actual parcel sizes. A wrong assumption towards more light packages of one and two kilograms can lead to an overestimation of the advantage of the Wang and Sheu model.

Therefore, in the following, the customer parcel weights are changed such that no multiple deliveries are possible in the Wang and Sheu model. This means that all parcels with a weight of one kilogram are increased to three kilograms. Since the carrying capacity of drones are set to three kilograms, this results in single deliveries for the drones for all customers for the Wang and Sheu model. The weight increase has no influence on the Sacramento model since the amount of drone customers does not change and here only single drone deliveries are allowed.

Reference	Objective	Drone Delivery
Sacramento et al.	6,30	7,73
Wang & Sheu	5,51	11,33
Wang & Sheu increased weight	5,62	11,00

Table 10: Average Results for increasing the Parcel Weight

The average results for the Wang and Sheu model with only single drone deliveries due to an increased parcel weight are displayed in Table 10. The results show a small increase of 2 percent of average transportation costs for the Wang and Sheu model with single drone deliveries. However, the average costs are still 10.7 percent lower than the costs by using the Sacramento model. The number of drone deliveries decrease with single drone deliveries compared to multiple drone deliveries in Wien Alsergrund by 2.9 percent. Overall, it can be seen that the results for testing with only single deliveries for the Wang and Sheu model are relatively stable and only slight changes to the main testing can be observed.

Even when removing the advantage of allowing several drone customers within one flight in the Wang and Sheu model, the results change only minimal for the delivery in the 9th district of Vienna. There is still a large cost advantage visible compared to the Sacramento model. For both cases - a single and a multiple drone delivery - the VRP-D by Wang and Sheu delivers clearly better solutions.

Changing the Number of Dronable Customers

In the following sensitivity analysis, again the customers' parcel weight was changed to see the effects on both models. This time, the weights were increased such that less dronable customers remain. In the first run, 10 dronable customers remain. Four customers have a demand of 1 kg, five customers have 2 kg, and one customer has 3 kg demand. This means that for the Wang and Sheu (2019) model several multi-customer trips are possible without exceeding the drone's carrying capacity of 3 kg. Now, both models have the same maximum number of possible drone deliveries. The Wang and Sheu model is limited to a maximum of 10 drone deliveries among 20 customers by the increased parcel weight (instead of 15 dronable customers in the main testing) and the Sacramento et al. (2019) model is again restricted by the maximum of 10 drone deliveries due to the maximum of 50 percent drone deliveries among all customers (see Chapter 3.5).

	15 dronable customers		10 dronable customers		5 dronable customers	
Reference	Objective	Drone Deliveries	Objective	Drone Deliveries	Objective	Drone Deliveries
Sacramento et al.	6,30	7,73	6,43	6,33	6,24	3,40
Wang & Sheu	5,51	11,33	6,06	6,93	6,39	3,27

Table 11: Average Results for decreasing the Number of dronable Customers

In Table 11 the average objective of both models increases when reducing the number of dronable customers. The transportation costs for the Wang and Sheu model rise by 10 percent while the costs for the Sacramento et al. model increases only by 2 percent. In this way, the results of both models converge. However, the VRP-D by Wang and Sheu still offers lower transportation costs for 10 dronable customers. A similar effect can be observed for the average number of drone deliveries which decreases for both models while the Wang and Sheu model still uses slightly more drone deliveries in average. Both models do not exploit the maximum possible number of 10 drone customers but use only 6 to 7 drone deliveries

in average. The results indicate that for 50 percent of dronable customers the VRP-D by Wang and Sheu still offers better results for the delivery in the 9th district of Vienna.

In the second run, all instances were tested with five remaining dronable customers. Two customers have a demand of 1 kg, two customers have 2 kg and one customer have 3 kg. By this, in the testing with the VRP-D by Wang and Sheu multiple drone trips during one trip are still possible for the parcels lighter than 3 kg. All other customers have a parcel weight higher than the drones' carrying capacity and can therefore only be delivered by drone. Table 11 shows that the Sacramento et al. model for the first time has lower transportation than the Wang and Sheu model, even when the difference is only very small (0.15). Furthermore, for the first time the Sacramento et al. model uses slightly more drone deliveries. For only 25 percent dronable customers, the Wang and Sheu model cannot exploit its advantages of allowing multi-customer drone trips. Moreover, the force for the trucks to visit both docking hub stations increases overall travel costs when the additional visits of these hubs cannot be compensated by a high number of drone trips starting from there.

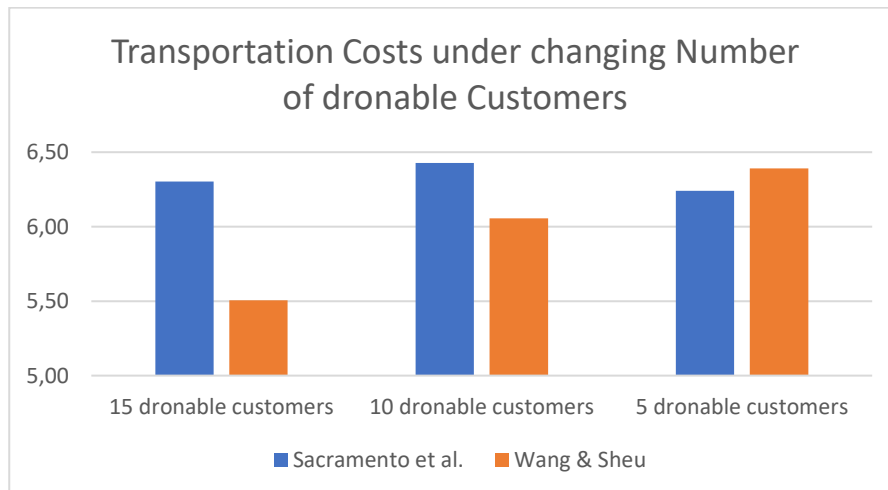


Figure 13: Impact of dronable Customer Number on Transportation Costs

Table 13 illustrates the impact of the change in dronable customers on the overall transportation costs. Here it becomes apparent that the objective in the Wang and Sheu model increases strongly when reducing the number of possible drone customers. The Sacramento et al. model, on the other hand, shows a great robustness and the transportation costs even decrease slightly for the testing with five dronable customers. The results indicate that the Wang and Sheu model is more beneficial if the percentage of dronable customers is higher than 50 percent, while the Sacramento et al. VRP-D should be applied if only a small percentage of parcels are carriable by drone. Ergo, the decision for a Truck-and-Drone model is dependent on the parcels' weight and should therefore be considered beforehand. This means, that the service provider must evaluate the expected weight distribution of parcels for the referring delivery area before choosing a model.

5. Discussing the Research Findings

5.1 Truck-and-Drone Models in recent Research

In the first part of this thesis, the literature review provides an overview on the state of the art of Truck-and-Drone models. Forty three models that were published between 2017 and 2020 could be found from which it can be concluded that this topic is of current relevance. The majority of papers uses delivery planning models based on well-known optimization problems such as the TSP or the VRP. The FSTSP by Murray and Chu can be understood as a reference for several other researchers who propose extensions of this model. Only two papers among the 43 models propose new optimization problems. There is also little variation between models with regard to the objectives. Most models focus on minimizing the delivery time, while only five models aim to reduce costs. Since the cost pressure in last-mile delivery is high, it is interesting to see, that costs are not considered by most researchers. However, by minimizing travel time, costs may also decrease with reduced labour costs when drivers must be hired less hours for the same number of deliveries. Moreover, a time related objective may reduce the waiting time for customers. Since the competition in e-fulfilment as well as customer expectations are high, a shorter waiting time may be a competitive advantage for service providers. This may be the reason for the focus of many researchers regarding time minimization.

While the objectives as well as the mathematical models of most models show low variation, they do differ in regards to the proposed delivery systems. Some models intend that only the drone carries out the delivery while the truck serves as a moving warehouse only. Other models intend the truck to perform the delivery while the drone moves between depot and truck for the resupply of orders that have just arrived. In most models, drones are allowed to launch and land at the roof of the truck. However, other models include docking hub stations to ensure a safe landing of the drone. The flexibility of models increases for such models that do not assign truck and drone so that drones may land on a different truck than from which they launched before. Nine of the 43 models allow the drone to deliver several parcels within one flight. However, the models make no reference to actual delivery drones that can retrieve one parcel while keeping the remaining parcels. To the knowledge of the author, delivery drones that were proposed by companies are usually designed as such that they can hold a single parcel only (DHL, 2021; French, 2015; DPD, 2019). Therefore, it is doubtful that a delivery of multiple customers in one drone flight will be realisable in the close future.

The literature review shows that while most models are based on similar mathematical models, they do differ in many specific details, a lot of them referring to the drones' attributes. Companies interested in implementing a Truck-and-Drone delivery can choose from a large pool of different models. For a same-

day delivery models that include a drone resupply from the depot may be ideal. Companies that only deliver small, lightweight items may choose a model in which drones deliver the parcels while the truck has a subordinate role.

However, since e-commerce deliveries are usually diverse and the parcels' weight may range from small electronic items to heavy furnishings, a delivery system must be able to react accordingly. Latter items must be carried by a truck due to the capacity constraints of delivery drones. Only 40 percent of the models consider that not all parcels may be carried by a drone. This implies that 60 percent of the models found are not universally applicable to an e-commerce delivery. Equally unexpected is the fact that most of the models are formulated with only one delivery truck. For the application in e-commerce in densely populated areas this is not practical due to high demands that require for a fleet of trucks.

Finally, only five models meet the requirements of an urban e-commerce delivery. The result remains below expectations as the models have already been selected in advance so that they are generally suitable for a delivery in the field of e-commerce.

5.2 Evaluating the Implementation of Drones for the Delivery Planning in Vienna's 9th District

The second part of the thesis, the case study, underlines the results of the literature review by creating a delivery scenario using real-life data. The scenario includes two trucks and two drones for the delivery of 20 customers that are in the 9th Viennese district. After the general and cursory examination of the models, the application of two models of the previously filtered five best-suited models for an urban e-commerce delivery could generate a closer and more detailed look on the advantages and disadvantages of both models.

The results of the main testing show that the Wang and Sheu model uses 47 percent more drone deliveries than the Sacramento et al. model. This difference arises from the different designs of delivery systems. While the Sacramento et al. VRP-D allows only one customer delivery per flight, the Wang and Sheu model does not have such a restriction. While the drone delivers a parcel, the truck must continue its tour in the Sacramento et al. VRP-D since no cyclic drone trips are allowed. Hereby, the maximum amount of possible drone deliveries is restricted to 50 percent among all customers. The Wang and Sheu model has not such a restriction since truck and drone operate independently from each other and are not synchronised in the same way. Here, the only upper limit for drone deliveries is the number of dronable customers. This is reflected in the amount of drone deliveries among all test instances for Wien Alsergrund: The maximum of 14 drone deliveries is reached in instances 3 and 5.

The Sacramento model includes a synchronization variable that ensures that the waiting times between truck and drone are optimized. Hereby the tour is created in a way that the vehicles' delivery time at each customer is considered and no long waiting time occurs. The VRP-D by Wang and Sheu does not include time related variables. This means, that delivery time or the tour length are not considered in the solution

as well as the time of the docking hub visit. Docking hubs may be visited at a late point within the tour. Only after the visit of the truck and the drop-off of parcels drones can begin their deliveries. This may result in unnecessarily long waiting times for customers. A solution for this problem may be an additional constraint that forces the truck to visit the docking hub stations within the first part of the tour.

The results for the main test indicate that the application of drones for the last-mile delivery in Vienna's 9th district may bring significant cost reductions compared to a conventional delivery. More precisely, cost reductions account to 44.7 percent for the VRP-D by Wang and Sheu and 36.8 percent for the Sacramento et al. model.

The VRP-D model by Wang and Sheu allows a higher number of drone deliveries through its different design compared to the VRP-D by Sacramento et al. Therefore, since drone deliveries are both faster and cheaper, the former model could realize lower transportation costs. However, in this computation variable transportation costs are considered only. Ergo, fixed costs for employing a truck are not considered and therefore the number of cars included in the solution are not examined. Moreover, the costs for renting, setting up and maintaining the docking hub stations which are required for the VRP-D by Wang and Sheu are not considered. The stations must be checked regularly and repaired in the case of failures. These costs may significantly add to the overall delivery costs and reduce the flexibility of the system: Before an area can be supplied by truck and drone using the Wang and Sheu model, sufficient locations for the docking hub stations must be found, rented and equipped. This requires for a certain lead time before the start of a Truck-and-Drone delivery. Moreover, in the case of a decline in the demand in the delivery area, unused or underutilized stations may be a negative cost factor. Another disadvantage arises from the fact that the Wang and Sheu model assumes a parachute drop delivery. This type of parcel hand-over is not only critical in terms of a precise delivery of the item but also appears to not be the preferred way for companies implementing drone delivery. The Sacramento model on the other hand, does not require additional infrastructure that must be maintained. Therefore, it can be immediately applied to a delivery area or retracted if no longer required. Moreover, the model assumes a landing delivery which ensures a safe and precise landing of the parcel and may therefore be preferred.

5.3 Impacts of Changing the Parameter Settings

The altering of parameters has yielded further insights that may support the evaluation of both Truck-and-Drone models. It has become apparent that the transportation cost savings are directly dependent on the percentage of customers with a demand that is carriable by a drone. For a percentage of over 50 percent, the VRP-D by Wang and Sheu delivers better results and more drone deliveries. For a percentage of 75 percent dronable customers this applies even when multiple drone visits are not possible. If only 25 percent among all customers order light weight parcels, the model by Sacramento et al. offers lower transportation costs. An analysis of the weight of the customers' demand should therefore be performed

before choosing a delivery model. Since the Wang and Sheu model requires docking hub stations which add to the transportation costs, it appears additionally reasonable to only choose this model when there is potential for a high amount of drone deliveries. It follows, that the same service provider may choose the Sacramento et al. model for delivery areas where the expected demand weight is higher and choose the Wang and Sheu model for delivery areas that have an expected low weight demand.

Moreover, it could be found out that a relatively low drone speed of 30 km/h may be optimal not only in terms of safety aspects but also in terms of transportation costs. This applies to both VRP-D models. For the Wang and Sheu model, one docking hub station for the delivery in Wien Alsergrund may be sufficient. While transportation costs slightly increase compared to the scenario with two docking hubs, costs are still lower than the results of the comparative model. Furthermore, reducing the number of docking hub stations may significantly reduce additional costs that arise with renting, setting up and maintaining these stations. Due to the small size of Wien Alsergrund, each location can be reached by drone. A second docking hub station may be favourable for a bigger delivery area. In this case, the right positioning of several docking hubs can increase the radius for drone deliveries. However, for the scenario analysed, a second docking hub station provides no such added value.

The VRP-D by Wang and Sheu shows lower transportation costs for almost all scenarios created. Nevertheless, the model includes docking hub stations that decrease the flexibility of the system and increase overall costs for rent and maintenance that are not included in the calculation of transportation costs. The Sacramento et al. model, on the other hand, is highly flexible as it does not require infrastructure. It can be applied to a delivery location without any preparation time. Therefore, it may be the best fit for most delivery areas for which the demand weight forecast is not specifically high or not exactly measurable. The assumption made at the beginning that the introduction of drones to last-mile delivery may reduce costs and increase efficiency could be confirmed. This finding corresponds with the results of other researchers (Agatz, et al., 2018; Das, et al., 2020; Sacramento, et al., 2019).

5.4 Limitations to the Research

The literature analysis faces limitations due to the selection of platforms and search terms, and the choice of inclusion and exclusion criteria. However, the author is confident that the results of the analyse could detect the most relevant Truck-and-Drone models.

Due to the mathematical complexity of the VRP-D models, finding an exact solution for larger instances is not possible. Linear programs are able to solve scenarios with up to eight customers to optimality only. The choice of 20 customers for the case study was therefore a compromise between the computational complexity on the one hand and the request for a practical scenario on the other hand. However, the scenario does not reflect an actual delivery since in real-life each delivery truck supplies around 10 times

as many customers. The results are not representative. The implementation of a heuristic may be useful to simulate realistic scenarios.

Further limitations arise from the fact, that the focus on transportation costs does not reflect all relevant cost factors. As stated in chapter 2.2, delivery costs consist of the three factors driver costs, opportunity costs and transportation costs. In this thesis, only variable transportation costs are considered. Resulting from the delivery system by Wang and Sheu, further costs for the docking hub stations occur, which are not included here.

A general limitation to Truck-and-Drone model addresses the fact that none of the papers reviewed provide a detailed explanation of how the packages delivered by drones reach the end customers. Some researchers specify the type of parcel release; however, it is not clear how the item find its way to the customer. Especially in urban areas, where customers live in apartment buildings, parcels cannot be left in front of the door. Parcel boxes in front of buildings where the drone can simply drop off the item may be a solution as well as customers' balconies as drop-off locations. However, for commercial use of Truck-and-Drone models, a practical solution to this problem must be found.

The introduction of drones to last-mile delivery cannot be decided based on costs alone. A more holistic view on the impact of drone technology is necessary since it affects not only service providers but also a range of other parties. The privacy aspect is one major factor which may affect public acceptance. Drones are usually equipped with an integrated camera which may invade privacy by filming through windows and into private properties. Furthermore, studies have shown that the sound of drones is more stressful and disturbing to humans than the noise made by road vehicles. If the noise issue is not addressed by drone manufacturers, it could put the commercialisation of drones at risk (Martinez, 2020). Security aspects consider the possibility of air accidents but also the handling of drones around embassies. In Wien Alsergrund for instance, the U.S. embassy requires special security measures. The consideration of no-fly zones as proposed by Jeong et al. (2019) may be useful for many delivery areas.

Environmental considerations should not be disregarded either. While the implementation of drones to last-mile delivery has the potential to significantly reduce CO₂ emissions due to the reduced distance travelled by trucks, drones may interfere in the living environment of birds and other wildlife. Since many city councils aim to reduce vehicle traffic and the pollution caused by road traffic, further research may address the benefits of Truck-and-Drone models in terms of reducing travelled distance by trucks and by this, CO₂ emissions. The implementation of heuristics may be useful to solve large instances and simulate realistic scenarios. In general, the application of drones in densely populated urban areas may face great barriers since here many opposing interest meet. Legal regulations for the commercial use of drones are a limiting factor as well. The upcoming years will show how governments approach this topic.

6. Conclusion

In this thesis, a categorical and detailed literature review of the most recent Truck-and-Drone models is provided. By means of the literature review, the state of the art in Truck-and-Drone models could be found. Between 2018 and January 2021, 43 papers could be found that propose a delivery model for e-fulfilment using combined delivery with trucks and drones. The large number of published papers within a relatively short period shows the high relevance of Truck-and-Drone models among researchers. Linear routing models such as the TSP and the VRP are predominantly applied and further developed for the combined delivery of trucks and drones. The models' delivery systems show great variations in terms of the role the referring vehicle plays within the progress. In some models, only one vehicle type delivers parcels to the customers while the other is used for supporting tasks only. In other models, both vehicle types directly supply customers. In general, drones are assumed to have lower transportation costs and travel faster than trucks. Among the found models, each linear routing Truck-and-Drone model is NP-hard. Resulting, the exact solution can be found for small instances only and heuristics may be necessary for the implementation of large customer scenarios. Five models that fulfil the requirements of an urban e-commerce delivery were detected. The most relevant demands for a delivery system in an urban delivery area in the field of e-Fulfilment involve the possibility to include multiple trucks. This results from the high parcel volume in urban areas which makes the delivery with a single vehicle impossible. Furthermore, the model must include the parcels' weights so that heavy parcels will be automatically delivered by a truck and only parcels that are carriable by a drone will be delivered by drone.

In a case study which simulates an e-commerce delivery in Vienna's 9th district, the theoretical findings were supported by an application using real-life data. Two models, namely the VRP-D by Wang and Sheu (2019) and the VRP-D by Sacramento, Pisinger and Ropke (2019), were compared to find the best fitting Truck-and-Drone model in regards of cost reduction. CPLEX Optimization Studio was used to solve the models. Fifteen instances with 20 customers each were tested.

The implementation of both models showed in a comparison with a conventional truck-only routing that the usage of drones could significantly reduce costs. The VRP-D by Wang and Sheu could generate transportation cost savings of 44.7 percent and the VRP-D by Sacramento et al. could generate savings of 36.8 percent when applied in Vienna's 9th district. This implies that drone technologies have the potential to decrease costs and increase efficiency for last-mile delivery in e-commerce. However, due to the small instance size, the results are not representative.

The Wang and Sheu model could generate better results compared to the Sacramento et al. model for almost all scenarios created. However, the VRP-D by Wang and Sheu requires docking hub stations. The rent, set-up, and maintenance of these stations add to the delivery costs and reduce the flexibility of the model. It could be shown that one docking hub station for the delivery in Wien Alsergrund is sufficient.

The Wang and Sheu model should be considered if the demand forecast for a delivery area shows a high proportion of packages with a weight that can be carried by drones. Otherwise, the Sacramento et al. model should be chosen due to the high flexibility and the fact that no infrastructure is required. Transportation costs are significantly lower compared to a conventional delivery and the delivery area can be expanded and downsized without lead-time.

Several Truck-and-Drone models that are suited for an urban delivery in e-commerce could be found during the literature review. By implementing two models to a scenario using actual data, a detailed evaluation could be carried out. For an urban e-commerce delivery, the VRP-D by Sacramento et al. has proven to be the best fit since it generates significant costs reductions compared to the truck-only solution and is highly flexible in terms of the delivery area.

The introduction of drones for last-mile delivery requires for a holistic view that includes all relevant parties and their interests. However, this thesis may serve as a basic decision support for service providers that consider the implementation of drones. An overview on the most recent Truck-and-Drone models could be given as well as an assessment regarding the fit for an urban e-commerce delivery. The comparison of two models allowed a very precise and detailed view and could show which model is to be preferred. For future research it is worth considering carrying out tests with larger instances using heuristics. In order to enable the commercial use of drones it is necessary to find a solution to the critical aspect of the parcel handout from drone to customer. Moreover, the introduction of Truck-and-Drone models shall be discussed considering additional viewpoints such as ecology or urban policy.

Drones can contribute considerably to an increase in efficiency and save costs in last-mile delivery and have the potential to play a significant role in e-fulfilment in the future.

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Appendix

Abstract

English Version

The worldwide rise in e-commerce has significant impact on logistical processes and puts e-fulfilment increasingly under pressure. The last-mile is claimed to be the most inefficient and costly part along the supply chain. Therefore, it is the target of many researchers who aim to find innovative solutions for the last-mile. Drones have seen an increased level of interest in the past years due to low operating costs and the independence from the road network. Truck-and-Drone models are delivery models, in which drones and trucks fulfil a delivery to multiple customers combined and synchronised.

The aim of this thesis is to obtain an overview on recent Truck-and-Drone models that are particularly relevant for an urban delivery, which may be used as a decision support for service providers that consider the implementation of drones. This is accomplished by posing the following research question: “What is the state of the art for Truck-and-Drone delivery, and which is the best suited model for urban delivery in e-commerce?”

A systematic literature review is performed in order to answer the first part of the question. The scientific papers found are categorised based on 12 criteria. Following, two models are compared using real-life data. Hereby, the theoretical findings of the literature review are substantiated by the application of the models in the 9th district of Vienna. A linear solver is used for the implementation of two linear Truck-and-Drone models for small instances. With a focus on transportation costs, the models’ results are compared to find the best-suited model for the delivery in this area.

Ultimately, this thesis answers the question whether the use of drones leads to cost reductions in last-mile delivery and which model is particularly suited for an urban e-commerce delivery with the focus on transportation costs.

German Version

Der weltweit starke Anstieg des E-Commerce hat im letzten Jahrzehnt zu einer Verlagerung hin zu einem Business-to-Customer-Markt geführt. Diese Entwicklung hat insbesondere Auswirkungen auf die logistischen Prozesse und setzt das E-Fulfilment zunehmend unter Druck. Die letzte Meile gilt als der ineffizienteste und mit den höchsten Kosten verbundene Teil des gesamten Logistikprozesses. Daher haben sich viele Forscher zum Ziel gesetzt, innovative Lösungen für die letzte Meile zu finden. Insbesondere Drohnen haben in den letzten Jahren aufgrund der niedrigen Betriebskosten und der Unabhängigkeit vom

Straßennetz an Interesse gewonnen. Truck-and-Drone-Modelle sind Liefermodelle, bei denen Drohnen und Lieferwagen kombiniert und synchronisiert eine Lieferung an mehrere Kunden durchführen.

Ziel dieser Arbeit ist es, einen Überblick über jene Truck-and-Drone-Modelle zu geben, die insbesondere für die Zustellung in urbanen Räumen geeignet sind. Diese Übersicht kann als Entscheidungshilfe für Dienstleister dienen, die den Einsatz von Drohnen in Erwägung ziehen. Die folgende Forschungsfrage dient der Erreichung dieses Ziels: „Was ist der Stand der Technik hinsichtlich Truck-and-Drone Modellen und welches ist das am besten geeignete Modell für die städtische Auslieferung im Bereich E-Commerce?“

Zur Beantwortung des ersten Teils der Frage wird eine umfangreiche und systematische Literaturrecherche durchgeführt. Die in diesem Rahmen gefundenen wissenschaftlichen Arbeiten werden anhand von 12 Kriterien kategorisiert. Anschließend werden zwei Modelle anhand von realen Daten verglichen. Dabei werden die theoretischen Erkenntnisse der Literaturrecherche durch die Anwendung zweier Modelle im 9. Wiener Gemeindebezirk untermauert. Für die Implementierung der Truck-and-Drone-Modelle wird ein linearer Solver verwendet und auf Lieferszenarios mit einer geringen Kundenzahl angewandt. Die Ergebnisse der Modelle werden mit Fokus auf die Transportkosten verglichen, um das am besten geeignete Modell für die Zustellung in diesem Liefergebiet zu finden.

Letztendlich konnte im Rahmen der Arbeit herausgefunden werden, ob der Einsatz von Drohnen zu Kostensenkungen in der letzten Meile führt und welches Modell für eine urbane E-Commerce-Zustellung mit dem Fokus auf Transportkosten besonders geeignet ist.

Attachment 1: Results of the Literature Research

Reference	Amount of Vehicles		Roles of Vehicles					Solution Method								
	Trucks	Drones (per Truck)	Objective	cyclic Drone Trips	Customer per Drone Trip	all parcels can be delivered by Drone	Truck supporting Drone	Drone supporting Truck	same-Level	both Vehicles deliver	proposing mathematical Model	Problem Formulation	exact Solution	Heuristic	Meta-heuristic	Road Map Testing
(Agatz, et al., 2018)		single	single	yes	one	yes			x	yes	x		x			
(Bakır & Tiniç, 2020)	VRPFD (with flexible drones)	multiple	multiple	no	one	yes		x		yes	x	MILP			x	
(Chang & Lee, 2018)	TSP	single	multiple	yes	one	yes	x			no (only drones)	x	NLP	x	x		
(Crisan & Nechita, 2019)	FSTSP	single	single	no	one	no		x		yes			x			
(Das, et al., 2020)	VRPTW & Synchronized Truck and Drone Routing	multiple	single	no	one	yes			x	yes	x	?			x	
(Dayarian, et al., 2020)	VRPDR (drone resupply)	multiple	multiple	yes	multiple	yes (from depot to truck)		x		no (only truck)	x				x	
(De Freitas & Penna, 2018b)	FSTSP	single	single	no	one	no		x		yes		MILP	x		x	
(Dell'Amico, et al., 2019)	FSTSP	single	single	no	one	no		x		yes		MILP	x	x		
(Dell'Amico, et al., 2020)	PDSTSP (parallel drone scheduling TSP)	single	multiple	yes	one	no		x		yes	x	MILP			x	
(Es Yurek & Ozmutlu, 2018)	TSP-D	single	single	no	one	yes			x	yes		MILP	x	x		
(Euchi & Sabok, 2021)	VRPD	multiple	single	no	one	yes			x	yes	x	MILP	x		x	

Table 1: Full Results of the Literature Analysis (1/4)

Reference	mathematical Model	Amount of Vehicles		Roles of Vehicles							Solution Method					
		Trucks	Drones (per Truck)	cyclic Drone Trips	Customer per Drone Trip	all parcels can be delivered by Drone	Truck supporting Drone	Drone supporting Truck	same-Level	both Vehicles deliver	proposing mathematical Model	Problem Formulation	exact Solution	Heuristic	Meta-heuristic	Road Map Testing
(Freitas & Penna, 2018)	FSTSP	single	single	no	one	no		x		yes		MILP			x	
(Gomez-Lagos, et al., 2021)	TSPDR (TSP with drone and parking)	single	multiple	yes	one	yes	x			yes	x	MILP	x		x	
(Gonzalez-R, et al., 2020)	TDTL (truck-drone team logistic)	single	single	no	multiple	yes			x	yes	x	MILP		x		
(Ha, 2018)	TSP-O	single	single	no	one	yes			x	yes	x	MILP			x	
(Jeong, et al., 2019)	FSTSP-ECNZ (energy consumption, no fly zones)	single	single	no	one	no		x		yes	x	MILP		x		
(Karak & Abdeighany, 2019)	HVRDP (Hybrid Vehicle Drone Routing Problem)	single	multiple	yes	multiple	yes	x			no (only drones)	x	MILP		x		
(Kitjacharoenchai & Lee, 2019)	VRPD	multiple	multiple	no	one	yes		x		yes	x	MILP	x			x
(Kitjacharoenchai, et al., 2019)	mTSPD	multiple	multiple	no	one	yes		x		yes	x	MILP			x	
(Kitjacharoenchai, et al., 2020)	2EVRPD (2-Echelon VRPD)	multiple	multiple	no	multiple	no		x		yes	x	MILP	x		x	
(Li, et al., 2020)	joint delivery system with drones and trucks	single	multiple	yes	one	yes	x			no (only drones)	x	CA		x		
(Moshref-Javadi, et al., 2020a)	MTRPD (Multi-trip Traveling Repairman Problem with Drones)	single	multiple	yes	one	yes		x		yes	x	MILP			x	x

Table 2: Full Results of the Literature Analysis (2/4)

Reference	mathematical Model	Objective	Amount of Vehicles		Roles of Vehicles							Solution Method				
			Trucks	Drones (per Truck)	cyclic Drone Trips	Customer per Drone Trip	all parcels can be delivered by Drone	Truck supporting Drone	Drone supporting Truck	same-Level	both Vehicles deliver	proposing mathematical Model	Problem Formulation	exact Solution	Heuristic	Meta-heuristic
[Moshref-Javadi, et al., 2020b]	STRPD (Simultaneous Traveling Repairman Problem with Drones)	minimize sum of waiting time of customers	single	multiple	no	one	no	x	x	yes	x	MILP		x		x
	mFSTSP	minimize time to service all customers	single	multiple	no	one	no	x	x	yes	x	MILP	x			x
[Nguyen, et al., 2020]	TSP-D	minimize makespan	single	single	yes	one	no	x	x	yes		MILP		x		
[Peng, et al., 2019]	joint routing and scheduling problem for wide-area vehicle-drone cooperative inspection	minimize total time consumption	single	multiple	yes	multiple	yes	x		no (only drones)	x	multiple LPs			x	
	TSPRDDR (TSP with Release Dates and Drone Resupply)	minimize total delivery time to serve all customers	single	single	yes	multiple	yes	x	x	no (only truck)	x	MILP	x			
[Polkonen & Golden, 2019]	MRPD (mothership + drone routing problem) & MRPD-IC (+ minimize completion time infinite-capacity drone)	minimize completion time	single	single	no	multiple	yes	x		no (only drone)	x	IP		x		
[Polkonen & Golden, 2020]	k-MVDRP (k-Multi-visit Drone Routing Problem)	minimize completion time	single	multiple	yes	multiple	yes		x	yes	x	MILP	x			
[Polkonen, et al., 2019]	TSP-D	minimize completion time	single	single	yes	one	no	x	x	yes	x	NLP		x		x
[Raj & Murray, 2020]	mFSTSP-VDS (with variable drone speeds)	minimize delivery time	single	multiple	no	one	no	x	x	yes	x	MILP	x		x	
[Sacramento, et al., 2019]	VRPD	minimize costs	multiple	single	no	one	no	x	x	yes	x	MILP		x		
[Salama & Srinivas, 2020]	JOCR (jointly optimize delivery locations clustering and truck-drone routing)	minimize total cost, minimize completion time	single	multiple	yes	one	no	x	x	yes	/				x	

Table3: Full Results of the Literature Analysis (3/4)

[Schermer, et al., 2018]	VRPD	minimize maximum completion time	multiple	multiple	no	one	yes	x	yes	x	MILP	x	x
	VRPDERO (en route operations)	minimize makespan	multiple	multiple	no	one	yes	x	yes	x	MILP		x
	VRPD	minimize time to service all customers	multiple	multiple	yes	one	no	x	yes	x	MILP	x	x
	VRPD	minimize max. (total) completion time of all vehicles	multiple	multiple	no	one	no		x	yes	MILP	x	
[Tang, et al., 2019]	TSP-D	minimize completion time	single	single	yes	one	yes	x	yes	x	MILP		x
	TSP-mD (multiple drones)	minimize total transportation costs	single	multiple	no	one	yes		x	yes	Markov decision process	x	x
[Ulmer & Thomas, 2018]	SDOPHF (Same Day Delivery routing problem with heterogeneous fleets of drones and vehicles)	maximize the expected number of customers served with SDD	multiple	multiple	yes	one	yes	x	yes	x	MILP	x	
	TSP-D	minimize duration of truck route	single	single	no	one	no (flight range limit)	x	yes	x	MILP	x	x
[Wang & Sheu, 2019]	VRPD	minimize costs	multiple	multiple	no	multiple	no	x	yes	x	BILP	x	
[Wikarek, et al., 2019]	CVRPD	minimize distance covered by drones	single	multiple	yes	multiple	yes	x	no (only drones)	x	BILP	x	

Table 4: Full Results of the Literature Analysis (4/4)

Attachment 2: Location Lists of the Instances

1	2	3	4	5
Lustkandlgasse 44, 1090 Wien	Nußdorfer Straße 12, 1090 Wien	Wilhelm-Exner-Gasse 34, 1090 Wien	Hernalser Gürtel 28, 1090 Wien	Müllnergasse 1, 1090 Wien
Galileigasse 3(SCHULE), 1090 Wien	Zimmermannngasse 14, 1090 Wien	Thurygasse 11/8, 1090 Wien	Schlagergasse 1, 1090 Wien	Währinger Straße 15/1, 1090 Wien
Höfergasse 1A/2, 1090 Wien	Pramergasse 8/1, 1090 Wien	Hahngasse 2 Uni Wien Rossau, 1090 Wien	Stroheckgasse 7, 1090 Wien	Badgasse 25/1, 1090 Wien
Alser Straße 24, 1090 Wien	Nordbergstraße 2, 1090 Wien	Garnisongasse 18/3, 1090 Wien	Borschkegasse 2, 1090 Wien	Alserbachstraße 4-4A, 1090 Wien
Schwarzspanierstraße 8, 1090 Wien	Lustkandlgasse 26-28/2, 1090 Wien	Salzergasse 13, 1090 Wien	Porzellangasse 50, 1090 Wien	Meynertgasse 6, 1090 Wien
Sobieskigasse 4, 1090 Wien	Nordbergstraße 14/12, 1090 Wien	Schubertgasse 7, 1090 Wien	Ferstelgasse 1, 1090 Wien	U-Bahn-Bogen 131-132(BETRIEB), 1090 Wien
Badgasse 6/3, 1090 Wien	Rooseveltplatz GEG.9(BUFFET), 1090 Wien	Roßauer Gasse 2, 1090 Wien	Schulz-Straßnitzki-Gasse 16, 1090 Wien	Nußdorfer Straße 30, 1090 Wien
Gilgegasse 12(SCHULE), 1090 Wien	Säulengasse 16, 1090 Wien	Strudlhofgasse 13, 1090 Wien	Wiesengasse 26, 1090 Wien	Schubertgasse 19, 1090 Wien
Währinger Straße 40-42, 1090 Wien	Boltzmanngasse 21, 1090 Wien	Ingen-Housz-Gasse 5, 1090 Wien	Türkenstraße 8, 1090 Wien	Boltzmanngasse 16 Amerikanische Botschaft, 1090 Wien
Währinger Straße 27, 1090 Wien	Wasserburgergasse 1-3/13, 1090 Wien	Frankgasse 4, 1090 Wien	Lazarettgasse 41, 1090 Wien	Währinger Gürtel 18-20 Obj. 611, 1090 Wien
Viriogasse 4/1, 1090 Wien	Marktgasse 1, 1090 Wien	Währinger Gürtel 18-20 Obj. 36, 1090 Wien	Badgasse 4/1, 1090 Wien	Badgasse 20, 1090 Wien
Rooseveltplatz 8(PFARRE VOTIVKIRCHE), 1090 Wien	Garnisongasse 20/1, 1090 Wien	Gilgegasse 18, 1090 Wien	Wiesengasse 2-12/6, 1090 Wien	Achamergasse 5, 1090 Wien
Wilhelm-Exner-Gasse 1, 1090 Wien	Lazarettgasse 37, 1090 Wien	Frankplatz 3, 1090 Wien	Türkenstraße 14, 1090 Wien	Lustkandlgasse 47, 1090 Wien
Seegasse 32, 1090 Wien	Bindergasse 11, 1090 Wien	Servitengasse 11, 1090 Wien	Alser Straße 32, 1090 Wien	Thurngasse 3, 1090 Wien
Nordbergstraße 18/7, 1090 Wien	U-Bahn-Bogen 151-152(BETRIEB), 1090 Wien	Porzellangasse 43, 1090 Wien	Latschkagasse 12, 1090 Wien	Pramergasse 18, 1090 Wien
Grünentorgasse 30, 1090 Wien	Rummelhardtgasse 5, 1090 Wien	Sensengasse 6, 1090 Wien	Alfred-Grünfeld-Gasse 1, 1090 Wien	Canisiusgasse 1, 1090 Wien
Lichtentaler Gasse 4/1, 1090 Wien	Badgasse 4/3, 1090 Wien	Fechtergasse 22(GARAGE), 1090 Wien	Prechtlgasse 5, 1090 Wien	Clusiusgasse 10, 1090 Wien
Sobieskigasse 33, 1090 Wien	Peregringasse 2, 1090 Wien	Mosergasse 11, 1090 Wien	U-Bahn-Bogen 328/331(BETRIEB), 1090 Wien	Liechtensteinstraße 87, 1090 Wien
Badgasse 25/2, 1090 Wien	Alser Straße 34, 1090 Wien	U-Bahn-Bogen 111(BETRIEB), 1090 Wien	Währinger Straße 43, 1090 Wien	Althanstraße 27, 1090 Wien
Van-Swieten-Gasse 16, 1090 Wien	Vereinsstiege 4, 1090 Wien	Berggasse 17/2, 1090 Wien	Nußgasse 5/3, 1090 Wien	Seegasse 22, 1090 Wien

Table 5: Adress Lists for the Instances tested (1/3)

6	7	8	9	10
Prechtlgasse 7, 1090 Wien	Nußdorfer Straße 32, 1090 Wien	Julius-Tandler-Platz 11, 1090 Wien	Thurngasse 8, 1090 Wien	Nadlergasse 1/2, 1090 Wien
Schlickplatz 4/2, 1090 Wien	Wiesengasse 19-21, 1090 Wien	D'Orsaygasse 3-5/1, 1090 Wien	Canisiusgasse 16, 1090 Wien	Sobieskigasse 30/2, 1090 Wien
Zimmermannplatz 10, 1090 Wien	Sobieskigasse 30/1, 1090 Wien	Währinger Gürtel 78, 1090 Wien	Wasserburgergasse 1-3/14, 1090 Wien	Schwarzspanierstraße 15/2, 1090 Wien
Lazarettgasse 19, 1090 Wien	Nußgasse 4, 1090 Wien	Michelbeuerngasse 2, 1090 Wien	U-Bahn-Bogen 140(BE-TRIEB), 1090 Wien	Lazarettgasse 20, 1090 Wien
U-Bahn-Bogen 170-171(BETRIEB), 1090 Wien	Liechtensteinstraße 23, 1090 Wien	Wilhelm-Exner-Gasse 15, 1090 Wien	Meynertgasse 4, 1090 Wien	Salzergasse 8-10, 1090 Wien
Wasagasse 11, 1090 Wien	Michelbeuerngasse 9A/1, 1090 Wien	Nußgasse 5/4, 1090 Wien	U-Bahn-Bogen 336-345, 1090 Wien	Badgasse 9/1, 1090 Wien
Währinger Straße 24, 1090 Wien	Nußgasse 6/2, 1090 Wien	Schwarzspanierstraße 22, 1090 Wien	Zimmermannplatz 6, 1090 Wien	Alserbachstraße 20A, 1090 Wien
Seegasse 2, 1090 Wien	Lustkandlgasse 54, 1090 Wien	Tendlergasse 15, 1090 Wien	U-Bahn-Bogen 181(BE-TRIEB), 1090 Wien	Seegasse 13, 1090 Wien
Boltzmanngasse 21, 1090 Wien	Latschkagasse 3-5/6, 1090 Wien	Boltzmanngasse 21, 1090 Wien	Althanstraße 15, 1090 Wien	Währinger Gürtel 152, 1090 Wien
Maria-Theresien-Straße 7, 1090 Wien	Tepserngasse 3/11, 1090 Wien	Rummelhardtgasse 4, 1090 Wien	Müllnergasse 24, 1090 Wien	Pfluggasse 10, 1090 Wien
Wiesengasse 2-12/5, 1090 Wien	Badgasse 4/3, 1090 Wien	Währinger Straße 28, 1090 Wien	Zimmermannplatz 9, 1090 Wien	Salzergasse 2/4, 1090 Wien
Türkenstraße 4 Schule, 1090 Wien	Garnisongasse 2, 1090 Wien	Georg-Sigl-Gasse 2, 1090 Wien	Löblichgasse 2, 1090 Wien	Spitalgasse 5-9, 1090 Wien
Meynertgasse 3/2, 1090 Wien	Alexander-Nehr-Gasse 2/9, 1090 Wien	Thuryhof STG. 1, 1090 Wien	Glasergergasse 6, 1090 Wien	Währinger Gürtel 96, 1090 Wien
Salzergasse 9, 1090 Wien	U-Bahn-Bogen 166(BE-TRIEB), 1090 Wien	Newaldgasse 6-10, 1090 Wien	Fechtergasse 16, 1090 Wien	Schwarzspanierstraße 2A, 1090 Wien
Althanstraße 49/4, 1090 Wien	Tendlergasse 6, 1090 Wien	Hernalser Gürtel 26/2, 1090 Wien	Ayrenhoffgasse 6, 1090 Wien	Kinderspitalgasse 12, 1090 Wien
Lustkandlgasse 48, 1090 Wien	Borschkegasse 17, 1090 Wien	Porzellangasse 28, 1090 Wien	Währinger Gürtel 132, 1090 Wien	Althanstraße 11-13/4, 1090 Wien
Clusiusgasse 10, 1090 Wien	Clusiusgasse 10, 1090 Wien	Clusiusgasse 10, 1090 Wien	Servitengasse 12, 1090 Wien	Lazarettgasse 12, 1090 Wien
Himmelfortstiege 4, 1090 Wien	Alexander-Nehr-Gasse 3/B, 1090 Wien	Galileigasse 1, 1090 Wien	Währinger Gürtel 14, 1090 Wien	Pramergasse 23/1, 1090 Wien
Währinger Straße 24, 1090 Wien	Liechtensteinstraße 18, 1090 Wien	Clusiusgasse 9, 1090 Wien	Thuryhof STG. 1, 1090 Wien	Garnisongasse 18/10, 1090 Wien
Tepserngasse 3/2, 1090 Wien	U-Bahn-Bogen 180(BE-TRIEB), 1090 Wien	Sobieskigasse 1, 1090 Wien	Lustkandlgasse 49, 1090 Wien	Schulz-Straßnitzki-Gasse 8, 1090 Wien

Table 6: Adress Lists for the Instances tested (2/3)

11	12	13	14	15
Roßauer Lände 45, 1090 Wien	Alserbachstraße 17, 1090 Wien	Schulz-Straßnitzki-Gasse 8, 1090 Wien	Wasagasse 9, 1090 Wien	Canisiusgasse 16, 1090 Wien
Salzergasse 13, 1090 Wien	Lustkandlgasse 26-28/1, 1090 Wien	Ingen-Housz-Gasse 5, 1090 Wien	Rooseveltplatz 9, 1090 Wien	Hahngasse 24-26/2, 1090 Wien
Harmoniegasse 5, 1090 Wien	Alser Straße 34, 1090 Wien	Mariannengasse 9, 1090 Wien	Spittelauer Platz 2, 1090 Wien	Höfergasse 5, 1090 Wien
Servitengasse 17, 1090 Wien	Rotenhausgasse 6, 1090 Wien	Liechtensteinstraße 89, 1090 Wien	Mariannengasse 24/1, 1090 Wien	Spitalgasse 1A, 1090 Wien
Türkenstraße 22-22A ROSSAUER KASERNE, 1090 Wien	Wilhelm-Exner-Gasse 5/5, 1090 Wien	Mariannengasse 25, 1090 Wien	Porzellangasse 24A, 1090 Wien	Währinger Straße 57, 1090 Wien
Pramergasse 19, 1090 Wien	Clusiusgasse 13, 1090 Wien	Mariannengasse 28, 1090 Wien	Mariannengasse 32, 1090 Wien	Clusiusgasse 2, 1090 Wien
Müllnergasse 29, 1090 Wien	Porzellangasse 58/6, 1090 Wien	Währinger Gürtel 130, 1090 Wien	Salzergasse 16, 1090 Wien	Höfergasse 1A/2, 1090 Wien
Sobieskigasse 25, 1090 Wien	Nußgasse 3/1, 1090 Wien	Servitengasse 3/1, 1090 Wien	Mosergasse 16, 1090 Wien	Alser Straße 32, 1090 Wien
Fluchtgasse 4, 1090 Wien	Sechsschimmelgasse 12, 1090 Wien	Währinger Straße 6-8, 1090 Wien	Hahngasse 24-26/1, 1090 Wien	Dreihackengasse 8, 1090 Wien
Zimmermannngasse 4-6, 1090 Wien	Ferstelgasse 1, 1090 Wien	Kinderspitalgasse 4, 1090 Wien	Harmoniegasse 8, 1090 Wien	Sechsschimmelgasse 15, 1090 Wien
Fechtergasse 2, 1090 Wien	Tendlergasse 13, 1090 Wien	Sobieskigasse 9, 1090 Wien	Tepserngasse 3/7, 1090 Wien	Glasergergasse 10, 1090 Wien
Nadlergasse 6, 1090 Wien	Säulengasse 18/1, 1090 Wien	Marktgasse 27/1, 1090 Wien	Wiesengasse 30, 1090 Wien	Währinger Gürtel 134, 1090 Wien
Währinger Gürtel 166, 1090 Wien	Tepserngasse 3/1, 1090 Wien	Severingasse 15, 1090 Wien	Garnisongasse 18/4, 1090 Wien	Währinger Straße 44, 1090 Wien
Währinger Straße 62, 1090 Wien	Wasagasse 21/2, 1090 Wien	Sobieskigasse 18, 1090 Wien	Georg-Sigl-Gasse 1, 1090 Wien	Porzellangasse 33A/4, 1090 Wien
Lazarettgasse 11, 1090 Wien	Sobieskigasse 7, 1090 Wien	Türkenstraße 12, 1090 Wien	Grünentorgasse 19A, 1090 Wien	Georg-Sigl-Gasse 6, 1090 Wien
Nordbergstraße 15/4, 1090 Wien	Säulengasse 26, 1090 Wien	Boltzmanngasse 4, 1090 Wien	Müllnergasse 15, 1090 Wien	Alserbachstraße 15, 1090 Wien
Nußdorfer Straße 92/1, 1090 Wien	U-Bahn-Bogen 92(BE-TRIEB), 1090 Wien	Währinger Gürtel 78, 1090 Wien	Schlickplatz 10, 1090 Wien	U-Bahn-Bogen 92(BE-TRIEB), 1090 Wien
Servitengasse 14, 1090 Wien	Rooseveltplatz 9, 1090 Wien	Löblichgasse 6, 1090 Wien	Glasergergasse 15, 1090 Wien	Alser Straße 32, 1090 Wien
Widerhofergasse 3, 1090 Wien	Müllnergasse 21/2, 1090 Wien	Währinger Gürtel 150, 1090 Wien	Kolingasse 18, 1090 Wien	Canisiusgasse 18, 1090 Wien
Höfergasse 1A/2, 1090 Wien	Lazarettgasse 11, 1090 Wien	Lustkandlgasse 46, 1090 Wien	Latschkagasse 12, 1090 Wien	Schlagergasse 7, 1090 Wien

Table 7: Adress Lists for the Instances tested (3/3)

Attachment 3: Full Code of VRP-D by Wang & Sheu (2019) in CPLEX Optimization Studio

```
/******  
  
* OPL 20.1.0.0 Model  
* Author: gisli  
* Creation Date: 13.04.2021 at 11:59:15  
*****/  
  
// Wang & Sheu final model (2 central hubs)  
  
// initialization of variables and sets:  
  
int c=...; // number of customers (w/o docking hub nodes)  
int n=...; // number of arcs  
int OS=...; // start node  
int OT=...; // end node  
{int} N =...; // set of all nodes  
{int} C={i | i in N: 2<i <n+1}; // customer nodes: nodes from 3 to n+1  
{int} O={i | i in N: 0<i<3}; // hub nodes: node 1 and 2  
  
tuple arc {int i; int j;} //arcs  
setof(arc) Arc= {<i,j> | i,j in N: i!=j}; //set of arcs  
// defined for all combinations of i and j if i is not j  
  
int M=...; // large number  
{int} K=...; // set of trucks  
{int} D=...; // set of drones  
  
int LD=...; // max load of parcels for drone  
int LR=...; // max load of drones on truck  
int LS=...; // max drones per hub (LR>LS)  
int LT=...; // max load of parcels on truck  
float TD=...; // max flying duration  
  
float CT=...; // transport costs truck per time unit  
float CD=...; // transport costs drone per time unit  
  
int Tspeed=...; // truck speed  
int Dspeed=...; // drone speed  
int dronable=...; // number of dronable customers  
int runtime=...;  
int g[C]=...; // weight of demand  
  
float tT[Arc]=...; //travel time truck  
float tD[Arc]=...; //travel time drone  
  
//decision variables:  
dvar boolean x[Arc,K]; // truck travel  
dvar boolean y[Arc,D]; // drone travel  
dvar boolean z[Arc,K,D]; // truck carries drone d  
dvar boolean u[Arc,K]; // truck carries a drone at all  
dvar float+ v[N,D]; // cumulative flying time drone  
dvar int+ wD[N,D]; // cumulative weight units of parcels drone carries  
dvar int+ wT[N,K]; // cumulative weight units of parcels truck delivers  
  
// setting a run time:  
execute{  
cplex.tilim = runtime;
```

```

}

// objective function:
minimize
CT*(sum(<i,j> in Arc, k in K)tT[<i,j>]*(x[<i,j>,k]+ u[<i,j>,k]))
+CD*(sum(<i,j> in Arc, d in D)tD[<i,j>]*y[<i,j>,d]); // w/o fixed costs of employing
a truck

// constraints:
subject to {

    sum(<i,j> in Arc:i==OS, k in K)x[<i,j>,k]+ sum(<i,j> in Arc:i==OS, k in
K)u[<i,j>,k]
    == sum(<i,j> in Arc:j==OT, k in K)x[<i,j>,k]+sum(<i,j> in Arc:j==OT, k in
K)u[<i,j>,k]; //(3)

    sum(<i,j> in Arc:i==OS, d in D)y[<i,j>,d]+ sum(<i,j> in Arc:i==OS, k in K, d
in D)z[<i,j>,k,d]
    == sum(<i,j> in Arc:j==OT, d in D)y[<i,j>,d]+sum(<i,j> in Arc:j==OT, k in K, d
in D)z[<i,j>,k,d]; //(4)

    forall(j in C) //(5)
    sum(<i,j> in Arc, k in K)x[<i,j>,k]+sum(<i,j> in Arc, d in
D)y[<i,j>,d]+sum(<i,j> in Arc, k in K)u[<i,j>,k]==1;

    forall(i in C) //(6)
    sum(<i,j> in Arc, k in K)x[<i,j>,k]+sum(<i,j> in Arc, d in
D)y[<i,j>,d]+sum(<i,j> in Arc, k in K)u[<i,j>,k]==1;

    //added constraints: each hub must be visited at least once in order to drop
off parcels

    forall(j in O) //(5.1)
    sum(<i,j> in Arc, k in K)x[<i,j>,k]+sum(<i,j> in Arc, k in K)u[<i,j>,k]==1;

    forall(i in O) //(6.1)
    sum(<i,j> in Arc, k in K)x[<i,j>,k]+sum(<i,j> in Arc, k in K)u[<i,j>,k]==1;

    forall(k in K, i in O union C) //(7)
    sum(j in N: i!=j)x[<i,j>,k] +sum(j in N: i!=j)u[<i,j>,k]
    == sum(j in N: i!=j)x[<j,i>,k] +sum(j in N: i!=j)u[<j,i>,k];

    forall(d in D, i in O union C) // (8)
    sum(j in N: i!=j)y[<i,j>,d]+sum(k in K, j in N: i!=j)z[<i,j>,k,d]
    == sum(j in N: i!=j)y[<j,i>,d]+sum(k in K, j in N: i!=j)z[<j,i>,k,d];

    forall(<i,j> in Arc, k in K) // (9)
    sum(d in D) z[<i,j>,k,d]<= LR;

    // constraint (10) becomes obsolete due to added constraints and adaption
(=launching only at docking hubs)

    forall(d in D, i in N) // (11)
    v[i,d]<= TD;

    forall(d in D, <i,j> in Arc: i in C) //(12)
    v[j,d] >= v[i,d]+ tD[<i,j>]+(y[<i,j>,d]-1)*M;

    forall(d in D, <i,j> in Arc : i <3) // (13)

```

```

v[j,d]>= tD[<i,j>]+(y[<i,j>,d]-1)*M;

forall(d in D,i in C)      //(14)
wD[i,d]<=LD;

forall(d in D, <i,j> in Arc :j in C)      //(15)
wD[j,d]>=wD[i,d]+ g[j]+(y[<i,j>,d]-1)*M;

forall(k in K,i in C)      //(16)
wT[i,k]<= LT;

forall(k in K, <i,j> in Arc: j in C)      //(17)
wT[j,k]>= wT[i,k]+g[j]+(x[<i,j>,k]+u[<i,j>,k]-1)*M;

forall(k in K, <i,j> in Arc: j in O)      //(18)
wT[j,k]>= wT[i,k]+(x[<i,j>,k]+u[<i,j>,k]-1)*M;

forall (k in K, <i,j> in Arc)      //(19.1)
1+(u[<i,j>,k]-1)*M <= sum(d in D)z[<i,j>,k,d];

forall(k in K, <i,j> in Arc)      //(19.2)
sum(d in D)z[<i,j>,k,d] <=u[<i,j>,k]*M;

forall(k in K,<i,j> in Arc)      //(20)
x[<i,j>,k]+u[<i,j>,k]<=1;

forall(d in D, <i,j> in Arc)      //(21)
y[<i,j>,d]+sum(k in K)z[<i,j>,k,d]<=1;

forall(<i,j> in Arc :i in C, k in K, d in D)      //(22)
sum(<a,i> in Arc) y[<a,i>,d]<=(1-z[<i,j>,k,d])*M;

}

// defining the printout
execute to {

writeln("overall costs: "+ cplex.getObjValue());
writeln("customer number: ",c);
writeln("set of trucks: ",K);
writeln("set of drones: ",D);
writeln("docking hub nodes: ", 0);
writeln("truck speed: ", Tspeed);
writeln("drone speed: ", Dspeed);
writeln("drone endurance: ",TD);
writeln("number of droneable customers ", dronable);
writeln("run time: ", runtime);

for (var i in N)
{
    for (var k in K)
{
        if (wT[i][k]>0 && i>2)
            writeln ("truck delivery: ",i)
        }
    }
}
}

```

```

/*****
* OPL 20.1.0.0 Data
* Author: gisli
* Creation Date: 13.04.2021 at 11:59:15
*****/

OS=0;
OT=23;
N={0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23};
K={1,2};
D={1,2};
runtime=10800;

SheetConnection
data1 ("VRP_Instance_Wang20.1.xlsm");

M from SheetRead(data1, "M");
n from SheetRead(data1, "n");
c from SheetRead(data1, "customer");
TD from SheetRead(data1, "e");

LD from SheetRead(data1, "Dcap");
LR from SheetRead(data1, "LR");
LS from SheetRead(data1, "LS");
LT from SheetRead(data1, "Q");
FT from SheetRead(data1, "FT");
CT from SheetRead(data1, "CT");
CD from SheetRead(data1, "CD");
g from SheetRead(data1, "demand");
tD from SheetRead(data1, "tD");
    tT from SheetRead(data1, "tT");

    Tspeed from SheetRead(data1, "Tspeed");
Dspeed from SheetRead(data1, "Dspeed");
dronable from SheetRead(data1, "dronable");

```

Attachment 4: Full Code of VRP-D by Sacramento et al. (2019) in CPLEX Optimization Studio

```

/*
* OPL 20.1.0.0 Data
* Author: gisli
* Creation Date: 07.03.2021 at 15:08:51
*****/
/*****/

int c =...; // number of customers
{int} N=...; // set of all nodes
{int} C={i | i in N: 0<i<c+1}; // subset of all customers
{int} N0={i | i in N: i<c+1}; // subset of outgoing nodes
{int} Nplus={i | i in N: i>0}; // subset of ingoing nodes
{int} deltaplus={ i | i in Nplus};
{int} deltaminus={i | i in N0};
{int} V=...; // set of trucks

int Dcap=...; // added! max. capacity of a drone
int q[C]=...; // customer demand
{int} Cdrone={ i | i in C: q[i] <=Dcap}; // subset of dronable customers

tuple arc {int i; int j;} // arcs
setof(arc) Arc= {<i,j> | i in N0, j in deltaplus : i!=j };

int Q =...; // capacity of trucks
float e=...; // flight endurance of drone
int SL=...; // launching time
int SR=...; // recovering time
int M=...; // large number
int Tmax=...; // tour length maximum

float CT=...; // added! transportation cost truck/time unit
float CD=...; // added! transportation cost drone/time unit
int SeT=...; // service time truck for each customer set equally
int SeD=...;
float tT[Arc]=...; // truck travel duration
float tD[Arc]=...; // drone travel duration

//float SeT[C]=...; // service time truck

int Tspeed=...; // truck speed
int Dspeed=...; // drone speed
int dronable=...;
int runtime=...;

tuple p {int i; int j; int k};
setof(p) P ={<i,j,k>| i in N0, j in Cdrone : i!=j, k in Nplus :
k!=i&&k!=j && SL+SR +tD[<i,j>]+tD[<j,k>]+SeD<= e};

//start in N- {c+1}, customer in Cdrone : j!=i, k in N-{0}:k!=i && k!=j};

dvar boolean x[Arc,V];
dvar float+ u[N,V];
dvar float+ zT[N,V]; // =ti
dvar float+ zD[N,V]; // =t'i
dvar boolean PV[N0,C,V];

```

```

dvar boolean y[P,V];

execute{
cplex.tilim=runtime;      //setting the run time
}
// adapted objective:

minimize CT*(sum(<i,j> in Arc, v in V)tT[<i,j>]*x[<i,j>,v])
+CD*(sum(<i,j,k> in P, v in V)(tD[<i,j>]+tD[<j,k>])*y[<i,j,k>,v]);

// constraints:
subject to{
forall(j in C)                // (2)
sum(i in deltainus:i!=j, v in V)x[<i,j>,v]
+ sum(<i,j,k> in P:j in Cdrone, v in V)y[<i,j,k>,v] == 1;

forall (v in V)                // (3)
sum(j in Nplus)x[<0,j>,v] <= 1;

forall(v in V)                // (4)
sum(i in N0)x[<i,c+1>,v] <= 1;

forall(v in V)                // (5)
x[<0,c+1>,v]==0;

forall(j in C, v in V)        // (6)
sum(i in deltainus: i!=j)x[<i,j>,v] == sum(k in deltaplus: k!=j)x[<j,k>,v];

forall(<i,j>in Arc, v in V)    // (7)
u[i,v]+1 <= u[j,v]+ M*(1-x[<i,j>,v]);

forall(j in Nplus, v in V)    // (8)
u[j,v]<= M*sum(i in deltainus: i!=j)x[<i,j>,v];

forall(v in V)                // (9)
sum(j in C, k in deltaplus :k!=j)q[j]*x[<j,k>,v]
+sum(j in C, <i,j,k> in P:j in Cdrone)q[j]*y[<i,j,k>,v]
<= Q;

forall(i in N0, v in V)       // (10)
sum(<i,j,k> in P) y[<i,j,k>,v]<=1;

forall(k in Nplus, v in V)    // (11)
sum(<i,j,k> in P)y[<i,j,k>,v]<=1;

forall(<i,j,k> in P, v in V)   // (12)
2*y[<i,j,k>,v] <= sum(h in deltaplus : i!=h)x[<i,h>,v]
+ sum(l in deltainus: l!=k)x[<l,k>,v];

forall(v in V)                // (13)
zT[0,v]==0;

forall(v in V)                // (14)
zD[0,v]==0;

forall(v in V)                // (15)
zT[c+1,v]<= Tmax* sum(i in N0)x[<i,c+1>,v];

forall(v in V)                // (16)

```

```

zD[c+1,v]<= Tmax*sum(<i,j,k> in P)y[<i,j,c+1>,v];

forall(<h,k> in Arc, v in V) // (17)
  zT[h,v]+tT[<h,k>] +SeT
  +SL*(sum(<h,j,k> in P: h in N0) y[<h,j,k>,v])
  +SR*(sum(<h,j,k> in P: k in Nplus)y[<h,j,k>,v])
  <= zT[k,v]+ Tmax*(1-x[<h,k>,v]);

forall(<i,j> in Arc, v in V) // (18)
  zT[i,v]+tD[<i,j>]+SL
  -Tmax*(1-sum(<i,j,k> in P: i in N0 && j in Cdrone)y[<i,j,k>,v]) <= zD[j,v];

forall(j in Cdrone, k in deltaplus : k!=j, v in V) // (19)
  zD[j,v] + tD[<j,k>]+SeD+SR
  -Tmax*(1-sum(<i,j,k> in P : j in Cdrone && k in Nplus)y[<i,j,k>,v]) <= zD[k,v];

forall(i in N0, v in V) // (20)
  zT[i,v]-Tmax*(1-sum(<i,j,k> in P: i in N0)y[<i,j,k>,v]) <= zD[i,v];

forall(i in N0, v in V) // (21)
  zT[i,v]+Tmax*(1-sum(<i,j,k> in P: i in N0)y[<i,j,k>,v]) >= zD[i,v];

forall(k in C, v in V) // (22)
  zT[k,v]-Tmax*(1- sum(<i,j,k> in P : k in Nplus)y[<i,j,k>,v])<= zD[k,v];

forall(k in C, v in V) // (23)
  zT[k,v]+Tmax*(1- sum(<i,j,k> in P : k in Nplus)y[<i,j,k>,v])>= zD[k,v];

forall(i in N0, k in Nplus, v in V) // (24)
  e +Tmax*(1-sum(<i,j,k> in P :i in N0 && k in Nplus)y[<i,j,k>,v])
  >=zD[k,v]-zD[i,v];

forall(i in N0, j in C: j!=i, v in V) // (25)
  (u[j,v]-u[i,v])<= (M*PV[i,j,v]);

forall(i in N0, j in C: j!=i, v in V) // (26)
  (u[j,v]-u[i,v])>= M*(PV[i,j,v]-1)+1;

forall(i in N0, k in Nplus, b in C, v in V) // (27)
  zD[k,v]-Tmax*(3- sum(<i,b,k> in P: i in N0 && k in Nplus)y[<i,b,k>,v]-
  sum(<i,b,k> in P : b in N0)y[<i,b,k>,v]- PV[i,b,v]) <= zD[b,v];
}
execute to{

writeln("overall costs: "+ cplex.getObjValue());
writeln("customer number: ",c);
writeln("number of trucks: ",V);
writeln("truck speed: ", Tspeed);
writeln("drone speed: ", Dspeed);
writeln("drone endurance: ",e);
writeln("number of droneable customers ", dronable);
// writeln("run time: ", runtime);

for(var v in V)
{
  for (var i in C)
  {
    if (u[i][v]>0.1 && i<c+1)

```

```

        writeln ("serviced by truck: ",i);
    }
}

/*****
* OPL 20.1.0.0 Data
* Author: gisli
* Creation Date: 10.03.2021 at 10:39:29
*****/
N={0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21};
V={1,2};
runtime= 10800;
SheetConnection
data1 ("VRP_Instance1_Sacramento20.3.xlsm");

M from SheetRead(data1, "M");
c from SheetRead(data1, "customer");
SL from SheetRead(data1, "SL");
SR from SheetRead(data1, "SR");
Tmax from SheetRead(data1, "Tmax");
Q from SheetRead(data1, "Q");
e from SheetRead(data1, "e");
SeT from SheetRead(data1, "SeT");
SeD from SheetRead(data1, "SeD");
CT from SheetRead(data1, "CT");
CD from SheetRead(data1, "CD");
q from SheetRead(data1, "demand");
Dcap from SheetRead(data1, "Dcap");
tT from SheetRead(data1, "tT");
tD from SheetRead(data1, "tD");
Tspeed from SheetRead(data1, "Tspeed");
Dspeed from SheetRead(data1, "Dspeed");
dronable from SheetRead(data1, "dronable");

```

Attachment 5: Full Code of the VRP (based on the Miller Tucker Zemlin Formulation) in CPLEX Optimization Studio

```
/******  
 * OPL 20.1.0.0 Model  
 * Author: gisli  
 * Creation Date: 11.05.2021 at 10:34:50  
 *****/  
// parameters and sets  
int M=...;  
int c=...; // number of customers  
int OS=...; // depot = start node  
int OT=...; // depot = end node  
{int} N=...; // set of nodes  
{int} C={i|i in N: 0<i<c+1}; // set of customers  
{int} N0={i|i in N: i<c+1}; // set of nodes from which a vehicle may depart  
{int} Nplus={i|i in N: 0<i}; // set of nodes to which a vehicle may arrive  
  
tuple arc {int i; int j;}  
setof (arc) Arc={<i,j> |i in N0, j in Nplus: i!=j}; // set of arcs  
  
{int} K=...; //set of trucks  
int LT= ...; // max load on truck  
float CT=...; // transport costs truck per time unit  
float d[C]=...; // demand of customer  
int Tspeed=...; // truck speed  
int runtime=...; // cplex run time  
float tT[Arc]=...; //travel time  
  
//decision variables  
dvar boolean x[Arc,K];  
dvar int+ u[N,K];  
  
execute{  
    cplex.tilim= runtime;  
}  
//objective function  
minimize  
CT* (sum(<i,j> in Arc, k in K)tT[<i,j>]*x[<i,j>,k]);  
  
// constraints  
subject to{  
  
forall(j in C) // (2) all customers must be left once  
    sum(<i,j> in Arc, k in K)x[<i,j>,k]==1;  
  
forall(k in K) // (3) depot can be left at most once, not all vehicles must be  
used  
    sum(j in Nplus)x[<0,j>,k]<=1;  
  
forall(k in K) // (4) depot can be reached at most once  
    sum(i in N0)x[<i,c+1>,k]<=1;  
  
forall(k in K) // (5) no direct travel between depot nodes  
    x[<OS,OT>,k]==0;  
  
forall(k in K) // (6) truck capacity constraint
```

```

sum(j in C, i in C: i!=j)d[j]*x[<i,j>,k]<= LT;

forall(k in K, i in C)           // (7) flow conservation
sum(j in Nplus:i!=j)x[<i,j>,k]==sum(j in N0:i!=j)x[<j,i>,k];

forall(<i,j> in Arc, k in K)      // (8) subtour elimination constraint (Miller-Tucker-
Zemlin)
u[i,k]-u[j,k]+(c-1)*x[<i,j>,k] <= c-2;
}

execute to{
writeln("overall costs: "+ cplex.getObjValue());
writeln("customer number: ",c);
writeln("set of trucks: ", K);
writeln("truck speed: ", Tspeed);
writeln("run time: ", runtime);
}

/*****
* OPL 20.1.0.0 Data
* Author: gisli
* Creation Date: 11.05.2021 at 10:34:50
*****/

N={0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21};
K={1,2};
runtime=600;
OS=0;
OT=21;

SheetConnection
data1 ("VRP_Instance1_Sacramento20.1.xlsm");

M from SheetRead(data1, "M");
c from SheetRead(data1, "customer");
LT from SheetRead(data1, "Q");
CT from SheetRead(data1, "CT");
tT from SheetRead(data1, "tT");
Tspeed from SheetRead(data1, "Tspeed");
d from SheetRead(data1, "demand");

```

Attachment 6: Results of the Sensitivity Analysis

Sacramento			Wang & Sheu		
Instance	Objective	Drone Deliveries	Objective	Drone Deliveries	
1	6,64	9	5,35	14	
2	6,94	9	5,66	15	
3	6,91	7	5,66	13	
4	5,94	9	5,38	13	
5	6,50	9	5,47	14	
6	5,80	8	5,14	11	
7	6,32	9	5,97	10	
8	5,71	9	5,34	10	
9	6,48	9	5,62	13	
10	6,12	5	5,59	13	
11	4,83	9	5,21	10	
12	6,15	8	5,24	12	
13	6,23	7	5,55	10	
14	6,51	7	5,50	13	
15	5,66	8	5,69	10	
Average	6,34	8,13	5,52	12,07	

Table 1: Drone Speed 40 km/h

Sacramento			Wang & Sheu		
Instance	Objective	Drone Deliveries	Objective	Drone Deliveries	
1	6,02	9	5,26	13	
2	6,18	8	5,66	15	
3	6,47	8	5,40	15	
4	5,91	10	5,38	13	
5	7,38	6	5,47	13	
6	6,38	7	5,14	11	
7	6,24	8	6,03	12	
8	5,10	9	5,34	10	
9	6,00	7	5,59	9	
10	5,90	8	5,59	13	
11	5,69	6	5,67	7	
12	6,48	10	6,48	10	
13	6,49	8	5,29	8	
14	5,97	9	7,04	7	
15	5,36	7	5,36	9	
Average	6,16	7,82	5,49	11,00	

Table 2: Drone Speed 30 km/h

Test Instance	Sacramento		Wang & Sheu 2 Hubs		Wang & Sheu one Hub	
	Objective	Drone Delivery	Objective	Drone Delivery	Objective	Drone Delivery
1	6,63	8	5,35	12	5,44	11
2	6,74	8	5,66	12	5,54	14
3	6,46	8	5,40	14	5,60	14
4	5,81	9	5,38	13	6,06	12
5	6,73	9	5,47	14	5,64	13
6	5,74	8	5,14	10	5,14	12
7	6,39	8	5,98	9	5,66	13
8	5,81	8	5,34	10	6,21	12
9	6,22	9	5,62	13	5,79	11
10	5,90	6	5,66	13	5,69	10
11	5,85	8	4,98	10	5,25	10
12	5,87	6	5,90	6	6,40	12
13	7,96	5	5,53	10	5,79	11
14	6,81	8	5,50	13	5,57	13
15	5,64	8	5,69	11	5,28	10
Average	6,30	7,73	5,51	11,33	5,67	11,87

Table 3: Wang & Sheu Model with one Hub

Instance	Sacramento		Wang & Sheu		Wang & Sheu increased Weight	
	Objective	Drone Deliveries	Objective	Drone Deliveries	Objective	Drone Deliveries
1	6,63	8	5,35	12	5,48	12
2	6,74	8	5,66	12	5,83	15
3	6,46	8	5,40	14	5,60	12
4	5,81	9	5,38	13	5,60	11
5	6,73	9	5,47	14	5,71	13
6	5,74	8	5,14	10	5,27	11
7	6,39	8	5,98	9	6,14	9
8	5,81	8	5,34	10	5,49	10
9	6,22	9	5,62	13	5,75	8
10	5,90	6	5,66	13	5,77	13
11	5,85	8	4,98	10	5,17	10
12	5,87	6	5,90	6	5,46	12
13	7,96	5	5,53	10	5,62	10
14	6,81	8	5,50	13	5,67	13
15	5,64	8	5,69	11	5,73	6
Average	6,30	7,73	5,51	11,33	5,62	11,00

Table 4: Wang & Sheu Model with increased Weight

5 dronable customers: 10 dronable customers: 15 dronable customers:

Sacramento				Wang & Sheu				Sacramento				Wang & Sheu				Sacramento				Wang & Sheu			
Instance	Objec- tive	Drone Deliver- ies	Objec- tive	Drone Deliver- ies	Objec- tive	Drone Deliver- ies	Objec- tive	Drone Deliver- ies	Objec- tive	Drone Deliver- ies	Objec- tive	Drone Deliver- ies	Objec- tive	Drone Deliver- ies	Objec- tive	Drone Deliver- ies	Objec- tive	Drone Deliver- ies	Objec- tive	Drone Deliver- ies			
1	6,97	3	6,76	4	8,12	7	6,49	8	6,63	8	5,35	12											
2	6,37	4	6,47	5	7,00	8	6,19	9	6,74	8	5,66	12											
3	6,42	4	6,42	4	5,92	9	5,96	9	6,46	8	5,40	14											
4	5,98	5	6,08	3	6,20	8	5,69	6	5,81	9	5,38	13											
5	6,37	5	6,35	5	6,07	9	5,95	10	6,73	9	5,47	14											
6	5,88	4	6,06	4	5,62	9	5,49	9	5,74	8	5,14	10											
7	6,35	3	6,55	2	6,49	6	6,31	7	6,39	8	5,98	9											
8	6,32	2	6,44	2	6,59	4	6,23	4	5,81	8	5,34	10											
9	6,33	2	6,87	3	6,19	5	6,49	4	6,22	9	5,62	13											
10	6,00	1	6,16	3	6,30	6	5,97	6	5,90	6	5,66	13											
11	5,72	4	5,81	2	6,26	5	5,55	6	5,85	8	4,98	10											
12	6,34	3	6,50	3	6,34	5	6,31	7	5,87	6	5,90	6											
13	5,77	4	6,16	3	6,66	5	5,66	8	7,96	5	5,53	10											
14	6,60	4	6,62	2	7,04	4	6,44	6	6,81	8	5,50	13											
15	6,18	3	6,62	4	5,60	5	6,09	5	5,64	8	5,69	11											
Average	6,24	3,40	6,39	3,27	6,43	6,33	6,06	6,93	6,30	7,73	5,51	11,33											

Table 5: changing the Number of dronable Customers