MSc Thesis in Transport, Infrastructure and Logistics

Introduction of drones in the last-mile logistic process of medical product delivery

A feasibility assessment applied to the case study of Benu 't Slag

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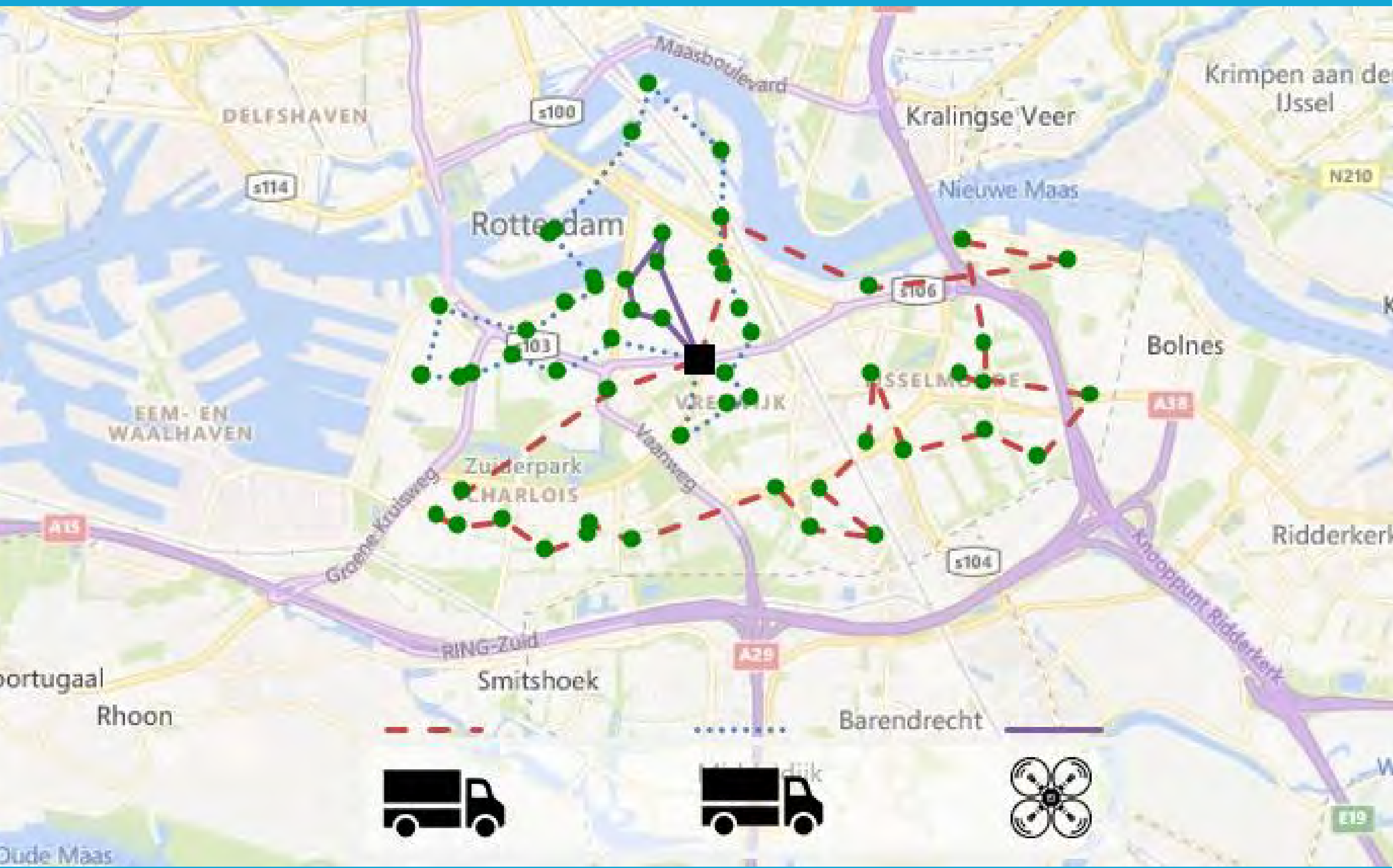

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Introduction of drones in the last-mile logistic process of medical product delivery

A feasibility assessment applied to the case study of BENU 't Slag

by

Irene Zubin

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This published thesis is an adjusted version, confidential information omitted.
The appendix is not the complete versione as well.

Preface

This master thesis is the result of 7 months of research on the introduction of new technologies in the vehicle fleet composition of the last-mile logistic process of medical product delivery. The study was conducted together with the pharmacy BENU 't Slag, located in Rotterdam, and is the final step before concluding the master program *Transport, Infrastructure and Logistics* at the faculty of Civil Engineering and Geosciences at the Delft University of Technology.

I would like to express my utmost gratitude to all the people that helped me throughout these two years and gave me the opportunity to achieve this important goal. First of all, I would like to thank the members of my graduation committee, for their interest, support and availability. I would like to thank my daily supervisors dr. Bart Wiegmans and dr. Ron van Duin for all the guidance they gave me. Their advice and their feedback were always a good support to my research, and they were always available to help me even when not in the university, via phone calls and Skype calls. I would like to thank prof. dr. ir. Bart van Arem, the chairman of my committee, for the encouraging feedback and constructive critics during all the meetings. Finally, I would like to thank my external supervisors ms. Maria Frijmersum from BENU 't Slag and mr. Arjen Rodenburg from the Future Mobility Network, for their precious insights on the pharmaceutical sector and on the new technologies of drones and their applications.

A special gratitude goes to my parents, for supporting me in all my decisions and be on my side in every good and bad moment I faced in the last two years. Studying at the TU Delft I learnt how to go out of my comfort zone, how to live by myself and how to cope with the difficult choice of studying abroad. I am very grateful to my new family here in Delft, to all my new international friends for creating a lot of nice memories but also for supporting me during difficult times.

Irene Zubin
Delft, June 2019

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Acronyms

AIA	Arospace Industries Association
B2C	Business to Customer
BnB	Branch and Bound algorithm
CBA	Cost Benefit Analysis
CEA	Cost Effectiveness Analysis
CVRP	Capacitated Vehicle Routing Problem
DCVRP	Distance Constrained Vehicle Routing Problem
DVRPTW	Dynamic Vehicle Routing Problem with Time Window
EV	Electric Vehicle
FIH	Farthest Insertion Heuristic algorithm
FSTSP	Flying Sidekick Travelling Salesman Problem
KPI	Key Performance Indicator
LNS	Large-scale Neighbourhood Search
MCA	Multi Criteria Analysis
OVRP	Open Vehicle Routing Problem
PDSTSP	Parallel Drone Scheduling Travelling Salesman Problem
SE	System Engineering
TSP	Travelling Salesman Problem
UAV	Unmanned Aerial Vehicles
UTM	Unmanned Traffic Management
VRP	Vehicle Routing Problem
VRPLIFO	Vehicle Routing Problem with Last In First Out
VRPMT	Vehicle Routing Problem with Multiple Trips
VRPPD	Vehicle Routing Problem with Pick-up and Delivery
VRPTW	Vehicle Routing Problem with Time Window
VTOL	Vertical Take-Off and Landing

1
Introduction

The term last mile delivery refers to the final leg of a business-to-customer (B2C) service, in which a product is shipped from a depot or a retail store to the final point, that can be either customer's home or a designated pick-up point (Gevaers et al., 2014). It is the final part of a bigger logistic and production chain that starts from the manufacturing and ends when the product is delivered to the end user.

Last-mile logistics are currently operated by means of road transport systems, such as vans and trucks, which ship the product from the retailer's transportation hub to the final delivery destination. The fast progress in global online retail sales that characterised the last few years has a potentially important impact on urban logistics and traffic network, especially in residential area (Visser et al., 2014). According to ITV (2018) the growing demand of home deliveries is increasing the number of vans on the road, causing in most of the cases network congestion. This phenomenon, together with infrastructure limitation, is one of the conditions that mostly curbs the last-mile delivery process, leading to delayed shipments, cost inefficiency and customer dissatisfaction.

As a mean to boost and support the growth of the last-mile sector, several studies have been conducted on the potential introduction of drones in the transportation field, with a focus on the last-mile delivery sector (Choi-Fitzpatrick et al., 2016). The reasons behind the popularity that drones have gained lies on the peculiar characteristics of drones. Drones are not bounded to the road infrastructure, being thus able to deliver goods in highly populated areas that suffer from heavy congestion and/or reach places that might be inaccessible via road transport.

1.1. Problem definition

The use of drones for last-mile logistics is a new and recent solution that has not been elaborately investigated yet. In the past few years, potential applications of drones and prototypes have been linked to parcel distribution. The first company who envisioned the adoption of this new technology was Amazon, with the CEO Jeff Bezos announcing in December 2013 that the world's largest e-commerce company was carrying out several tests on drone parcel deliveries (Yoon, 2018). Following the same path, German courier company DHL launched its Parcelcopter Hern, 2015 while Google introduced its X-Labs' Project Wing (Madrigal, 2014).

When searching into the literature of drones used for delivery purposes, several studies can be found. The common thread concerns the performance capabilities and the technical aspects of drones, focusing on the potential applications of these vehicles in different disciplines. Examples of previous studies on parcel delivery and emergency supply distribution can be found in Claesson et al. (2017), Thiels et al. (2015) and Scott and Scott (2017).

Despite the results obtained so far, the scientific aspect of optimisation models and network development has not been thoroughly investigated yet. When referring to the last-mile delivery process, the main transport means are trucks and vans (Dell'Amico and Hadjidimitriou, 2012). Therefore, optimisation models and network development are generally focused on road-bound vehicles. When referring to drones, difficulties arise in terms of adapting the current road optimisation models to flying drones, considering a certain number of depots or charging stations, the number of drones to be used for the shipment and the distribution in time and space given a certain demand.

1.2. Case study

The challenges that are faced by last-mile delivery differ between cases. The definition of a proper case study is thus important to determine the implications that this feasibility investigation will have on the delivery market. This study on drones for last-mile delivery will be supported by a collaboration with BENU Apotheek, one of the biggest pharmaceutical companies in the Netherlands. The interest in this pharmaceutical company lies on their omni-channel retailing options: consumers can purchase all kind of products from a variety of retail channels, with the possibility of having the product delivered directly at their home. Together with the pharmacy involved, a thorough research on the current logistic process and the actual demand for home delivery of medical supplies is carried out. The cost associated will be compared to the ones found for the drone delivery network through optimisation models. In this way, the pharmacy involved will have a scientific assessment on the feasibility of drone last-mile deliveries, that might help them with the decision on whether to implement this innovative transportation means in the near future.

1.3. Research objectives and research questions

When conducting a quantitative study, it is important to state some hypotheses that will be supported or falsified throughout the research. The leading hypothesis of this research concerns the feasibility of using drones for the last-mile logistic process. A specific mean of transport becomes feasible if it is allowed and safe and, at the same time, it is less expensive than other conventional means. This hypothesis can be formulated as follows:

H. **Drones provide a feasible fleet addition for the last-mile logistic process, when added to conventional transportation means that are currently in use.**

To measure this feasibility, optimisation theories for road transport network will be adapted for aerial vehicles. In this model, the distribution in time and space for a given market segment will be optimised, considering the number of depots and the number of vehicles to be used. Comparing the results of the optimisation model with simulations of the current delivery methods will assess the veracity of the hypothesis.

Following the definition of the hypothesis, the objectives of the research can be stated. The most important objective concerns the feasibility assessment of a network that includes drones in the vehicle fleet for last-mile delivery of medical supplies, adapting the current road-based models to aerial vehicles. Another important objective is data collection. To confer a scientific relevance, data gathering, and data analysis are two fundamental aspects of this research. Data on drone capabilities, geographical area of shipment and product to be shipped will be then collected to be used for the model implementation and validation.

Considering what discussed so far, the proposed research question is formulated as follows:

RQ. **How can the pharmaceutical sector benefit from the introduction of drones for the last-mile logistic process, in combination with the current means of transport?**

To help answering the main research question, some sub questions are formulated. It is decided to maintain the number of sub questions as limited as possible, for them to be a guidance throughout the research, without averting the attention from the main question.

SQ1. *What are the main characteristics of a B2C last-mile delivery process?*
A thorough analysis on the features of last-mile delivery is conducted, to provide the basis for a last-mile network comparison. In fact, to assess the feasibility of a drone freight network, it is important first to understand the characteristics of this logistic process.

SQ2. *Who are the main stakeholders involved in the last-mile logistic process, in relation to the case study?*
The identification of the stakeholder involved in the process is an important step to ensure the feasibility and the success of a project. By answering this sub-question, a list of people interested in the introduction of drones in the last-mile logistic process of pharmaceutical product delivery is created, focusing on their relative interest and power.

SQ3. *What are the main KPIs, data and design methodologies for a comparative analysis of last-mile delivery transport networks?*

The first step to conduct a comparative analysis is to define a set of Key Performance Indicators that will measure how a specific network operates in comparison to other networks or to standardised values. Based on these KPIs, several data will have to be retrieved. These data will then be used as inputs for a comparative design method, chosen based on network characteristics.

SQ4. *How to adapt the chosen design methodology for last-mile delivery networks to fit the case study requirements?*
When the most suitable design methodology is chosen, an important step is to adapt the known formulation found in literature in order to tailor it to the case study. The answer will provide the design methodology to be used to assess the drone last-mile delivery network.

SQ5. *What network alternative is the most promising in the case of last-mile logistic of medical products for home deliveries?*
Once the performance of the current situation are analysed in comparison with the future scenario, it is possible to define which network alternative is most beneficial for the health care sector.

1.4. Research methodology

A structured methodological approach sets the base for the whole research, rationalising the theoretical framework of the study. Therefore, a systematic procedure must be arranged. For the development of complex systems, the System Engineering (SE) approach as formulated by Dym and Little (2000) is an example of well-structured methodology. This step-wise approach helps the designer to achieve reliable, efficient and cost-effective results in several fields, including transport network development (Sage and Armstrong, 2000). The steps that are followed in this approach start with the problem formulation, moving to the problem analysis and concluding with the problem interpretation. The outcome is a complete design that addresses the identified problems and complies with the system requirements. Referring to the approach of Dym and Little (2000), the report is structured in the following way.

Problem definition
Introduction - The research procedure starts with a clear identification and definition of the problem. The motivation behind the project will open the way to the problem statement identified as research gap, research objectives and research question.

Conceptual design
System description: Last-mile delivery of medical products - In this initial part of the research, a thorough description of the system is provided. Related to the case study, the geographical location, the product to be delivered and the current last-mile delivery modes are defined, by conducting a series of interviews and literature study. A proposed scenario for future home deliveries is elaborated, which will be used later on for the comparison analysis together with the current situation. Although not the main focus of the research, a brief explanation on legal issues related to the use of drones in the Netherlands is here included. The chapter is concluded with the stakeholder analysis, that defines the important actors involved in the system.

Theories and models on last-mile logistic network and network comparison - Following the system description, this section provides an overview of the theories on network optimisation, focusing on last-mile delivery networks. In this chapter, a list of KPIs and related data that must be retrieved is provided. Methodologies for data gathering are explained, focusing on the elaboration of a cost model for what concerns cost data. The chapter continues with an analysis and description of different mathematical models that can be found in literature to assess transport networks. This section ends with the definition and formulation of the most suitable model to be used for the case study.

Model optimisation last-mile logistic - This chapter starts with the model conceptualisation, in which data to be used in the implementation are displayed by means of the cost model results. The focus then moves to the implementation of the model, setting up the solution approach. In the same way,data and procedures for model verification and validation are displayed.

Detailed design
Results and analysis - This section will contain all the results obtained in the model optimisation phase. With an overview of the main results obtained in the implementation phase, it is possible to pertinently

answer the research question.

Design communication
Conclusions and further recommendations - This last section will contain the conclusion of the whole research. Based on the results obtained in the previous chapters, it will be possible to answer the main research question stated at the very beginning of the process. Furthermore, considering the limitations of the study, further recommendations for future studies will be provided.

1.5. Scope of the research

The scope of this research is to assess the feasibility of introducing drones in the available fleet of the last-mile delivery process. This valuation is carried out through a comparison with the transportation means that are currently used in this logistic process. Several scenarios will be hypothesised, going from a network fully operated by drones, to an optimal combination of new and old technologies.

1.5.1 Data for comparative analysis of last-mile networks

An important step to be made to reach the main goal is data gathering. Data to be collected regard the geographical area and the product to be delivered, related specifically to the case study, but also drone capabilities, characteristics and features. Different data collection techniques can be found in Cyfar (2018). Relevant for this research are the Interview technique, the Observation/Testing technique and the Documents and Records technique.

In the system description and background analysis, the case study is introduced. Following the description of the product to be shipped and the geographical area of interest, data that are needed for the research regard the geographical location and the product characteristics. Geographical data can be retrieved from the data portal of the Dutch Government and in the Municipality offices. Geographical data consist of municipal information (e.g. planning zones, and nearby utilities) and geo-hydrological information (such as land form, soil maps, rivers and lakes). Data on population are also important for determining the feasibility of a drone network in medical supplies delivery. Such information regards the average age of the population, the percentage of elderly people, the number of physically impaired people, the number of chronically ill people and the number of households with several children. These are indeed considered to be potential target groups, given the limited possibility and ease of reaching a pharmacy.

For what concerns the product to be delivered, it is important to define the characteristics and the particularities of those specific products. To gather this type of data, literature research, interviews and observations might be suitable techniques. Interviews with the company related to the case study are also important to define the demand and the offer of product deliveries.

Data about drones concern mostly their flight range, autonomy and payload. Several challenges related to last-mile delivery concern the distance to be travelled and the number of parcels that can be delivered in one trip. Knowing the capabilities of drones is hence of fundamental importance to properly assess a last-mile transport network. Data can be retrieved conducting a literature study on existing drones and interviews with drone companies.

1.5.2 Limitations of the research

Given the extensive broadness of the research and the time constraint, some limitations must be decided upon. As stated before, the scope of the research is to assess the feasibility of a drone transport network for last-mile deliveries. Therefore, the focus will be on reaching a proper scientific level in the field of operation research by means of data gathering, optimisation model formulation and model testing.

For this reason, the societal aspect of drones will be left out of scope. In the past several papers have addressed people acceptance to flying drones. Rao et al. (2016) have studied how drones influence society, analysing the communal perception of drones being a surveillance equipment, and hence harming privacy and private properties. The perceived safety of drones has been analysed by Pappot and de Boer (2015), who conducted a quantitative risk analysis together with a qualitative analysis on people acceptance of drone's risks. A survey conducted among industries, regulator and civil society organisations regarding privacy, data protection and ethics for civil drone practice can be found in Finn and Wright (2016). Other examples of studies concerning the societal aspect of drones can be found in Boucher (2016), Ramadan et al. (2017) and Clothier et al. (2015).

Regulations are also not included in the research. Different countries have different restrictions regarding the use of Unmanned Aerial Vehicles, albeit it is not considered as the focus of the research. On the other hand, given the importance of providing a business case in the Dutch territory, it might be interesting to shortly investigate on the regulations in force in The Netherlands regarding commercial use of drones.

1.6. Thesis outline

Figure 1.1 provides a visual representation of the thesis structure. For each step of the research methodology, the chapter subdivision is reported, with a brief explanation of the concerning content. This visualisation also shows the chapter in which each sub question is answered.

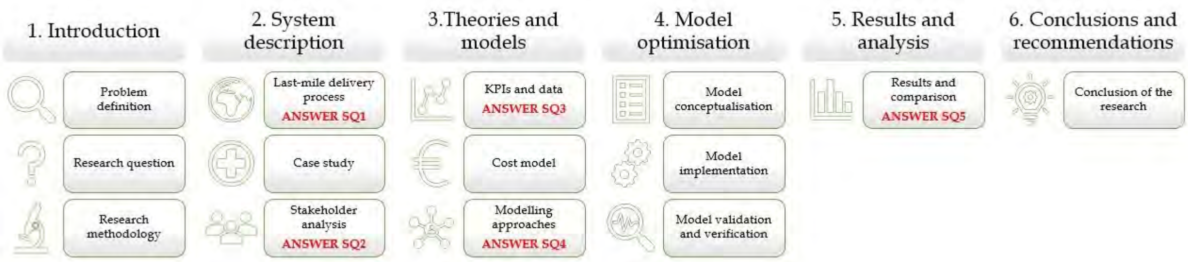


Figure 1.1: Outline of the thesis

2
System description: Last-mile delivery of medical products

This initial part of the research contains a thorough description of the system. A study on the last-mile delivery process is first carried out on a general basis. Current challenges related to the last-mile delivery sector are explained, together with the transportation modes that are used for product shipment. Narrowing down to the case study, the system description is then related to the geographical location, the product to be delivered and the vehicles used by BENU Apotheek. The system is then extended to one proposed future scenario that will lead to the introduction of drones in the daily last-mile operations. The description of this scenario is followed by legal and technical analyses on drones flight possibilities and on the stakeholders involved in the system.

2.1. Last-mile delivery process

The concept of last-mile delivery concerns the final leg of a business-to-customer (B2C) service, in which a product is shipped from a depot to the final destination. Depending on the delivery agreement, the shipment destination can be a cluster of collection points, customer's home or common pick up distribution centres.

According to Gevaers et al. (2009), the last-mile logistic process can be described as composed by four logistic decisions: the starting point of the last-mile, the place of delivery, the type of delivery and the shipment specifics. Starting points are usually pick-up locations of suppliers, such as warehouses, depots, or retail shops. The second step is to define the place of delivery, i.e. the final destination in which the products will be shipped. Depending on the delivery agreement, the product can be shipped to a pick-up distribution centre or directly to customer's house. In the latter, the delivery agreement might or might not require the presence of the customer, hence it can be attended or unattended. Another place of delivery that has recently gained popularity is a clustering point. Clustering points provide a common storage space in which several types of products for different customers can be stored. Examples are reception boxes, collection points and post offices. Figure 2.1 shows the tree diagram of the last-mile logistic process. Following this structure, it is possible to identify the challenges that this sector encounters. The effectiveness and efficiency of last-mile delivery is hampered by several characteristics, that can be related to the logistic process itself, the shipment agreement, or the final point to which deliver the items.

Cost reduction - Studies have shown that the last-mile leg is the most expensive part of the delivery process, for which costs account for up to 75% of the total cost of the logistic chain (Gevaers et al., 2011). A detailed analysis on the costs related to the last-mile delivery process can be found in Appendix A.

Traffic congestion and pollution - Commonly, last-mile services are carried out with several vans that deliver the product directly to the customer or to a pick-up point. In this process, delivery points are partitioned within the delivery area, and each destination is assigned to one specific vehicle (Dell'Amico and Hadjidimitriou, 2012). The primary methods for last-mile delivery are parcel trucks and third-party private cars (Edwards et al., 2010). As a result of the increased popularity in last-mile delivery, the number of trucks that are introduced for last-mile delivery purposes, is steadily increasing, with the consequence that congestion and pollution are also increasing in parallel. To provide a faster and more cost-efficient transportation chain for last-mile delivery, companies are now striving for new technologies (Agatz et al., 2018). In the context of urban areas, electric cargo bikes have been found to be an efficient alternative to trucks, addressing the problem of congestion and limited-access areas (Gruber et al., 2014). Cargo bikes can use a much denser road network, being able to run in both directions even on one-way roads. For what concerns accessibility, delivering cargo with electric bikes will help the shipment of products in limited- or no-access zones, such as pedestrian zones. Moreover, the fact that less parking space is required, it becomes easier to deliver in areas with narrow streets, without causing congestion or excessive roadblock (Reiter et al., 2014). A very recent alternative that has been proposed to solve congestion, pollution and infrastructure limitation, is the use of Unmanned Aerial Vehicles (UAVs), or mostly referred as drones (Agatz et al., 2018). Drones are fast and can operate without a human driver, saving thus time on congested road and having a low cost per kilometre. On the other hand, given the small size of a drone and the payload limitation, there is an upper limit to the size of the package to be delivered. Moreover, the battery-powered system, causes the drone to have a limited range. To overcome the drawbacks of drone delivery, the University of Cincinnati together with AMP Electric Vehicles, has conducted a study on a combined truck-drone mode (Wohlsen, 2014). The concept is that while the delivery truck visits a set of locations to make delivery, a drone simultaneously visits another set of locations, returning to the truck after each delivery, to pick up another package. In this way, the benefits of trucks (long range, high payload capacity) are combined with the benefits of drones (high speed and high accessibility), to provide an efficient and cost-effective delivery service.

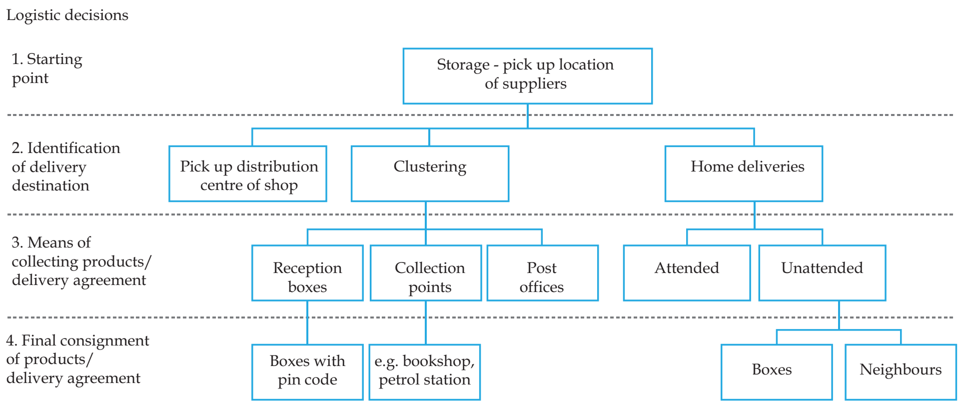


Figure 2.1: Last-mile logistic process. Adapted from Gevaers et al. (2009)

2.2. Home delivery of medical products: a case study

The case study that supports the research involves the delivery of medical products, from the retail store (pharmacy) to the end user. The pharmacy that has been selected is the BENU Pharmacy 't Slag, located in Rotterdam and part of the BENU Apotheek franchising. BENU has shown particular interest in the development of new technologies for its pharmacies, and envisions a potential introduction of drones in the delivery fleet. From the side of the researcher, the interest towards this pharmacy is connected to the wide range of services that it provides. Besides the conventional sale of generic and prescribed medicines, 't Slag allows its customers to order online and have their products shipped at a prearranged location. Delivery points are either pick-up points, collection machines or customer's addresses. They also allow a third person to collect the product, by prior agreement and authorisation. In the case that the customer is not at home by the time of delivery, a second agreement can be arranged.

Figure 2.2 shows the complete delivery process of BENU Apotheek franchising, from the production place to the end user, highlighting with a red square the focus of the research. Drug products are manufactured in specific plants. Then they are shipped into warehouses, where they are stored for a specified amount of time. From the warehouses, products are first shipped to retail stores (i.e. pharmacies) and then they are either sold directly to the customer at the pharmacy or delivered to a destination point. For the case of BENU Apotheek, warehouses are placed in three different locations: Amsterdam, Maarssen and Eindhoven. These depots serve 365 pharmacies all around The Netherlands, and the focus of the case study will be 't Slag, in the Southern part of Rotterdam. For the last leg of the delivery process, vans are the vehicles currently in use. Being smaller than trucks, they are more suitable for urban roads, while still able to carry the required amount of product. The red square in the figure defines the scope of the research, focusing only on the final leg of the delivery process, discarding all the previous step.

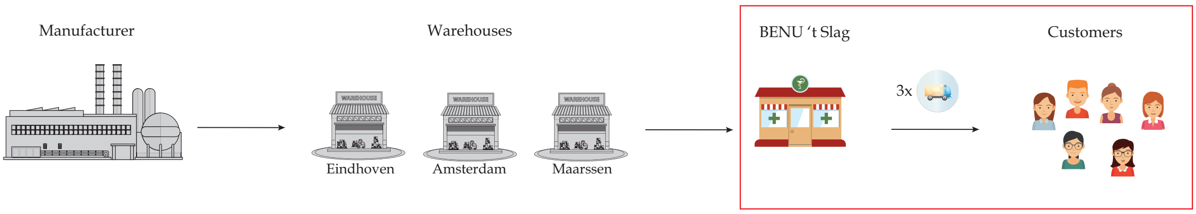


Figure 2.2: Complete delivery process, with research focus

2.2.1 Delivery process of BENU 't Slag

Referring to Figure 2.1 and together with the owner of the pharmacy Maria Frijmersum, it is possible to define the last-mile logistic process for the BENU Apotheek 't Slag (Frijmersum, 2018). The starting point is the Pharmacy located in Rotterdam, Sandelingplein 16A. Destination points are usually the personal address of the customer, since 't Slag does not rely on pick up distribution points or clustering places (in opposition to some other BENU pharmacies). With pre-arrangements, it is possible to deliver the product at the customer's work place. The type of delivery is generally attended, with arranged time windows and a track and trace system. Prior to the shipment, the customer receives a message announcing the time of delivery (it can be either during the day or specified before noon). In the case that customers are not at home and unable to receive the package, they can either pick it up directly from the pharmacy location on a later moment or arrange a second appointment. Referring to the logistic decisions displayed in Figure 2.1, the same process for BENU 't Slag is shown in Figure 2.3.

Besides in-store purchase and home delivery, a third option has recently been introduced, in which customers fetch their products from an ATM arranged in front of 't Slag. This ATM is filled up on a daily basis with different medical and non-medical products. For the collection of prescription drugs, the customer must provide an identification document together with the date of birth, as a double security.

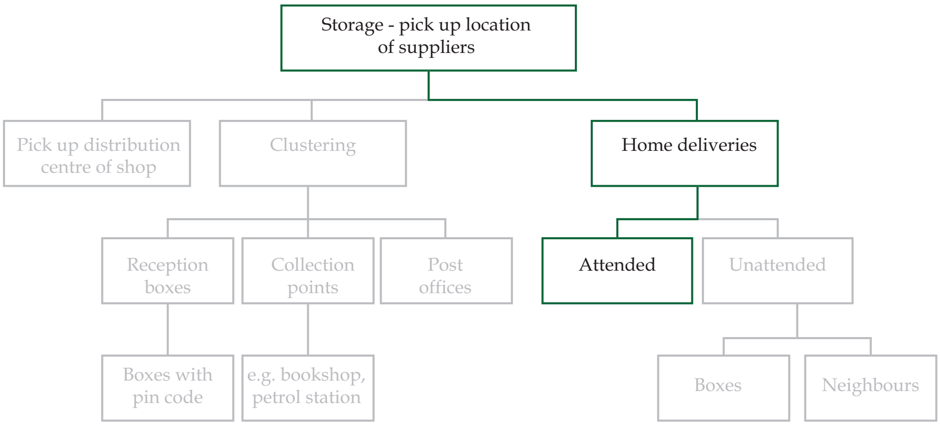


Figure 2.3: Last-mile logistic process for BENU 't Slag. Adapted from Gevaers et al. (2009)

2.2.2 Geographical area of delivery

BENU Pharmacy 't Slag operates in the southern part of Rotterdam, between the canals Nieuwe Maas and Oude Maas. The system with which areas are classified is by means of postcodes; a total of 14 postcodes are covered with the delivery service. Figure 2.4a shows the catchment area of Rotterdam south in which BENU Apotheek ‘t Slag operates the home delivery service.

In Figure 2.4b, the borders within the catchment area are shown, based on the 14 postcodes provided by the pharmacy. The red dot in the figure shows the position of the pharmacy BENU ‘t Slag. The position is relatively central in relation to the delivery area. For each postcode, it is possible to count the number of housing units. Table B.1 provides the list of the postcodes reached by the home delivery service; for each postcode, the number of streets and the number of housing units are provided. With a population of 630,000 inhabitants in 2014, Rotterdam is a densely populated urban area, with 3,043 inhabitants per square kilometre (WorldPopulationReview, 2018). As can be seen from Figure 2.4b, the pharmacy serves a clear predefined area. This results from previous agreements with the delivery company Farma Cleaning and Service. Potentially, this area could be expanded in the case that more vehicles or more efficient means of transport are introduced. From the picture, it can be estimated that the area covered by BENU Pharmacy ’t Slag is around 35 square kilometre, meaning a total of approximately 106,505 people (MapDevelopers, 2019).

(a) Catchment area

(b) Border area and pharmacy location

Figure 2.4: Geographical area of delivery (Frijmersum, 2018)

2.2.3 Medical products available for delivery service

The amount of deliveries varies per day, depending on the number of requests the pharmacy receives. To start a delivery trip, a single request is sufficient, hence no minimum number of product is required to start the delivery and when a shipment is scheduled, it is always completed.

The products available for delivery are the same ones that are sold in the store. Both prescription drugs and generic drugs are shipped, as well as cosmetic products, baby food and other essential goods. For products such as medicine to treat diabetes, incontinence and bed aid, a specific branch of BENU Apotheek takes over, to reduce the amount of daily deliveries that each pharmacy has.

The delivery of urgent medicine is guaranteed with a speedy delivery service. If an urgent consignment must be placed, the vehicle changes its route to reach as fast as possible the new destination and straightaway deliver the urgent package. The same line of reasoning is applied to those medicines that need to be stored in a cool environment: the route might be readjusted in order for the customer to receive the medicine as soon as possible.

Beside the different prescription and non-prescription medicines that are sold and delivered, BENU ’t Slag provides a service tailored for specific customers. Twice a week, pre-packaged medications are delivered to patients. These small boxes must fit into the customer’s mail box and contain the essential weekly medications that customers usually take.

2.2.4 Delivery transport means and associated costs

Figure 2.5: Vehicle used for home deliveries (own picture)

BENU 't Slag entrusts the management of deliveries to an external company, the Farma Cleaning and Service, which takes care of every single delivery for a fixed monthly payment. Deliveries are carried out via road transport, using 3 vans Mercedes Citan 108 cti, compact version. The capacity of the vehicle allows for transportation of products up to a volume of 2.4mc and a weight of 490 kg. CO2 emissions are around 119 – 112 g/km and fuel consumption in urban environment is around 5.0 – 4.7 l/100km (Mercedes-Benz, 2018). Figure 2.5 shows a picture of one of the vans that are used for deliveries.

The delivery service is free of charge, meaning that it is provided to the consumer for free. BENU 't Slag directly pays the delivery company, with a fixed amount per month. The cost was fixed to euros per month until February 2018 and then reduced to euros per month from February 2018 on. This reduction was the consequence of a diminution of delivery demand noticed after the introduction of the ATM.

The number of deliveries changes every day and does not follow a specific trend. Nonetheless, over the year it has been noticed that the peak of sales was during the colder months (November, December and January), with a small drop during the summer period, most likely related to the seasonal flu. Figure 2.6 shows the number of deliveries for the year 2018. Data have been retrieved on December 20th, meaning that for the month of December the total value is only for 20 days and not for the whole month. The graph shows only the number of home deliveries that have been registered by the three delivery men. It does not account for the purchases made at the counter or collected at the ATM. On a general basis, the introduction of the ATM in the month of February, brought a decrease in the total number of home delivery.

Figure 2.6: Total home deliveries for the year 2018 (Frijmersum, 2018)

The number of streets and housing units of each postcode can now be extended considering also the amount of deliveries per day per postcode. An average number of deliveries per month is obtained from Figure 2.6. Considering an average value of 21 working days per month, the pharmacy carries out, on average, deliveries per day, using the 3 vans available in the vehicle fleet. These deliveries can then be distributed to each postcode based on the size of the postcode and on the number of housing units. The results of the weighted division are rounded up to the closest integer value and are shown in Table B.1 of section B.1.

2.3. Last-mile delivery of medical product: proposed scenarios

Following the description of the current situation, several scenarios are envisioned. Each of them is then assessed in a qualitative way, according to the objectives of the research. The one that better complies to these objectives is then referred as the proposed scenario and used for the comparison analysis with the current situation.

2.3.1 Scenarios for future home delivery service for BENU 't Slag

Scenario 1 – No changes are made. This first scenario suggests to not apply any changes with respect to the current situation, keeping the 3 vehicles and the ATM, not expand the current area of delivery and the available fleet.

Scenario 2 – Drones only. All deliveries are carried out via drones, eliminating the current fleet of vans. The delivery area is expanded due to the elimination of infrastructure limitation.

Scenario 3 – Drones for speedy deliveries only. A fleet of drone is purchased only to take care of the speedy deliveries. Whenever an urgent delivery is requested, a drone is used instead of a van, which can in this way continue with the scheduled deliveries and avoid any change of route.

Scenario 4 – Hybrid van-and-drone deliveries. A drone is attached to the roof of the van and acts as a sidekick to the van, so that drone and van can split the deliveries, while the drone can transport light weights and can recharge on the roof.

Scenario 5 – Combination of drones and vans. Introduction of a new fleet of drones that cooperate with the existing vans. Deliveries are carried out based on an optimised system that minimises costs and assigns to each customer the most suitable vehicle.

The main objective of the research is to evaluate the feasibility of a drone transport network and to compare the performances of this network with the performances of the current one. Appendix B provides a table with arguments for and against each proposed scenario, with potential improvements or deterioration compared to the current situation. Based on the content of that table and the objectives of the research, for the comparison analysis scenario 1 and scenario 5 are selected, in such a way that the current situation, protracted in scenario 1, will be compared to the envisioned future situation depicted in scenario 5. The choice to use a parallel operation of vans and drones, instead of a synchronised one, is also supported by the study conducted by Murray and Chu (2015) and explained in subsection F.1.1. Their results showed that with a parallel drone scheduling, better service time improvements are found compared to a synchronised mode where drones serve as sidekicks to the van fleet. Moreover, the size of the delivery area is not such as to justify synchronised operations. The benefits of choosing a combined mode van-and-drone are stated in Agatz et al. (2018). Drones are fast and less expensive in terms of costs per kilometre, but they have a rigid limitation in the size of the package and flight range. Vans, on the contrary, can carry heavier packages for a bigger range, but being bounded to the physical road infrastructure they can be slow and subjected to congestion. Another positive effect that could be achieved using drones for last-mile delivery of medical products, is the reduction of vibration. Packages transported with drones are less subjected to vibration, which can cause the protein decay of some particular medicine (Vliet and Zaman, 2019). Moreover, temperature and humidity conditions might be preserved in a better way, due to a faster service (WorldHealthOrganization, 2011).

2.3.2 Description of chosen alternative: combination of vans and drones

From the proposed scenarios elaborated in Appendix B, the combination of vans and drones is selected, according to which deliveries are carried out based on an optimised system that minimises costs and assigns the most suitable vehicle. This choice has also been made according to an important feature described in Appendix B. Twice a week, [redacted] products are delivered directly to the customer's mail box, without requiring any signature or physical collection. This might cause some issues in case of drone delivery, given the difficulties that a drone might have when it comes to deliver a package directly in the mail box. For this reason, a combined mode of van and drone is proposed. The pharmacy will have available a fleet of vans and a fleet of drones. Depending on the trip characteristics, such as location, type of product, urgency of delivery and traffic flow, either a drone or a van is used. The following paragraphs contain a more in-depth description of the proposed scenario, with a depiction of the transport means, the delivery process, the geographical area and the products that will be delivered.

The *proposed means of transport* is then non-synchronised a combined mode van-and-drone, in which drones and vans carry out their own delivery, each of them starting and ending at the pharmacy. Although really attractive from a technology perspective, synchronised combinations are not considered, in which drones assist the deliveries carried out by the main vehicles already in use.

According to the International Civil Aviation Organisation, drones are defined as pilot-less aircraft which are flown without a pilot-in-command on-board and are either remotely and fully controlled from another place or programmed and fully autonomous (ICAO, 2011). Referring to Appendix C, the most suitable drone for last-mile delivery results to be the Fixed-Wing Hybrid drone. Although still on its development phase, the flying characteristics of this type of drones make the Fixed-Hybrid drone the best choice for a feasibility assessment. Combining the advantages of both Fixed-Wing and Rotor drones, the Hybrid typology allows for vertical take-off and landing (VTOL) while assuring a long-endurance flight (Chapman, 2016).

Drone provision could be arranged in several ways. A first option could be to delegate to a third company, in the same way as the current vans and service are provided by Farma Clean and Service. A second option might be the leasing of drones from private owners, who provide the aerial vehicles whenever needed. An additional choice is for the pharmacy to purchase the drones itself, after a careful analysis of the return on investments.

The *delivery process* remains unchanged compared to the current situation, with the pharmacy as starting point and the personal address of the customer as destination point. It implies that no distribution points or clustering centres are introduced in the system. The attended nature of the current delivery system, with pre-arranged delivery time will also remain unchanged. In the current situation, the customer receives a message announcing the time of delivery; in the proposed scenario, the same delivery agreement is envisioned, together with a second message announcing the arrival of the drone. Once customers receive the second message, they can collect their purchase directly from the drone, using a specific code provided by the pharmacy (in a similar way as they collect products from the ATM). The code can be either their birth date, as for the ATM, or it can change from shipment to shipment and communicated through SMS exchange. A box that can be used to transport medicines and other medical products, is found in Figure 2.7. This prototype was developed by a team of students from the faculty of Mathematics and Applied Science of Leiden, within the master track of Physics, and presented during the Drones in the City Event organised by The Future Mobility Network in the city of Katwijk, on the 31st of January. The concept of this prototype is that it is composed by separated compartment, each of them storing one medicine (or a set of medicine) that must be delivered to the customer. Each compartment can be opened by the customer only, using the code provided by the pharmacy. With the prototype of Figure 2.7, it can be assumed that a capacity of   products is considered for a single drone.

Figure 2.7: Box prototype (own picture)

The *geographical area* of delivery can potentially be expanded compared to the current situation. There are no legal limitations that confine the area of shipment to the current border defined in Figure 2.4. If the feasibility study provides positive results for the drone delivery network, a new catchment area could potentially be defined, based on the drone range and future demand.

For what concerns the *medical products* to be shipped, no differences are applied in the proposed scenario. As introduced at the beginning of this section, the only restriction is on the customised products that are delivered twice a week that do not need an attended delivery and thus are dropped off into the mail box. The problem with this type of delivery lies on current drone technology; the physical act of dropping the package off into the mail box results complicated to be carried out by a drone, and thus still needs to be accomplished by a delivery man. A specific type of medicine that might suite the new drone system belongs to the category of urgent shipment. In the current situation, when an urgent shipment is required the route is re-arranged to comply to the destination of the speedy delivery. This change in route comes with some drawbacks, especially on the cost of the shipment and delays on the scheduled deliveries. The proposed alternative is that these urgent deliveries are carried out by the new drone system, without any negative impact on the scheduled consignments.

2.3.3 Stakeholder analysis of a drone logistic network for BENU 't Slag

A stakeholder can be an individual, a group of individuals or an organisation that are actively involved in a project. They can express their interest up to a certain extent and they have a pre-arranged power on important decisions. The extent to which stakeholders are affected by a project and the influence they have on final decisions determines their typology. According to Gladden and De Mascia (2013), four categories are defined:

- Key stakeholders, that have significant influence upon project decisions;
- Primary stakeholders, that are most affected by the realisation of the project;
- Secondary stakeholders, who are indirectly affected by the realisation of the project;
- Tertiary stakeholders, who are least impacted by the project.

The stakeholder analysis is used for evaluating needs, power and interest of each actor involved in the project management. By carrying out an effective study, it is possible to identify stakeholders' interests, potential risks and misunderstandings, possible ways to influence other stakeholders in a positive manner, a list of people that must be informed in the execution phase and the potential stakeholders that might affect the project in a negative way (Eden and Ackermann, 1998).

The most common ways of conducting a stakeholder analysis is to use a so-called stakeholder matrix. In literature, 7 different matrices can be found, each of them assessing different aspects. For a complete description, the reader is referred to Appendix E.

It is chosen to use the power – interest matrix, to understand the importance of each stakeholder involved in the project, and to estimate the extent to which their opinion is considered in the decision phase. The steps to be taken to construct a power – interest matrix, are described in Appendix E. The result of the analysis is the power – interest matrix of Figure 2.8.

According to the description provided by Eden and Ackermann (1998), stakeholders are divided into four main categories: leaders, subjects, crowds and players. Leaders are the one positioned in the top right part, with high power and high interest; in this case, key leaders are BENU Apotheek and BENU 't Slag. The Municipality of Rotterdam, despite the highest power, falls under the Players, given the relatively low interest compared to other actors. Subjects are the actors with a high interest in the project but a relatively low power (top left part of the matrix), identified in this case by the delivery company and the customers. The population of Rotterdam and other pharmacies are considered as crowds, given the relatively low interest and low power. The fact that customers are defined as crowds and thus have no important role in the project management, might be debatable. They have almost no decision power, but in theory they have a high interest per se. Nonetheless, when compared to other actors, their relative interest drops. Figure 2.8 shows the power-interest matrix that is developed according to the list and description of stakeholders for this case study, provided in section E.1.

With respect to the stakeholder typologies defined in Gladden and De Mascia (2013), key and primary stakeholders are the BENU Apotheek franchising, the pharmacy BENU 't Slag and the Municipality of Rotterdam. Despite the low-medium interest of the Municipality, it has the highest decision power, being the one involved in policies and regulations.

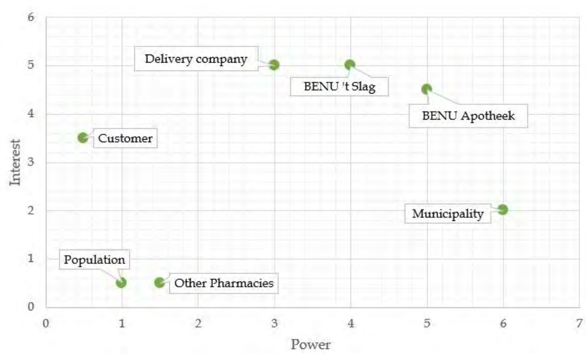


Figure 2.8: Power - Interest matrix. Own analysis

2.4. Legal issues related to the introduction of drones in last-mile logistics

Drones are classified as airborne objects, and as such they fall within aviation laws. Being a recent innovation technology, regulations on drones are still on an early phase. New procedures will be applied a year from now, which makes it important to state what is nowadays in force and what will be implemented in the near future.

The European research organisation SESAR JU - Single European Sky ATM Research Joint Undertaking - distinguishes four phases in the civilian development of drone use (Van Nieuwenhuizen Wijbenga, 2018):

1. Current situation: applications are limited to drone operations in sight distance and at a safe distance from people and buildings;
2. Second phase: the airspace in which drones will be able to flight is expanded. For what concerns urban areas, operations must remain within sight distance, whereas in rural areas they are broaden to out of sight distances;
3. Third phase: operations become possible for distances out of sight of operators, and drones will be able to fly above urban areas for parcel deliveries;
4. Fourth phase: full integration of drones into the sky, where full autonomous unmanned freight and passenger transport will be allowed, envisioned to start by 2030.

Pilot experiments are currently being conducted for the second phase of drone use development. An example is the first pilot experiment involving an out of sight distance flight, from Lauwersoog to Schiermonnikoog, for the delivery of medicines, a collaboration between the Ministry of Infrastructure and the Environment, the NLR (the Netherlands Aerospace Centre), ANWB Medical Air Assistance, UMCG Ambulance care, TU Delft and Dronehib GAE (Van Nieuwenhuizen Wijbenga, 2018). Results of pilot experiments provide standardisation for future regulations, and possible adjustments of existing ones. The integration of drones into the sky is possible with the introduction of an UTM - Unmanned Traffic Management - system, which enables communication between drones and other airspace users. Moreover, this integration is also enforced by technological aspects, such as development of new sensors, software and data technologies that can ensure higher level of safety and thus increased societal acceptance.

The following paragraphs provide a brief description of the current regulations on drone use and the future possibilities of drone development. More information on Dutch regulations and insurance policies are found in Appendix D.

2.4.1 Current regulations on drone use

A map of the Netherlands in which drones are currently allowed to fly is shown in Figure 2.9. From the map it is possible to notice that the amount of airspace in which flying a drone is permitted is quite restricted. Most of the airspace area is indeed already claimed by airports for passenger transport, or belongs to protected nature space. For what concerns the area of interest for the case study of BENU ’t Slag, current regulations do not allow drones to fly in the related airspace, being too close to a heliport. Other restrictions imposed by the law in force regard the conditions in which a drone can be flown: the maximum height is set to 120 meters, away from crowds, continuous buildings, roads, railways, industrial and port areas.

2.4.2 Future possibilities on drone use and regulations

New regulations regarding drones for parcel deliveries will be published by the end of 2019. The Netherlands will implement these regulations on a national level, and will comply with the European legislation imposed by EASA - European Agency for Security in Aviation. The map in Figure D.1 will be redacted, with more airspace available for drone operations. The area of Natura 2000 will become accessible, provided that no landings or take-offs will be performed. According to Vliet and Zaman (2019), the geographical area in which BENU ’t Slag operates will become accessible to drone flight, landing and take-off.

Figure 2.9: Outline map flying with drones (Rijksoverheid, 2018)

2.5. Conclusion

In this chapter, the picture of the system was metaphorically portrayed, starting with a general description of the last-mile logistic process, with the different strategies that can be followed to go from the retail store to customer locations and the related challenges that this growing business faces. With this general description, research sub question 1 was answered:

What are the main characteristics of a B2C last-mile delivery process?

Four logistics decisions were found to define this process, from the starting point to the final place of delivery. The first decision concerned the location from which products are shipped (e.g. warehouses, depots, retail shops). Then the second decision regards the identification of delivery destination, i.e. the place where product are consigned (e.g. pick up points, clustering points, customer's home). Once the delivery destination is set, the means of collecting product must be arranged. In case of clustering points, products can be collected through reception boxes, collection points or post offices. For home deliveries, collection might be attended or unattended. Lastly, the agreements on the final consignment of products must be arranged, e.g. pin code security in reception boxes, or neighbours pick ups for unattended home deliveries. The related challenges faced by the last.mile delivery sector were then identified in high costs of operations, traffic congestion and environmental damage.

Following this general description, the case study was introduced, with a thorough description of the home delivery service provided by BENU 't Slag, a pharmacy of the BENU Apotheek franchising located in the southern part of Rotterdam. Three different methods for purchasing medical and non-medical products are identified: in-store purchase, fetch of products using an ATM in front of the pharmacy and home delivery. For what concerns home deliveries, operations are carried out using three vans and three corresponding drivers that consign the products to customers on a daily basis. The demand pattern is also part of the system description. Therefore, this chapter includes the procedure that is followed to obtain the total demand per customer.

A proposal for the future scenario followed the description of the current situation, with an analysis of the potential logistic of the home delivery service. In this scenario, the main hypothesis is that drones provide a feasible fleet addition for the last-mile logistic process, when added to conventional transportation means that are currently in use. A stakeholder analysis was included in this stage of the research, to highlight the important actors involved in the system. At this point, the second research sub question was answered:

Who are the main stakeholders involved in the last-mile logistic process, in relation to the case study?

Relevant actors were identified in the BENU Apotheek franchising and the BENU pharmacy 't Slag, as the two most interested parts in this research. Moreover, delivery companies and the Municipality of Rotterdam were also identified as important stakeholders. Customers of BENU 't Slag, other pharmacies in Rotterdam and the general population were also defined as side stakeholders, having a small power on the project but a potential high interest in it. Each stakeholder is compared to the others based on their power and interests, which resulted in the power-interest matrix of Figure 2.8.

To conclude the chapter, some insights on Dutch regulations related to flying a drone are provided. Although not part of the research and out of the defined scope, investigating the legal issues related to drone utilisation helps to collocate the research in a potential real situation and to understand the applicability in the near future.

3
Theories and models on last-mile logistics and network comparison

To define the extent to which the pharmaceutical sector can benefit from the introduction of drones in the last-mile logistic process, and thus answer the research question, a comparison between the current situation and the proposed scenarios must be performed. The framework that will be used in this research consists of four steps.

Firstly, it is important to assess the parameters according to which the alternatives will be assessed on. For this purpose, a list of Key Performance Indicators (KPIs) and design requirements must be elaborated. With the term KPIs one refers to those attributes that describe the performance of the system, providing the starting point for a comparison analysis. Design requirements refer to the needs that a system aims to satisfy, and are closely related to the performance indicators that best describe the system. In this step, data are gathered via interviews with stakeholders, such as BENU 't Slag, the Municipality, delivery companies and drone providers.

Once the relevant data have been retrieved, and the general assumptions made, the second step concerns the definition of the costs associated with each scenario. Using the data retrieved on costs and operations, it is possible to build a cost model, which defines the costs associated with each scenario. These costs are then used on a further stage to assess the feasibility and the performance of each alternative.

To elaborate the retrieved data, a design methodology must be selected. Given the selected solution approach, the model is verified and validated, to quantify the accuracy of the model calculation. Once the model has been proved reliable, it is implemented using the input parameters specified for the case study.

After the model output are retrieved, it is possible to define the KPIs that characterise the system and hence perform a comparison analysis.

3.1. KPIs and design requirements for last-mile delivery

3.1.1 Key Performance Indicators

To conduct a comparative analysis between different scenarios, the first step is to define the parameters according to which the analysis is carried out. These parameters are known as Key Performance Indicators and are used by companies as measurable values to effectively track the achievement of business objectives and performance measures. Based on these KPIs, several data are needed for the comparison process. Key Performance Indicators that are usually used in last-mile delivery can be found in Robinson (2017) and Chen (2019). Given the nature of the research, the most relevant ones are summarised below:

1. Delivery cost per item: cost per item delivered, measured in *euro/item*.

2. Average service time: time needed to conclude the whole delivery service, starting from and ending at the retail store. This is mostly based on distance to be travelled, speed of the vehicle and possible hindrances along the way. It is calculated in hours, and an optimal feasible solution should provide a minimised service time, to guarantee a fast and reliable delivery;

3. Fuel and energy consumption: calculated averaging the total fuel cost per driver, and then summing that value for all the drivers, all vehicles and all routes and it is measured in *litres*. Minimising this element brings consistent savings in the delivery process, being the fuel cost a significant component in the delivery business;

4. CO2 emission: calculated by multiplying the total distance travelled by the delivery vehicles and the average CO2 emission per distance travelled. This parameter is highly influenced by the type of vehicle in the fleet, and reducing CO2 emission is one of the most important goals of new transport technologies;

5. Vehicle capacity used versus available capacity: ratio that estimates the actual payload of the vehicle compared to its maximum payload. Maximising this indicators means that more products can be shipped within one tour, improving thus the operations.

Other Key Performance Indicators that can be found in Robinson (2017), are the planned versus actual route length, the driver time spent in motion and stationary and the on-time delivery. Although these are very important KPIs to define the performance of a delivery network, especially the on-time delivery, they were not taken into account due to difficulties in retrieving proper. In fact, to analyse the extent to which deliveries are carried out within the intended time schedule, real observation might be needed, which goes beyond the scope of this research.

3.1.2 Design requirements for a combination of vans and drones in last-mile delivery network

The system in which these KPIs will be assessed must comply with network requirements. Requirements are defined as the needs that a particular design, product or project aims to satisfy. Based on their importance, requirements are divided into functional and not functional: the first term refers to the things that the system has to do, as a mandatory attribute for it to function; the second term refers to the qualities that the system has to have, preferably, in order for it to work properly (Verbraeck, 2016). Moreover, needs of different stakeholders are defined through user requirements, which describe how and the extent to which, each stakeholder wants to interact with the system. The definition of user requirements is made based on the stakeholder analysis of subsection 2.3.3. Needs of key and primary stakeholders will be taken into account, such as BENU Apotheek, BENU 't Slag and the Municipality of Rotterdam. Although not being part of this category, the needs of the customers and the delivery company are also considered, given their high interest.
Functional requirements:

- Medical products must be delivered to the intended customer;
- Medical products must be delivered within the intended arranged time;
- The model must assign a feasible vehicle to the trip, based on delivery characteristics;
- The chosen alternative must comply with existing regulations.

Non-functional requirements:

- The chosen alternative should lower the total cost of the delivery process;
- The chosen alternative should minimise the total time spent on the network;
- The sequence of chosen alternatives should provide a maximised vehicle utilisation.

Functional and non-functional requirements are used to define the boundaries of the design. By assessing what the system must comply with and what it should address, it is indeed possible to define the constraints that will make the network feasible.

3.1.3 Data for network analysis and comparison

Data needed for the network analysis and comparison are derived from the list of Performance Indicators, and are divided according to the indicator that they refer to. The following list provides the inputs that are required for the model comparison and that are gathered through interviews, literature review and experts consultations.

Delivery cost per item

- Average number of deliveries per day [*products*]: knowing the average number of deliveries per day (Frijmersum, 2018), it is possible to attribute each cost component to a single item delivered;
- Cost of storage area [*euro*]: portion of the pharmacy area that is dedicated to the storage of the products that must be delivered, retrieved from Numbeo (2019);
- Handling equipment [*euro*]: cost of the equipment needed to assist the drivers in the action of moving the products from the storage area into the vehicle, retrieved from LiftingEquipment (2019);
- Parking location [*euro*]: the pharmacy owns a communal parking spot for employees and for delivery vans. This area serves as parking location for vehicles that are not in use, but also as loading and unloading facility. Data on the squared metre needed are retrieved from Mercedes-Benz (2018), and data on cost of purchase from Numbeo (2019);
- Purchase cost of vehicles [*euro*]: cost of buying vehicles for the delivery fleet. For the van purchase cost refer to Mercedes-Benz (2018) whereas for the drone purchace cost to UAV (2019);
- License to operate [*euro*]: according to the FAA regulations, to operate a drone for home deliveries it is mandatory for the pilot to have a valid license (UAVCoach, 2019);
- ATM purchase [*euro*]: cost of purchase and allocation of an ATM built-in/through the wall machine, used for outdoor sales (CostOwl, 2019);
- Fees for outdoor sale: regional fees that allows outdoor sales, to be paid for the use of an ATM machine (CostOwl, 2019);
- Human labour [*euro/hour*]: cost per hour of a van driver (Glassdoor, 2019) and a drone pilot Vliet and Zaman (2019);
- Operation management [*euro/hour*]: cost per hour of a transport planner (Payscale, 2019), that organises and supervises the operation management;
- Insurance cost of vehicles: annual cost of insuring vehicles for the delivery fleet. For the van fleet refer to Mercedes-Benz (2018) and for the drone fleet to UAVCoach (2019);
- Regional taxes on vehicles [*euro*]: annual taxes to be paid for the vehicles of the delivery fleet (Belastingdienst, 2019);
- Operational costs of vans [euro/km]: costs associated with the use of a vehicle of the delivery fleet. For what concerns vans, this cost relates to the fuel consumption rate and the fuel price in the market (GlobalPetrolPrices, 2019);
- Operational costs of drones [euro/h]: costs associated with the use of a vehicle of the delivery fleet. For what concerns drones, it concerns the energy consumption rate and the energy price in the market MainEnergie (2019);
- Financial cost [*euro*]: cost related to the annual interests on loan (FitSmallBusiness, 2019).

Average service time

- Average speed of vehicle type [*km/h*]. Assumption of the model developer;
- Average loading and unloading time for vehicle type [*minutes*]. Assumption of the model developer;

Fuel and energy consumption

- Fuel consumption of vans [*litres/100km*] (Mercedes-Benz, 2018);
- Energy consumption of drones [*kWh*] (Xu, 2017);

CO2 emission

- CO2 emission per distance travelled, [*g/km*] (Mercedes-Benz, 2018).

Vehicle capacity used versus available capacity

- Maximum allowed payload for vehicle type [*products*]. Assumption of the model developer;
- Average used payload for vehicle type [*products*]. Output of the model.

For what concerns the cost per item, a more in depth analysis is carried out in section 3.2 and Appendix G with the generation of cost models for each network alternative. In these cost models, scenarios are assessed based on the cost of each component, in order to get an estimate of the cost per item in the considered alternatives.

3.2. Cost model for different sale options

A cost model is a mathematical framework in which all the costs of a specific activity are recorded (iSixSigma, 2019). For each system component, the corresponding cost is evaluated, in order to estimate the final cost of each scenario. Inputs for the model are the number and types of vehicles, the equipment needed, the technology used and potential human labour.

As explained in CIO (2018), the construction of a cost model starts with data gathering. Data on technologies used and economic indicators are used to develop a pricing scheme for each network design. The next step is to organise the data by removing and replacing missing data or standardise the values. In the case of missing data, assumptions can be made, based on historical data, averaging techniques and/or relevant literature.

Based on the scenario assessment in section 2.3 and the description of the current situation in section 2.2, the following alternatives will be analysed:

1. Deliveries are carried out using one vehicle type: vans. The alternatives for customers are either purchase the product directly at the pharmacy or having it delivered at home;
2. Deliveries are carried out using one vehicle type: vans. Beside purchase the product directly at the pharmacy or having it delivered at home, a third option for purchase is introduced: the ATM outside the pharmacy, through which customers can buy or collect their medicine at any time of the day;
3. Deliveries are carried out using two types of vehicles: vans and drones. The ATM is still available for customers who want to collect their medicine directly at the pharmacy, without being bounded by the opening hours. Drones are operated from the pharmacy and are forced to return there to charge their batteries and to load new products.

The output of the cost model will provide the total annual cost of each alternative, together with the fixed costs and the variable costs associated with the use of vans and the use of drones for last mile delivery of medical products. These values will be used in the selected design methodology to analyse the different network alternatives.

3.3. Model description for last-mile logistic problem

Last-mile delivery is a transport network problem in which products must be shipped from a depot to a set of customers, using a fleet of vehicles. The logistics of these deliveries should be such that the cheapest option is selected, providing thus an optimal tour that starts and ends at the depot and visits all the scheduled customers. In order to do so, the output data of the cost model must be elaborated through operation research, i.e. simulation techniques or optimisation modelling.

3.3.1 Transport network analysis: simulation approaches

The simulation of a transport network concerns the assessment of several different alternatives, without generating the best possible option. Simulation analyses scenarios by evaluating performances of alternatives, and it is particularly effective when many parameters with a substantial level of uncertainty define the problem, or in case that the analytical expression of the problem is difficult to formulate (Lee, 2019). The most common simulation approach in literature is the Travelling Salesman Problem (TSP), a non-deterministic problem used in operation research to find the shortest path that connects a set of nodes, for which the order of visit is not important. It takes its name from the analogy of a salesman who, given a set of destinations, must visit each one of them starting from a certain node and ending at his starting location. The goal of the problem is to minimise the total length of the tour. The mathematical formulation of the TSP, shown in Table 3.1, is found in Dantzig (2016). In this formulation, the objective function is to minimise the total cost of a daily operation. The decision variable x_{ij} refers to the binary integer value that returns 1 if the path goes from node i to node j and zero otherwise. The combinatorial model involves n cities and it only allows solutions that visit each node once and only once and that define a tour, i.e. a return to the initial node (Jenses, 2004). The model output is the shortest route that starts and ends at the depot, and visits all the defined nodes. This classical formulation considers only one vehicle and defines one single route. Several adaptations of the TSP, together with different solution approaches can be found in Appendix F.

OF	$min \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} * x_{ij}$		
ST	$min \sum_{i=1}^{n} x_{ij} = 1$	$1 \leq j \leq n$	(1)
	$min \sum_{j=1}^{n} x_{ij} = 1$	$1 \leq i \leq n$	(2)
	$x_{ij} \geq 0$	$1 \leq i \leq n, 1 \leq j \leq n$	(3)

Table 3.1: Mathematical formulation of the TSP

3.3.2 Transport network analysis: optimisation approaches

Optimisation approaches are used to find the most efficient solution to a problem. It consists on the translation of the problem description into a mathematical expression using decision variables, which expression is minimised (or maximised) while complying with a set of constraints. When converting the problem into a mathematical expression, several assumptions must be made. If poorly formulated, these assumptions might lead to an oversimplification of the problem, and thus to a wrong solution.

Regarding the assessment of transport networks, the most used optimisation approach is the Vehicle Routing Problem. The Vehicle Routing Problem (VRP) is a combinatorial optimisation and integer programming problem, which generalises the TSP. The goal of the VRP is to define the optimal tour given a set of nodes and a fleet of vehicles, such that each node is visited at least once and only once, and the costs of operations are minimised. Another objective function that is commonly used in delivery network optimisation is the minimisation of the total number of vehicles needed to serve all customers (Toth and Vigo, 2002). The mathematical formulation of the VRP, shown in Table 3.2, refers to the one provided by Fisher and Jaikumar (1978). The description of decision variables and parameters and the explanation of each constraint is provided in Appendix F. The model output is a set of k tours, where k corresponds to the number of vehicle available, which combination provides the most efficient sequence of customer visits starting and ending at the depot. Several adaptations of the VRP, together with different solution approaches are found in Appendix F.

OF	$min \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} * x_{ij}$		
ST	$\sum_{k=1}^{m} y_{ik} = 1$	$1 \leq i \leq n$	(1)
	$\sum_{k=1}^{m} y_{ik} = m$	$i = 0$	(2)
	$\sum_{i=1}^{n} q_i * y_{ik} \leq Q_k$	$1 \leq k \leq m$	(3)
	$\sum_{j=0}^{n} x_{ijk} = y_{ik}$	$0 \leq i \leq n, 1 \leq k \leq m$	(4)
	$\sum_{i=0}^{n} x_{ijk} = y_{jk}$	$0 \leq j \leq n, 1 \leq k \leq m$	(5)
	$\sum_{i \epsilon S} \sum_{j \epsilon S} x_{ijk} \leq \|S\| - 1$	$S \subseteq 1, ..., n,\ 1 \leq k \leq m$	(6)

Table 3.2: Mathematical formulation of the VRP

3.3.3 Selected approach for transport network analysis

The benefits and drawbacks of simulation techniques and optimisation modelling can be found in Table 3.3, adapted from DublinSchoolOfMathematics (2019) and Lee (2019).

The main objective of the research is to assess the feasibility of introducing drones in the last-mile logistic process and to compare this new network with current transportation means (i.e. home delivery service with vans). Data on costs and efficiency of vans are gathered through interviews with BENU 't Slag. In order to establish validity and obtain a solution as optimal as possible, an optimisation model will be created for the current situation and for the scenario with drones in the vehicle fleet. The solution of the optimised model will provide a list of van routes and a list of drone routes, with their respective travel times, defining thus the performance indicators for the network of the current situation and for the one of the future scenario. The costs associated with these networks will then be compared in order to perform the comparison analysis.

The output of the optimisation model will provide the data needed for the elaboration of the KPIs listed in subsection 3.1.1. Together with the data retrieved through the pharmacy, a complete analysis of the future scenario is made.

	Pros	**Cons**
SIM	Easy to build; handle several scenarios with minimal assumptions; handle time related issues such as delivery time distribution	Hard to debug; difficulty to obtain high quality solution; hard to establish validity; cannot produce optimal solution
OPT	Used in situations where strong constraints apply; solve tactical and operational issues; high quality analytical solution	Optimisation only for one variable; not for too complex problems; problem of oversimplified during modelling stage

Table 3.3: Pros and Cons of simulation and optimisation. Adapted from DublinSchoolOfMathematics (2019) and Lee (2019)

The choice on which optimisation model to use and specifically which adaptation, is made based on the characteristics of the new transport network of combined vans and drones. As defined in the previous sections, the classical model formulations for transport networks are the Travelling Salesman Problem and the Vehicle Routing problem.

Based on the description of the models in Appendix F and the evaluation of Table F.3, the choice for modelling the the different scenario alternatives is to use the Vehicle Routing Problem, adapted for considering the heterogeneity of the fleet and the inability of certain vehicles to carry out specific deliveries. The formulation of the Vehicle Routing Problem provided in Appendix F is then modified as shown in Table 6.1, for which the same notation applies. The objective of the formulation is to minimise the delivery costs, by providing the cheapest possible sequence of nodes to be visited and a feasible vehicle combination. The main difference with the basic VRP formulation is that now the cost is considered per each vehicle, by adding the subscript k to the cost c_{ij} and including it into the summation over k. Two constraints (constraints number 7, 8) are added, concerning the technical and spatial limitations of drones.

Model formulation

The objective of the formulation is to minimise the cost of the tour, by providing the cheapest possible sequence of nodes to be visited. The decision variable x_{ijk} assumes the value of 1 if customer j is visited immediately after customer i by vehicle k, and 0 otherwise. The variable y_{ik} defines whether customer i is visited with vehicle k. Constraint 1 sets that each customer i must be visited at least once, and only once by just one vehicle k. Vehicle are bounded to return to the depot by constraint 2, 4 and 5. The capacity of the vehicles is limited by constraint 3, in which q_i indicates the demand at each node visited by vehicle k and Q_k the capacity of vehicle k. Constraint 6 guarantees that not sub tours are generated. Constraint 7 refers to the flight time constraint, indicating that the total time from i to j using vehicle k must not exceed the maximum utilisation time T_k. Constraint 8 concerns the distance limitation, imposing that the distance covered by a vehicle must not exceed the maximum range R_k.

OF	$min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m} c_{ijk} * x_{ijk}$		
ST	$\sum_{k=1}^{m} y_{ik} = 1$	$1 \leq i \leq n$	(1)
	$\sum_{k=1}^{m} y_{ik} = m$	$i = 0$	(2)
	$\sum_{i=1}^{n} q_i * y_{ik} \leq Q_k$	$1 \leq k \leq m$	(3)
	$\sum_{j=0}^{n} x_{ijk} = y_{ik}$	$0 \leq i \leq n, 1 \leq k \leq m$	(4)
	$\sum_{i=0}^{n} x_{ijk} = y_{jk}$	$0 \leq j \leq n, 1 \leq k \leq m$	(5)
	$\sum_{i \epsilon S} \sum_{j \epsilon S} x_{ijk} \leq \lvert S \rvert - 1$	$S \subseteq 1, ..., n,\ 1 \leq k \leq m$	(6)
	$\sum_{i=0}^{n} \sum_{j=0}^{n} t_{ijk} \leq T_k$	$1 \leq k \leq m$	(7)
	$\sum_{i=0}^{n} \sum_{j=0}^{n} x_{ijk} * d_{ij} \leq R_k$	$1 \leq k \leq m$	(8)

Table 3.4: Mathematical formulation adapted from the VRP

Model implementation

Many solution approaches are available for solving the Vehicle Routing Problem. For this case study it is decided to use an open source spreadsheet solver specific for Vehicle Routing Problems, developed by Erdoğan (2017). By using an easy and familiar Microsoft Excel interface, several problems of commercial software packages are overcome. Besides the substantial cost of these packages, problems related to the geographical data acquisition, such as travel distances and travel duration, are not easy to solve. In the Excel solver of Erdoğan (2017), geographical locations, distances and travel times are easy to retrieve thanks to a built-in function based on GIS web service. Other implementation approaches that were considered for this model optimisation were the C-Plex solver and the Yalmip solver, both for the Matlab software environment. The main problem that was encountered while implementing the VRP with Matlab was the acquisition of the map of Rotterdam, and the distribution of exact location. Although the code was easy to write, the map visualisation was difficult to achieve, hence it was decided to avert this solution approach. Moreover, from an online research, several other VRP solver were found, such as the Routific (Routific, 2019), which provides solutions to VRPs using routing optimisation API, routing algorithms to solve NP-hard vehicle routing problems. The main drawbacks of these solvers is that they are specifically designed for companies and thus require a subscription providing the company name and a software purchase.

The VRP Spreadsheet Solver by Erdoğan (2017) uses the Large-scale Neighbourhood Search (LNS) algorithm, belonging to the category of constructive heuristic algorithm. This approach tries to find near optimal solutions by improving the current solution into a better solution in the neighbourhood of the current one (Ahuja et al., 2000). With the term neighbourhood, it is intended the set of similar solutions to the current one obtained, that is created applying simple modifications to the original solution. To help understanding the concept of LNS algorithm, the following explanation is retrieved from Pisinger and Ropke (2010). Given an instance I of a combinatorial optimisation problem and a finite large set X of feasible solutions, a function $c : X \rightarrow \mathbb{R}$ is defined, that maps from a solution to its cost. Being this a minimisation problem, the aim of the algorithm is to find a solution $x*$ such that $c(x*) \leq c(x) \forall x \in X$. A neighbourhood of a solution $x \subseteq X$ is defined as $N(x) \subseteq X$, with N being a function that maps a solution to a set of solutions. With this definition of neighbourhood, a solution x is locally optimal with respect of a neighbourhood N if $c(x) \leq c(x') \forall x' \in N(x)$. Having said that, a neighbourhood search algorithm starts from an initial solution x as input and gradually improves this solution computing $x' = argmin_{x'' \in N(x)} \{c(x'')\}$, which finds the cheapest solution x' in the neighbourhood of x. If an improved solution x' is found, for which $c(x') < c(x)$, the algorithm performs the update $x = x'$. Then it continues searching for an improved solution in the neighbourhood of the new solution x, stopping when a local optimum is reached.

Initial information such as the number of customers, the geographical location and the available fleet are stored in the Solver Console. Details on each customer (locations, time window, service time and demand) are then inserted in the Location sheet. Based on the address of each customer, geographical coordinates are computed by the model. These coordinates will then be used in the Distances sheet, where the distances between each customer (included the depot) are computed based on the GIS map of the considered area. Data on the available fleet, such as cost parameters, capacity, time and range limits, are inserted in the Vehicle worksheet. Costs associated with each vehicle are divided into fixed costs and operational costs. Based on all the input inserted, the model provides the optimal number of vehicles to be used, the sequence of visits, the cost associated with each vehicle, the distance and the time travelled by each vehicle and the total cost of operation. Furthermore, locations and routes can be visually inspected in the visualisation worksheet, where the tour for each vehicle is placed upon the map from the GIS web service.

Model validation and verification

Once the solution approach for model implementation is defined, the next step in model building is the model validation and verification. These two processes are important to quantify the credibility of the model (Thacker et al., 2004). In the procedure of developing the model (right-hand side of Figure 3.1), the role of validation and verification is to define the quantitative comparison between experimental outcome and simulation outcome, providing thus an estimation of the model accuracy. In this graph, the right-hand side shows the process of developing the model, whereas the left-hand side shows the process of experimental data and physical testing.

Model verification is the assessment activity between the mathematical model and the computer model, defined as the *process of determining that a model implementation accurately represents the developer's conceptual description of the model and the solution of the model* (AIAA, 1998). In other words, it ensure that the model does what it is intended to do. The process of model verification can be distinguish into two different phases: code verification and calculation verification (Thacker et al., 2004).

1. *Code verification* is usually carried out by both the code developer and the model developer. Code developers assure the software quality, by checking the reliability and robustness of the software; code modellers, on the other hand, verify the numerical algorithm, controlling the correctness of the numerical algorithm implemented in the code.

2. *Calculation verification* is carried out by the model developer and aims to quantify the errors introduced by the code implementation. By means of simplified models, it is possible to reduce the model to its minimal possible behaviour and then compare the numerical results obtained with the VRP model and the ones analytically obtained.

For what concerns model validation, Figure 3.1 shows that validate a model implies comparing the simulation outcome and the experimental outcome on a quantitative level. According to the definition of AIAA (1998), model validation is indeed the *process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model*. Therefore, in this phase of the model building process, it is assessed whether the outputs of a model are acceptable with respect to the real data-gathering process. Sargent (2010) proposes several validation techniques that can be applied to simulation and optimisation models. For validate the model used in this research, it is decided to use the extreme condition test method: setting all the input parameters to zero, the solution of the model is checked whether it is plausible and in accordance with the expected outcomes.

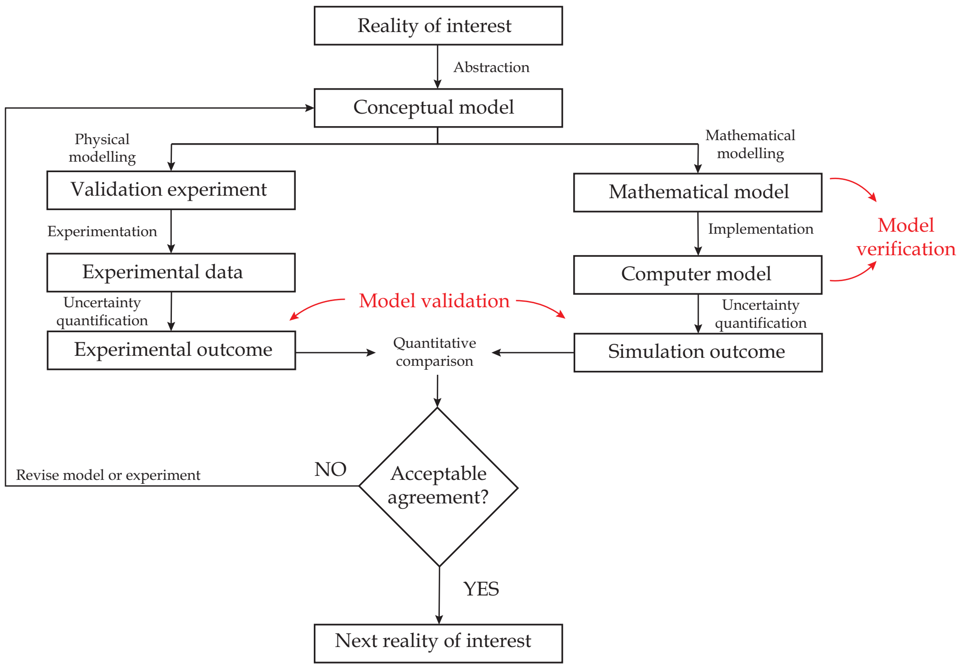


Figure 3.1: Model development. Adapted from Thacker et al. (2004)

Sensitivity analysis
When the outputs of the model are obtained, it is important to evaluate the effect that changes in one or more input parameters brings to the model behaviour and its outputs. The analysis can be carried out by describing the direction of changes (qualitative analysis) and the magnitude of changes (quantitative analysis). This testing method is valuable to define the parameters that cause significant changes in model's behaviour, so that the modeller can pay more attention to the their accuracy.

3.4. Methodology for transport network comparison

The comparison of alternatives is made based on the KPIs that are retrieved from the model outputs of the current situation and future scenario. Network alternatives are assessed based on four different criteria:

1. *Cost associated with network alternative*: comparison of cost components such as total annual costs, delivery cost per item and cost of power supply;
2. *Environmental benefit*: comparison of environmental components such as CO2 emission, fuel consumption and energy consumption;
3. *Service time*: comparing the total time needed to complete a sample day of operation indicates how fast the alternative is, and which network configuration is the most suitable for minimising the total time spent in the system;
4. *Payload utilisation*: this criteria will compare the vehicle load factor of each alternative, as a ratio between the vehicle capacity used and the maximum vehicle capacity available.

Furthermore, alternatives will be compared based on the extent to which they comply to functional and non functional requirements stated in subsection 3.1.2.

3.5. Conclusion

Last-mile logistics are assessed using models for transport network analysis. This chapter gave an overview of the mathematical models that are currently in use, together with the data that are needed to implement these models, the different solution approaches and the indicators that are generally used to assess the transport network performances. Based on this analysis, it is possible to answer the third research question:

What are the main KPIs, data and design methodologies for a comparative analysis of last-mile delivery transport networks?

The performance indicators to be used in the network comparison analysis concern costs, service time, environmental parameters and vehicle capacity. After a literature study and a series of interviews with relevant stakeholders, the following list of Key Performance Indicators is complied, together with the related data that must be retrieved:

- Delivery cost per item: average number of deliveries per day; cost of storage area; cost of handling equipment; cost of parking location; purchase cost of vehicles; license to operate a drone; ATM purchase and fees for outdoor sale; human labour (van drivers and drone pilots); operation management costs; insurance cost of vehicles; regional taxes per vehicle type; operational costs of vehicles; financial costs.
- Average service time: average speed for vehicle type; average loading and unloading time for vehicle type.
- Fuel and energy consumption: fuel consumption of vans; energy consumption of drones.
- CO2 emission: CO2 emission per distance travelled per vehicle type.
- Vehicle capacity used versus available capacity: maximum allowed payload for vehicle type; average used payload for vehicle type.

For what concerns the mathematical description of transport network problems, two main formulations are found in literature: the Travelling Salesman Problem and the Vehicle Routing Problem. For the definition of the constraints and therefore the boundaries of the design, a list of functional and non functional requirements was made.

- Functional requirements: medical products must be delivered to the intended customer; medical products must be delivered within the intended arranged time; the model must assign a feasible vehicle to the trip, based on delivery characteristics; the chosen alternative must comply with existing regulations.
- Non-functional requirements: the chosen alternative should lower the total cost of the delivery process; the chosen alternative should minimise the total time spent on the network; the sequence of chosen alternatives should provide a maximised vehicle utilisation.

Following this general description, the chapter contains the selection of the most proper approach, based on the requirements of the case study and the main objective. This led to the answer of research sub question four:

How to adapt the chosen design methodology for last-mile delivery networks to fit the case study requirements?

The Vehicle Routing Problem, as defined in Fisher and Jaikumar (1978), was adapted considering the needs and requirements for the current situation and future scenario. Constraints on flying time and range limitations are added, and the cost of each vehicle type is included in the objective function. A Large-scale Neighbourhood Search algorithm is chose as solution approach, having the benefit of being easy to implement but the drawback of not being able to provide a general optimal solution.

The chapter was then concluded with the mathematical formulation, the solution approach and the relevant testing methods that will be use to perform the comparison analysis. Further explanations on model conceptualisation, specification and implementation will be provided in the next chapter.

4

Model optimisation last-mile logistic

Following the model formulation and the solution approach defined in subsection 3.3.3, this chapter contains the optimisation development.

The alternatives that are assessed are the current situation, in which home deliveries are carried out using a vehicle fleet composed by three vans, and the future configuration, in which drones are introduced in the fleet, in combination with the already existing vans. The procedure for the model optimisation starts with the model conceptualisation, that simplifies the last-mile delivery process and connects input and output parameters through the model formulation in use. Then the network alternatives are described as scenarios to be tested in the model, explaining how the model implementation is performed. Finally, verification and validation tests of the model are run for the specific model implementation, to find the extent to which it represents the initial model formulation and resembles real world situations.

4.1. Model conceptualisation

The conceptual model contains the specifications according to which the scenarios are tested to find optimised performances. Specifications are primarily based on theoretical considerations (Allen, 1997); therefore, this process refers to the analysis conducted in chapter 3. Input and output parameters are linked together through the model, following the black box concept, as defined in Sweeting (2015): inputs and outputs have a causal relations; input and output are distinct; inputs and outputs are observable and relatable; the connection between inputs and outputs, i.e. the model, is non-openable to the observer, who remains in the dark regarding its functioning. Figure 4.1 shows the black box concept, including the inputs and outputs description.

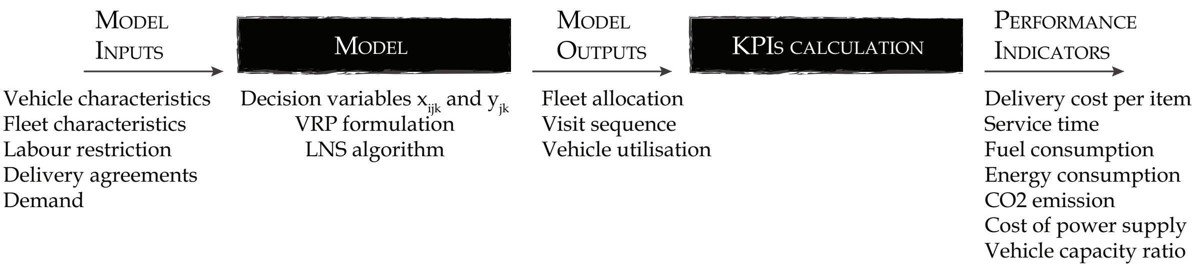


Figure 4.1: Black box concept with inputs and outputs description

4.1.1 Input parameters

Referring to Figure 4.1, input parameters are divided into vehicle characteristics, fleet characteristics, labour restriction, delivery agreements and product demand. More specifically, parameters that are inserted in the model are:

Vehicle characteristics

- Average van speed [*km/h*]

- Average drone speed [*km/h*]
- Fixed and distance costs of van [*km*]
- Fixed and distance costs of drone [*km*]
- Distance limitation for vans [*km*]
- Distance limitation for drones [*km*]
- Flight time limitation for drones [*hours*]
- Van capacity [number of products]
- Drone capacity [*number of products*]

Fleet characteristics

- Number of vehicle types [-]
- Number of vehicles per vehicle type [-]

Labour restriction

- Working time limit for van drivers [*hours*]

Delivery service characteristics

- Number of depots [-]
- Number of customers [-]
- Service time for products drop off [*hours*]
- Distance between customers [*km*]

Demand

- Product demand for each customer [*number of products*]

4.1.2 Model description

The description of the model aims to define the entities and the alternatives that are tested in order to optimise the home delivery service and allow for the comparison analysis between current situation and future scenario. An important part of the model are the decision variables, which link the input parameters to the output values.

Entities - Entities refer to real-world system components for which attributes are described. Model entities are listed according to the system description of chapter 2 and the model description of subsection 3.3.3: vehicles in the fleet (vans and drones); customers interested in the home delivery service; drivers that carry out deliveries via van; drone pilots that remotely control the drones. Vehicle characteristics are retrieved via interviews and literature study. For the cost components, two different cost models are developed, one referring to the current situation and one to the future scenario. Customers locations and total demand are retrieved conducting interviews with BENU 't Slag, and refer to the system description analysis of chapter 2.

Network alternatives - Network alternatives refer to the current situation and the future scenario as described in subsection 2.3.1. Both alternatives have the same demand value, the same customers locations and the same depot location. The differences concern the vehicle fleet composition (only vans for the current situation and a combination of vans and drones for the future scenario) and the cost characteristics (as result of the cost models).

Decision variables - Decision variables are the unknown information in an optimisation problem. In the case of the VRP, two binary decision variables are included in the model, one pertaining both the objective function and the constraint formulation and one used only for the constraint formulation. Given the set of customers i and j, and the set of vehicles k, the decision variables are x_{ijk} and y_{ik}.

The first one returns a positive value if customer j is visited after customer i using vehicle k and zero otherwise; the second one returns a positive value if customer i is visited with vehicle k. Referring to the model formulation of subsection 3.3.3, the decision variable y_{ik} is used for implementing the constraint on vehicle capacity, and to make sure that each customer is visited once and only once by one vehicle and each vehicle must start and finish its tour at the depot.

Cost model - The alternatives that are assessed in the following paragraph regard the current situation and the future scenario. For the current situation, two states of the system are evaluated, which relate to before and after the introduction of the ATM in February 2018 (Frijmersum, 2018). Demand is kept equal in all network alternatives. The pharmacy operates deliveries only during working days, from Monday to Friday (Frijmersum, 2019), leading to an average number of 21 working days per month. From the monthly number of deliveries found in Figure 2.6, an average amount of 2,205 deliveries per month is fixed, leading to a demand of 105 deliveries per day.

Starting from February 2018, customers that reach the pharmacy can either purchase the products at the pharmacy or make use of the ATM positioned at the entrance. The trend of home deliveries presented in Figure 2.6 shows a slight reduction of demand, combined with a reduction of delivery cost payed by the pharmacy (from 10,218 euros to 9,705 euros per month, see subsection 2.2.4). For this reason it is assumed that the number of kilometre travelled per year and the total working hour per day are slightly reduced (for the full calculation refer to Appendix G).

For the future configuration, the introduction of drones is considered. Products are sold through three different channels: directly at the pharmacy, through the ATM and via home deliveries. Now the fleet is expanded, including drones as means of transport, with the initial number of vehicles set to two vans and one drone. These values are a consequence of the demand analysis and the assumptions made on vehicle capacity. Data on drones refer to the model X8 Long range cargo drone, later displayed in Figure 4.3, having a total cost of 2,500.00 euros. Being a long-range cargo drone, it can fly up to almost 4 km carrying a payload of up to 2 kg (although it can reach 32 km at the expenses of the payload capacity). The maximum allowed flight time is set to 1 hour, and the vehicle speed is set to 70 km/h (Liu et al., 2018). These inputs are used to define the average flying hours per day and therefore calculate the time related cost.

A comparison of the results for the three different cost models is provided in Table 4.1. In this table, previous configuration refers to the situation in which home deliveries are carried out with three vans and no ATM is installed, current configuration refers to the combination of ATM and home deliveries with three vans, future configuration refers to the combination of ATM and home deliveries with two vans and one drone.

Component	**Previous configuration no ATM, 3 vans**	**Current configuration ATM, 3 vans**	**Future configuration ATM, 2 vans and 1 drone**
Total investment [euro]			
Depreciation [years]			
Annual investment [euro/year]			
Annual exploitation [euro/year]			
Other [euro/year]			
Annual cost [euro/year]			

Table 4.1: Comparison of annual costs of previous, current and future configurations

Relevant for the model implementation are the fixed and operational costs. Fixed costs per trip are found by adding the cost components that incur regardless of vehicle utilisation, and dividing their value in such a way that the dimension is euro per trip. Furthermore, costs that are not related to one specific vehicle (i.e. costs of storage area, handling equipment, parking spots, operation management and loan) are also divided by the number of vehicles, to be consistently spread per trip. The calculation for the fixed cost of vans is found in Equation 4.1, whereas for fixed cost of drones in Equation 4.3.

Operational costs are divided into distance cost and time related cost. For what concerns the van fleet, distance cost is given by the fuel consumption cost, considering an average of 5 litre/100km consumption (Mercedes-Benz, 2018) and 1.33 euro/litre diesel price (GlobalPetrolPrices, 2019). Time cost for the van fleet is given by the average wage of a delivery driver in Rotterdam, set to 15 euro/hour (PayScale, 2019). For the drone fleet, only time related components add up to the variable costs. The time cost of drones includes the cost of a drone operator (set to 21 euro/hour (Vliet and Zaman, 2019)) and the cost of the energy consumed. According to Xu (2017), the energy consumption of a drone carrying one package is 0.26 kWh. The price of 1 kW is currently set to 0.1024 euro per kW (MainEnergie, 2019). Multiplying these two values, a time cost of 0.03 euro/hour is found. Adding the energy cost to the human labour cost, a total of 21.03 euro/h is set for the time related cost.

The spreadsheet solver used in this case study does not consider time related costs. To overcome this drawback and still account for this cost component, the cost per hour of each driver is converted into cost per kilometre, assuming an average van speed of 35 km/h. The average wage of 15 euro/hour corresponds to 0.25 euro/minute. At a speed of 35 km/h, a vehicle covers 1 km in 1.7 minutes. Therefore, the cost of 1 kilometre is found multiplying 0.25 euro/minute times 1.7 minutes, which is equal to 0.43 euros. This value is added to the distance cost component related to fuel consumption, for a total of 0.50 euros (Equation 4.2). The same concept is applied to the drone fleet. Time-dimensional costs are translated into distance-dimensional cost, by considering an average speed of 70 km/h for the drone (Equation 4.4). In this way, a total cost of 0.30 euro/km is found for the conversion of time related components to distance related components.

One of the assumptions is that each vehicle performs one round trip per day, starting from the pharmacy, visiting the assigned customers and returning back to the depot. Fixed costs are intended per trip; therefore, to calculate the value of fix cost it is necessary to spread the value of fixed annual costs over the 3 vehicles. Investment costs such as locations and vehicle purchase, have a depreciation of 5 years. Although this depreciation value is correct for the van fleet, it seems too high for the drone fleet, for which a depreciation period of 1 or 2 years is more indicated. Nonetheless, given the small effect of drone purchase on the total annual costs, it was decided to keep the same depreciation period of 5 years. The average number of working days per month is fixed to 21 and all 12 months are considered.

$$
\begin{aligned}
fixed\ cost_{van} = {} & \frac{\sum_l location\ cost_l + ATM\ purchase}{3*5*12*21} + \frac{operation\ management}{3*12*21} \\
& + \frac{purchase\ cost}{5*12*21} + \frac{taxes}{12*21} + \frac{insurance\ cost}{21} \\
& + \frac{financial\ cost + outdoor\ fees}{3*21}
\end{aligned}
\tag{4.1}
$$

Equation 4.1 shows the components for the fixed cost of vans, expressed in *euro/trip*. Costs of locations and cost of ATM are depreciated over a period of 5 years, divided per day of operation (over the 12 months, 21 days per month) and per vehicle. Purchase cost is also depreciated over a 5 year period and divided per day of operation, but since it is already specific for each single vehicle, it is not spread over the 3 vehicles. Operation management is measured in *euro/year*, therefore its cost is divided per 12 (months) and 21 (working days per month) and spread over the 3 vehicles. Taxes are also measured in *euro/year*, so they are divided per 12 (months) and 21 (working days per month), but referring to each single vehicle, they are not spread over the 3 vans. Insurance cost is calculated in *euro/month*, so its value is only divided by 21 working days to obtain the daily value. Financial cost and outdoor fees are expressed in *euro/month*, so their value are spread over the 21 working days and over the 3 vans.

$$
distance\ cost_{van} = fuel\ consumption * fuel\ price + \frac{driver\ salary}{van\ speed} \tag{4.2}
$$

Equation 4.2 shows the distance cost of the van fleet, expressed in *euro/km*. The first term refers to the consumption cost, and it is based on how much fuel is consumed and its price. The second term refers to the translation of time related cost into distance related cost, by means of the average vehicle speed.

$$
\begin{aligned}
fixed\ cost_{drone} = {} & \frac{\sum_l location\ cost_l + ATM\ purchase}{3*5*12*21} + \frac{operation\ management}{3*12*21} \\
& + \frac{purchase\ cost + piloting\ area + license}{5*12*21} + \frac{taxes + insurance}{12*21} \\
& + \frac{financial\ cost + outdoor\ fees}{3*21}
\end{aligned}
\tag{4.3}
$$

Equation 4.3 shows the components for the fixed cost of drones, expressed in *euro/trip*. Costs of locations and cost of ATM are depreciated over a period of 5 years, divided per day of operation (over the 12 months, 21 days per month) and per vehicle. Purchase cost is also depreciated over a 5 year period and divided per day of operation, but since it is already specific for each single vehicle, it is not spread over the other 2 vehicles (vans). Operation management is measured in *euro/year*, therefore its cost is divided per 12 (months) and 21 (working days per month) and spread over the 3 vehicles of the fleet composition. Taxes and insurance costs are also measured in *euro/year*, so they are divided per 12 (months) and 21 (working days per month), but referring to each single vehicle, they are not spread over the 3 components. Financial cost and outdoor fees are expressed in *euro/month*, so their value are spread over the 21 working days and over the vehicle in the fleet.

$$
distance\ cost_{drone} = \frac{pilot\ salary + energy\ cost * energy\ consumption}{drone\ speed} \tag{4.4}
$$

Equation 4.4 shows the distance cost of the drone fleet, expressed in *euro/km*. All components are time related costs translated into distance related costs by means of the average vehicle speed. The first term refers to the pilot salary and the second term to the cost of energy consumed.

Table 4.2 shows a comparison of fixed and variable costs for vans and drone, for each of the three situation analysed. Fixed costs per trip are also completed with fixed costs per day and fixed costs per product. For the previous and the current configuration, three vans are considered. A [redacted] vehicle utilisation is assumed for the fixed cost expressed in *euro/trip* (based on the total demand of [redacted] products and the total capacity of vehicles of [redacted] products). Therefore, each vehicle is supposed to be loaded with [redacted] products. For the future configuration, two vans and one drone are considered. A [redacted] vehicle utilisation is assumed for the drone fleet and a [redacted] vehicle utilisation for the van fleet (found subtracting the [redacted] products carried by the drone from the total of [redacted] and divided by the total vehicle capacity of [redacted] products). Therefore, each van is supposed to be loaded with [redacted] products and the drone with [redacted] products.

Cost component	**Previous configuration no ATM, 3 vans**	**Current configuration ATM, 3 vans**	**Future configuration ATM, 2 vans and 1 drone**
Fixed cost van			
Distance cost van			
Fixed cost drone			
Distance cost drone			

Table 4.2: Comparison of fixed and variable costs for previous, current and future configurations

4.1.3 Output parameters

The outputs that will come out of the model and that will be used for calculating the performance indicators are the fleet allocation, the customer sequence and the vehicle allocation.

Fleet allocation and customer sequence

- Binary $n*n*k$ matrix with customer visit sequence and vehicle allocation

Vehicle utilisation

- Distance travelled per vehicle d_k [*km*]
- Driving time per vehicle t_k [*hour*]
- Working time per vehicle wt_k [*hour*]
- Number of stops per vehicle $n_{stop,k}$ [-]
- Initial loading per vehicle $Q_{used,k}$ [*products*]
- Cost of operations per vehicle c_k [*euro*]

4.2. Model specification

4.2.1 Input specification

Values of input parameters are retrieved conducting interviews with relevant stakeholders, literature study and making general assumptions. Cost components are calculated with the cost model for the current situation (1) and the future scenario (2).

Parameter	**Input value**	**Unit**	**Reference**
Average van speed		km/h	(Mercedes-Benz, 2018)
Average drone speed		km/h	(UAV, 2019)
Fixed cost van (1)		euro	Cost model
Fixed cost van (2)		euro	Cost model
Distance cost van		euro/km	Cost model
Fixed cost drone		euros	Cost model
Distance cost drone		euro/km	Cost model
Distance limitation vans		km	Assumption
Distance limitation drone		km	(UAV, 2019)
Flight time limitation drone		hour	(UAV, 2019)
Van capacity		products	Assumption
Drone capacity		products	Assumption
Number of vehicle type (1)		-	(Frijmersum, 2018)
Number of vehicle type (2)		-	Assumption
Working time limit driver		hours	Assumption
Number of depots		-	(Frijmersum, 2018)
Service time for drop off		hour	Assumption

Table 4.3: Input parameters specification

Number of vehicles per vehicle type results from an analysis based on the total demand and on the assumptions on vehicle capacity. Based on the total demand of   products per day and the assumption of a capacity of   products per van and   products per drone, it is assumed that the optimal combination is to use for the current situation a fleet of 3 vans and for the future scenario a fleet of 2 vans and 1 drone. This is also confirmed later on by the model implementation, which returns unfeasible values for smaller fleet and unused vehicles for larger fleet.

4.2.2 Implementation specification

The model formulation is an adaptation of the Vehicle Routing problem, including range and time constraints, and including a heterogeneous fleet in the objective function. The mathematical formulation of the model is found in Table 4.4, followed by a description of the model constraints.

OF	$min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m} c_{ijk} * x_{ijk}$		
ST	$\sum_{k=1}^{m} y_{ik} = 1$	$1 \leq i \leq n$	(1)
	$\sum_{k=1}^{m} y_{ik} = m$	$i = 0$	(2)
	$\sum_{i=1}^{n} q_i * y_{ik} \leq Q_k$	$1 \leq k \leq m$	(3)
	$\sum_{j=0}^{n} x_{ijk} = y_{ik}$	$0 \leq i \leq n, 1 \leq k \leq m$	(4)
	$\sum_{i=0}^{n} x_{ijk} = y_{jk}$	$0 \leq j \leq n, 1 \leq k \leq m$	(5)
	$\sum_{i\epsilon S} \sum_{j\epsilon S} x_{ijk} \leq \lvert S\rvert - 1$	$S \subseteq 1, ..., n,\ 1 \leq k \leq m$	(6)
	$\sum_{i=0}^{n} \sum_{j=0}^{n} t_{ijk} \leq T_k$	$1 \leq k \leq m$	(7)
	$\sum_{i=0}^{n} \sum_{j=0}^{n} x_{ijk} * d_{ij} \leq R_k$	$1 \leq k \leq m$	(8)

Table 4.4: Mathematical formulation adapted from the VRP

1. Each customer i is visited by only one vehicle k
2. Each vehicle k must come back to the depot
3. The demand at each node i should not exceed the vehicle capacity.
4. The number of vehicles leaving the pharmacy is the same as the number entering the pharmacy
5. Same for constraint number 4
6. Sub-tour prohibition, which forbid solutions consisting of several disconnected tours
7. The total time from i to j using vehicle k must not exceed the maximum utilisation time T_k
8. The distance covered by a vehicle must not exceed the maximum range R_k

The decision variable x_{ijk} assigns to each vehicle k a routing sequence, being x_{ijk} equal to 1 if customer j is visited after customer i with vehicle k. The second decision variable y_{ik} assigns one vehicle k to one customer i, guaranteeing that each customer is visited once and only once by only one vehicle.

The solver uses a Large-scale Neighbourhood Search (LNS) algorithm to implement the VRP. The LNS algorithm tries to find an optimal or quasi-optimal solution by means of iterations, finding in each step an improved solution in the neighbourhood of the current one, for which costs are minimised. The algorithm stops when a local optimum is reached. As drawback of this algorithm is that it does not provide a global optimal solution, due to the fact that improvements are locally based on a neighbourhood search.

4.2.3 Output specifications

Results are reported in terms of routing solutions, in which the routing sequence for each vehicle is visualised on top of the map of Rotterdam, and by means of tables containing for each vehicle the customer sequence, the distance and time travelled, the number of stops, the total load and the associated operational cost. The model output are then used as input values for the KPI calculation, for which the following equations are used:

- Delivery cost per item: total cost of operation divided by total number of daily deliveries

$$Delivery\ cost\ per\ item = \sum_{k} c_k / n_{deliveries} \quad [euro/item] \tag{4.5}$$

- Service time: sum over all vehicles of the time spent in the system, from when the vehicle leaves the pharmacy until when it comes back to the pharmacy

$$Service\ time = \sum_{k} t_k \quad [hours] \tag{4.6}$$

- Fuel consumption (FC): sum over all vehicles of the distance travelled, multiplied by the fuel consumption rate of the vehicle used. Consumption rate of vans is equal to 5 litre every 100 km; drones do not use fuel, being a fully electric vehicle

$$Fuel\ consumption = \sum_k d_k * 5/100\ with\ k \in van\ fleet\ \ [litres] \tag{4.7}$$

- CO2 emission: sum over all vehicles of the distance travelled, multiplied by the average CO2 emission per distance travelled, equal to 115 g per kilometre

$$CO_2\ emission = \sum_k d_k * 115\ with\ k \in van\ fleet\ \ [g] \tag{4.8}$$

- Energy consumption (EC): operating time of the drones (i.e. in flying motion) multiplied by the the average energy consumption of drones, set to 0.26 kWh

$$Energy\ consumption = \sum_k t_k * 0.26\ with\ k \in drone\ fleet\ \ [kW] \tag{4.9}$$

- Cost of power supply: sum of the total cost for the fuel consumed by the vans and the total cost for the energy used by the drone; fuel cost is set equal to 1.33 euro/litre and energy cost to 0.1024 euro/kW

$$Cost\ of\ power\ supply = 1.33 * FC + 0.1024 * EC\ \ [euro] \tag{4.10}$$

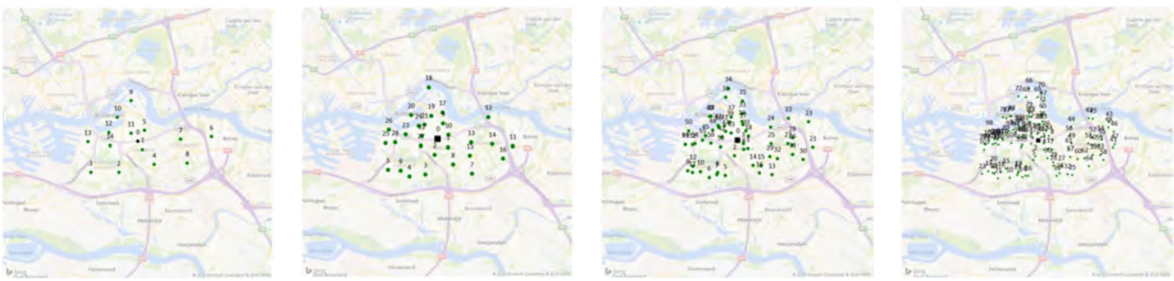
- Vehicle capacity ratio: ratio between the vehicle capacity used and the total available capacity

$$Vehicle\ capacity\ ratio = \sum_k (Q_{used,k}/Q_{available,k})/n_{vehicles}\ \ [\%] \tag{4.11}$$

4.3. Model implementation

The model is implemented using the Excel spreadsheet solver for VRP designed by Erdoğan (2017). This implementation is run using a laptop computer with a processor Intel i7, CPU running at 2.5 GHz with 8 GB of RAM.

Given the limited data available on the number of deliveries per day per customer, assumptions on the demand are made and customers are clustered according to their geographical location. A first iteration is run setting the number of nodes equal to the number of postcodes served; for each postcode a fixed location is defined, in which all the deliveries are concentrated. The number of daily deliveries per each postcode is retrieved from Table B.1, in which deliveries are distributed to each postcode according to the size of the neighbourhood.



(a) 14 customers (b) 28 customers (c) 56 customers (d) 112 customers

Figure 4.2: Increase in customer density with 14, 28, 56 and 112 nodes

For the next iterations, the number of nodes is increased to 28, 56 and 112. The demand is randomly spread among the customers, based on the initial daily demand per postcode. The last iteration is set to a number of nodes equal to 112 because with a higher number, the demand would be null for most of the customers. It is expected that increasing the number of customer will increase the cost of operation, given the higher number of stops and the longer route to be travelled. Figure 4.2 shows the increase in node density going from 14 customers to 112 customers. These maps refer both to the network with only vans and the network with vans and drones, since the customer location is considered to remain fixed in the current situation and future scenario. Two different cases are considered: the first relates to the current state, in which deliveries are optimised using a homogeneous VRP formulation with a fleet composed by 3 vans. The second concerns the future scenario, in which drones are introduced in the delivery operations, using a heterogeneous VRP formulation with a fleet composed by vans and drones. The optimal amount of vans and drones will be one of the output solution of the model.

The following paragraphs report the implementation procedure for the current situation and the future scenario, and refer to the tables displayed in Appendix H.

4.3.1 Model implementation of current situation

The current situation, described in section 2.2, involves the use of 3 vans and 3 corresponding drivers to carry out deliveries on a daily basis. Vehicle characteristics are retrieved from subsection 2.2.4 and cost components are defined in the cost model of section G.1. According to Goel and Gruhn (2006), a limitation of 6 hours of work is set for the drivers; therefore, for the time constraint, an upper bound of 4 hours in motion is set. For the vehicle speed, an average value of 35 km/h is used (Liu et al., 2018). The following paragraphs contain the steps to be taken during the model implementation, with respect to the first implementation with 14 nodes. When implementing the model with 28, 56 and 112 nodes, the only input that changes is the number of customers.

Problem setup
To implement the model, the first step is to set the VRP Solver Console, shown in Figure H.1. In this initial phase, the Bing Map is uploaded and the model characteristics are defined: the number of depots, number of customers, distance and time computation technique, average vehicle speed and fleet composition. The constraint that bounds each vehicle to come back to the depot after the last visit is also inserted in this phase, at sequence 4 of the Solver Control.

Customer location and demand distribution
Based on the number of customers, the model sets a list of locations (Figure H.2). In this case, 15 locations are defined (the depot and the 14 customers served). and for each of them, the address, the time window, the service time and the demand is set. Based on their addresses, the Excel Solver computes the latitude and the longitude of each location. Once latitude and longitude values are set, distances and travel time are computed between each node. Distances are calculated using Bing Map driving distances, which provides the real distances between nodes, based on the available physical infrastructure. Travel times are obtained dividing the distance computation results by the average vehicle speed. The route type is set to Fastest - Real time; in this way the estimates for distances and travel time are specific for the time in which the model is run, based on the traffic conditions at that specific time, conferring to the results a dynamic nature.

Vehicle characteristics
The next step is to set up vehicle characteristics. Capacity constraint, costs and time and distance limitations are imported. According to the VRP formulation, the model is constructed so that each vehicle has to start and return to the depot BENU 't Slag. Figure H.3 shows the Excel interface with the inputs inserted for the vehicle characteristics:

LNS iterations and solution visualisation
With these inputs, the model finds the optimal solution to carry out all the deliveries in the most efficient way, using the algorithm elaborated in Erdoğan (2017). For each vehicle, the number and the sequence of customer visits is provided, together with the distance travelled, the travel time, the arrival and departure time, the carried load and the total associated cost. Summing the cost of each vehicle used, it is possible to find the total cost of one day of operation.

The same procedure is followed for the implementation with 28, 56 and 112 nodes. Within a postcode, the demand is distributed randomly using the function $RANDBETWEEN(n_1, n_2)$ in the Excel spreadsheet, where n_1 is the lower bound for the demand (set to 0) and n_2 is the upper bound (set equal to the demand for that specific postcode). In this random distribution, the sum of demands within a postcode is kept equal to the initial demand, in order to be consistent between different implementations.

4.3.2 Model implementation of future scenario

The proposed scenario, described in subsection 2.3.2, involves a heterogeneous fleet composition, with vans and drones starting at and returning to the pharmacy in an independent way, each of them serving a specific set of customers. For what concerns vans, vehicle characteristics and cost components remain the same of the ones defined for the current situation. For the drone fleet, according to the analysis carried out in Appendix C and subsection 2.3.2, a fixed wing hybrid drone is proposed. Data on vehicle characteristics are retrieved with interviews, consultation with drone companies and online articles. Among the fixed wing hybrid drones, experts from UAV (2019) proposed their model X8 Long range cargo drone, displayed in Figure 4.3.

Figure 4.3: X8 Long Range Cargo Drone. (UAV, 2019)

Being a long-range cargo drone, it can fly up to 4 km carrying a payload of up to 2 kg (although it can reach 32 km at the expenses of the payload capacity). The maximum allowed flight time is set to 1 hour, and the vehicle speed is set to 70 km/h (Liu et al., 2018). As for the current situation, in order to adapt the model formulation to the Excel solver, the time related costs are included into the distance costs, by considering the average vehicle speed. The following paragraphs provide the steps for the implementation with 14 nodes.

Problem setup
Figure H.4 shows the initialisation of the model. The changes from the current situation are highlighted in the red box: the model is now set to 2 vehicle type, hence to a heterogeneous fleet.

Customer location and demand distribution
Locations, distances and demand inputs remain the same as the one found for the current scenario; therefore, Figure H.2 provides data on latitude, longitude and demand for the future scenario.

Vehicle characteristics
Vehicle characteristics are now expanded including the data for the drone. Data refers to the drone model X8 Long range cargo drone from UAV (2019). Capacity is set to 7 boxes, which corresponds to an estimated amount that could fit inside the prototype of Figure 2.7. Fixed costs and operational costs are retrieved from the cost model of Table 4.2. An initial value of 2 vans and 1 drone is set. Since the model does not return as an output the optimal number of vehicle for the fleet, different implementations are performed, varying the number of vehicles per each type. A minimum amount of 1 van and 1 drone is set, and the best combination is chosen according to the implementation that returns the lowest cost solution.

When setting the values for the distance limit and the flying time limit for the drone fleet, an important limitation must be addressed. For the van fleet and the drone fleet, distances should be calculated using two different computations: vans are bounded by the physical infrastructure, hence the travelled distances should be computed using the *Bing Maps driving distance*. Drones, on the other hand, can flight straight from point A to point B, therefore the distances should be computed using the *Bird flight distances* option. Moreover, the average vehicle speed of vans is set to 35 km/h, whereas the average speed of drones is 70 km/h. The consequence of these differences is reflected in the total distance and time travelled. Running the model first with the Bing Maps computation and vehicle speed of 35 km/h and then with the Bird flight computation and vehicle speed of 70 km/h, the results for distance and time travelled are on average respectively 37% and 65% higher in the first run. Therefore, the inability of the solver to use two different distance computations in the same implementation might bring biased results, assigning less customers to the drone route. For this reason, to calculate the total cost for the drones implementation, the distance limit is increased by 37% (allowing thus a maximum flight distance of 5 km) and the flight time is increased by 65% (hence up to 1 hour and 40 minutes). In this way, even if the initial parameter of average speed and distance computation do not match the real situation, the output values of time, cost and distance for the drone route can be post-processed using the real Bird flight distance and the real speed.

All this considered, Figure H.5 shows the input used in the implementation of the future scenario for the vehicle characteristics of the fleet of vans and drones.

LNS iterations and solution visualisation
With these inputs, the model finds the optimal solution to carry out all the deliveries in the most efficient way, using the algorithm elaborated in Erdoğan (2017). For each vehicle, the number and the sequence of customer visits is provided, together with the distance travelled, the travel time, the arrival and departure time, the carried load and the total associated cost. Summing the cost of each vehicle used, it is possible to find the total cost of one day of operation.

The same procedure is followed for the implementation with 28, 56 and 112 nodes. Within a postcode, the demand is distributed randomly using the function $RANDBETWEEN(n_1, n_2)$ in the Excel spreadsheet, where n_1 is the lower bound for the demand (set to 0) and n_2 is the upper bound (set equal to the demand for that specific postcode). In this random distribution, the sum of demands within a postcode is kept equal to the initial demand, in order to be consistent between different implementations.

4.4. Model verification

4.4.1 Test methods

According to what stated in Thacker et al. (2004), two different model verification techniques were proposed in subsection 3.3.3: code verification and calculation verification. The following paragraphs provide the procedure to carry out the verification of the model that used for the case study.

Code verification

Code verification is a two-step procedure that is carried out both by the code developer and the model developer. It assesses whether the implementation code provides reliable results and aims to find the gap with known existing solutions.

For what concerns the code developer part, in Erdoğan (2017) the author explains how this verification is carried out. To test the solution algorithm, a known problem is run with the VRP Excel Solver and the solutions obtained are then compared with the best know solutions. For this verification, a laptop computer Intel i7 is used, with CPU running at 2.5 GHz with 8 GB of RAM. The CPU time limit is set to 15 minutes and the initial number of customer is equal to 50, and linearly increased for larger instances. The benchmark data set used in his research is the data set provided by Christofides et al. (1981), containing data about Capacitated VRP and Distance Constrained VRP. The best known solution values are then compared to the solutions obtained with the VRP Excel spreadsheet solver.

For what concerns the model developer part, an example of a real world situation is run, with pickups and deliveries, 1 depot and 10 customer locations spread in the United Kingdom, made available by Erdoğan (2017) to verify the solution algorithm. The model is run using a laptop computer with similar specifications as the previous one: Intel i7, CPU running at 2.5 GHz with 8 GB of RAM.

Problem setup
The VRP Solver Console for the code verification test is shown in Figure H.6, and contains the initial

inputs of the model. The Bing Map of the UK is uploaded and the model characteristics are defined.

Customer location and demand distribution
The 10 customers are located in the United Kingdom, in 10 different cities: London, Leicester, Nottingham, Bristol, Southampton, Portsmouth, Colchester, Reading, Coventry, Cambridge and Oxford. Being a test run, delivery and pickup amounts are set to null, as well as the profit. Figure H.7 shows node localisation and demand distribution.

Vehicle characteristics
Vehicle characteristics are shown in Figure H.8. Being a test run, the fixed costs are set to null, and the capacity and distance cost have a unitary value. The distance limit depends on the size of the vehicle, being set to 450 km for minibus, 500 km for midibus and 560 km for bus. Five vehicles are available in the fleet (2 minibuses, 2 midibuses and 1 bus), with 5 drivers limited to 8 hours of driving time and 10 hours of total working time.

LNS iterations and solution visualisation
With these inputs, the model is run to find the optimal fleet utilisation and customer division, providing the tours that visit each customer once and only once and end at the depot.

Calculation verification

In the calculation verification test, numerical outputs obtained through the implementation of the model are compared to the ones obtained through analytical calculation. For the sake of simplicity, the model is reduced to a small sub-problem with only 6 nodes. The chosen number of nodes reflects the lower bound imposed by the Excel VRP spreadsheet: the software does not allow computations for less than 5 customers, hence the value of 6 nodes (5 customers plus 1 depot).

For the numerical solution, the Excel spreadsheet solver for the VRP is used.

For what concerns the analytical solution, the Farthest Insertion Heuristic (FIH) algorithm is utilised, belonging to the category of constructive heuristic algorithm. Using constructive heuristic methods for both the numerical and analytical solutions, it is believed that the verification test is more reliable. With the Farthest Insertion Heuristic algorithm, it is intended to construct a tour containing all the nodes by means of several iterations, starting with the smallest possible tour and adding nodes to it until all nodes are inserted (Van Essen, 2017). The selection of the new node to insert is made according to the farthest neighbour, meaning the node that maximises the length between the two initial nodes. The selected node is then inserted between two existing nodes according to a cost minimisation criterion, so that being i and j the initial nodes, the selected node k is inserted such that $d_{ik} + d_{kj} - d_{ij}$ is minimal. The algorithm stops when each node is visited and the vehicle is back to the depot. Locations are randomly selected from the 14 postcodes served by the pharmacy and their characteristics are shown in Figure H.9. Demand is kept equal to the initial demand value, even though being this a verification test, it could have also been set to 1. Figure 4.4 shows the visualisation of the node location on the map of Rotterdam. Distances (in kilometre) between nodes are shown in Table 4.5 and are computed using the real distances provided by Google Maps.

Figure 4.4: Map of node location for calculation verification test

	D	1	2	3	4	5
D	0.00	2.35	3.45	10.15	1.96	2.99
1	3.44	0.00	5.23	11.40	3.25	4.53
2	5.30	5.16	0.00	3.71	5.63	5.12
3	7.92	6.81	3.16	0.00	11.11	7.54
4	1.77	3.08	5.22	12.07	0.00	2.86
5	2.98	5.54	5.05	11.75	2.98	0.00

Table 4.5: Distances between nodes for calculation verification test

Vehicle characteristics are set equal to the ones in the main problem formulation. A single van in included in the fleet, having a capacity of [redacted] units and a distance limit of 560 km. Fixed cost and distance cost are the one used for the situation with only vans for home deliveries and refer to Figure G.2. Drivers have an upper bound of 4 hours of driving time and 6 hours of total working time.

The cost matrix that will be used in the FIH algorithm is created from the distance matrix of Table 4.5 using Equation 4.12, which is also used for computing the costs between each node in the numerical solution. Table 4.6 shows the cost matrix between each node. Values are expressed in euro.

$$cost_{ij} = fixed\ cost + distance\ cost_{ij} * distance_{ij} \tag{4.12}$$

Table 4.6: Cost between nodes for calculation verification test

4.4.2 Results

Code verification

For what concerns the code developer part, in Erdoğan (2017) computational results on fourteen benchmark instances are reported, seven of which refer to data on Capacitated VRP and the other seven on Distance Constrained VRP. Number of customers, fleet size and vehicle capacity are altered in each implementation. The best known solution values are then compared to the solutions obtained with the VRP Excel spreadsheet solver. As can be seen from Figure 4.5, both the CVRP and the DCVRP perform a 0% gap up to 100 customers. Increasing the number of customers, the gap between the best known solution and the VRP Spreadsheet Solver solution increases proportionally, with a maximum value of 2.46% when reaching the maximum allowed number of customer (which for the VRP Spreadsheet Solver is 200). Overall, the DCVRP performs better than the CVRP, with a maximum gap of 1.37% for the first variant and 2.46% for the second.

Instance name	Number of customers	Fleet size	Vehicle capacity	Distance limit	Best known solution value	VRP Spreadsheet Solver Average	Average gap	Best	Best gap
vrpnc1	50	5	160	N/A	524.61	**524.61**	**0.00%**	**524.61**	**0.00%**
vrpnc2	75	10	140	N/A	835.26	840.67	0.65%	**835.26**	**0.00%**
vrpnc3	100	8	200	N/A	826.14	841.05	1.80%	831.28	0.62%
vrpnc4	150	12	200	N/A	1028.42	1052.22	2.31%	1040.81	1.20%
vrpnc5	199	17	200	N/A	1291.29	1341.19	3.86%	1323.08	2.46%
vrpnc6	50	6	160	200	555.43	556.77	0.24%	**555.43**	**0.00%**
vrpnc7	75	11	140	160	909.68	913.13	0.38%	**909.68**	**0.00%**
vrpnc8	100	9	200	230	865.94	876.40	1.21%	**865.94**	**0.00%**
vrpnc9	150	14	200	200	1162.55	1181.77	1.65%	1170.81	0.71%
vrpnc10	199	18	200	200	1395.85	1435.27	2.82%	1415.02	1.37%
vrpnc11	120	7	200	N/A	1042.11	1047.82	0.55%	1047.61	0.53%
vrpnc12	100	10	200	N/A	819.56	821.29	0.21%	821.29	0.21%
vrpnc13	120	11	200	720	1541.14	1565.01	1.55%	1554.51	0.87%
vrpnc14	100	11	200	1040	866.37	886.41	2.31%	869.96	0.41%

Figure 4.5: Computational results on benchmark instances (Erdoğan, 2017)

For the model developer part, a test is run for a fictitious case of deliveries in the UK. The same test is run in Erdoğan (2017), and results obtained in both implementations are compared to check whether the model outputs are reproducible. Figure 4.7 shows a comparison between the routing sequence found in Erdoğan (2017) and the own solution found implementing the same model. Node visits and fleet allocation are the same in both solutions. The total cost of operation slightly differs between the two implementation, with a gap of 0.15%: the routing solution of Figure 4.7a has a total cost of 1,569.90 euros, whereas for the one in Figure 4.7b the total cost amounts to 1,572.24 euros.

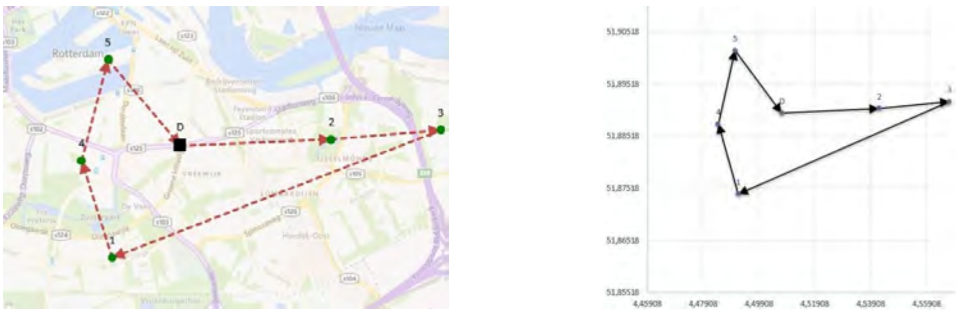
(a) Routing solution (Erdoğan, 2017)

(b) Routing solution

Figure 4.6: Comparison of routing solutions for code verification

Calculation verification

For the calculation verification, the sub-problem defined in subsection 4.4.1 is solved numerically using the VRP Excel Spreadsheet Solver and analytically using Farthest Insertion Heuristic algorithm (for which the complete procedure is described in subsection I.1.2). The same routing sequence is found in both solutions (D - 2 - 3 - 1 - 4 - 5 - D) and the total cost of operation slightly differs between the analytical and numerical solution: with the VRP Excel Spreadsheet Solver the total cost is equal to [redacted] euro, whereas with the FIH algorithm it amounts to [redacted] euro ([redacted] euro for the variable cost plus the fixed cost of [redacted] euro per trip), with a very small gap of 0.016%. The numerical errors induced by the use of the model is thus of the order of 0.016 percentage points, providing a marginally lower cost than the one obtained by analytical calculations.



(a) VRP Excel Spreadsheet Solver

(b) FIH algorithm

Figure 4.7: Comparison of routing solutions for calculation verification

4.5. Model validation

4.5.1 Test methods

The extreme condition test is carried out by setting all the input parameters to their extreme values; therefore, two situations are run: one with parameters set to zero and one with parameters approaching infinity. For this validation test, the future scenario with 56 customers is chosen, with a fleet combination of vans and drones.

For the first run, demand is set to zero, as well as fixed cost and operational cost. Network characteristics, such as locations and relative distances, as well as vehicle characteristics are kept unchanged from the model implementation run. The expected result is that by setting to zero demand and cost values, the model will return a null cost for the entire operation.

The second run is characterised by input parameters set to a large amount, representing infinity values. Demand is set to 100 units per customer, fixed cost is set to 100 euro/trip and operational cost to 100 euro/km. As for the previous case, network characteristics and vehicle characteristics are kept unchanged. It is expected that given the high values of demand, the problem will result to be unfeasible due to the capacity constraint for each vehicle. Furthermore, it is expected that the cost will grow exponentially.

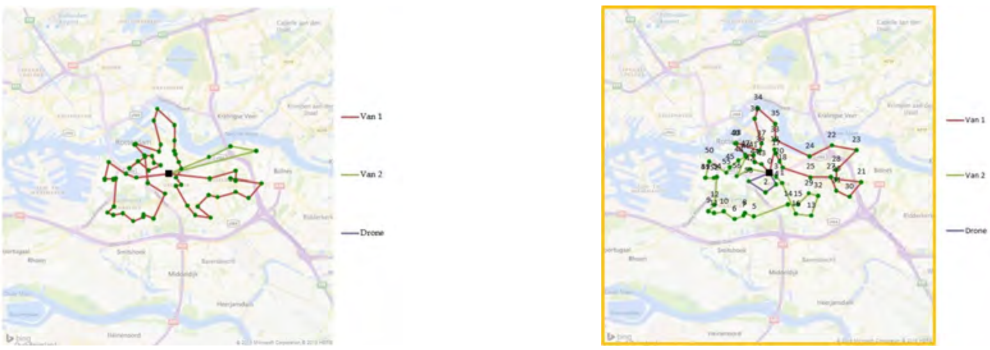
4.5.2 Results

Parameters set to zero

Demand is set to zero for each customer, as well as fixed and operational costs of both vehicles in the fleet. Network and vehicle characteristics are kept unchanged. Figure 4.8a shows the routing solution for this validation test. The full tables with numerical results are shown in subsection I.2.1. Setting the demand to zero implies that the capacity constraint is dropped. The only limitations for the customer and fleet allocation are now the distance and time constraints. For this reason, more deliveries can be carried out by one single van and the optimal solution provided by the Excel Solver allocates a fleet of only two vans, without including the drone. As expected, the total cost of operations is equal to zero, being the fixed cost and operational cost null.

Parameters set to high values

Demand is set to [redacted] units per customer. Fixed and distance related costs are set to 100 euro/trip and 100 euro/km respectively. As for the previous implementation, network and vehicle characteristics are kept unchanged. Figure 4.8b shows the routing solution for the extreme validation test with parameters approaching infinity, and the full tables with numerical results can be found in Figure I.2.1. Setting the demand to [redacted] implies that no vehicle can fit any of the deliveries in the routing sequence, being the vehicle capacity equal to [redacted] units for the van and [redacted] units for the drone. Therefore, as expected, the solution provided by the Excel Spreadsheet turns out to be not feasible even after 20 LNS iterations. The orange frame around the map shows that the routing solution is not feasible. The detected reason of infeasibility is the the capacity of the given fleet is not enough to transport the mandatory delivery. Moreover, cost of operation is very high, amounting to [redacted] euros, more than 200 times higher than the cost found in normal operative conditions.



(a) Parameters set to zero

(b) Parameters set to infinite

Figure 4.8: Routing solution for model validation - extreme condition test

4.6. Conclusion

Following the introduction on the model formulation of chapter 3, this chapter explained the steps to obtain the performance indicators according to the black box formulation. Input parameters were defined, together with the cost models associated with each alternative configuration. The model was then formulated as a Vehicle Routing Problem, with the addition of two constraints related to time limitation and distance limitation. The chosen solution approach was the VRP Excel Spreasheet Solver, developed by Erdoğan (2017), which makes use of a Large-scale Neighbourhood Search algorithm. It was shown how to implement the model, how the solution approach works and how from input values it is possible to obtain output parameters and thus performance indicators. Results of model implementation and KPIs analysis are provided in the next chapter.

The chapter is concluded with the test methods for model verification and validation. According to the results obtained, the verification of the model shows that the code is properly written, with a 0.6% average gap on best known VRP solutions and a 0.15% gap on model development. Model calculation also performs well, with a very small gap of 0.016% between numerical and analytical calculations. Moreover, the model proves to be valid, with the extreme condition test giving expected results both in a qualitative and quantitative way.

5
Results and analysis

5.1. Results and analysis of model implementation

This section contains the results of the model implementation described in chapter 4. For each network configuration (14, 28, 56 and 112 customers) the solutions of the current situation are compared with the ones for the future configuration, in which drones are added to the vehicle fleet. As explained in subsection 4.3.2, the inability of the solver to use two different distance computations and two different average vehicle speed in the same implementation might bring biased results, assigning less customers to the drone route. The results that have been found running the model first with the Bing Maps computation and vehicle speed of 35 km/h and then with the Bird flight computation and vehicle speed of 70 km/h, show that distance and time travelled are on average respectively 37% and 65% higher in the first run. For this reason, two implementations are run:

1. Inputs corresponding to the vehicle and network characteristics for the van fleet (average speed of 35 km/h and Bing Map distance computation with fastest route). To account for the differences in distance and travel time, drone distance limit is increased by 37% (hence 5 km) and the flight time is increased by 65% (hence up to 1 hour and 40 minutes);
2. Inputs corresponding to the vehicle and network characteristics for the drone fleet (average speed of 70 km/h, Bird flight distance computation with shortest route).

Results of the two implementations are then assembled to find the total cost of operation, in such a way that the route sequence and fleet allocation are still feasible, checking that each customer is visited once and only once by just one vehicle.

For each customer density (14, 28, 56 and 112 delivery locations), results are reported in terms of routing solutions, in which the routing sequence for each vehicle is visualised on top of the map of Rotterdam. Moreover, a KPI comparison is provided using bar charts. In these charts, values are expressed in terms of day of operation, with the exception of delivery cost per item, which is specific for each item delivered. For the KPI calculation, formulas to be used are found in subsection 4.2.3.

Table 5.1 shows an overview of the results obtained for 14, 28, 56 and 112 customers, with a comparison between the performance indicators for the current situation (three vans) and the future configuration (two vans and one drone). Values are expressed per day of operation, hence they refer to the sum of all the operating vehicles, except for the delivery cost per item which refers to each single product delivered.

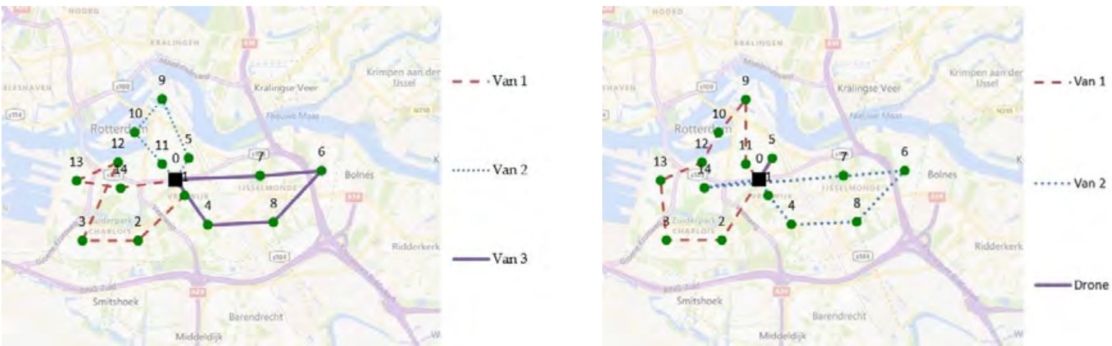
Customer density	Performance indicators	Current situation	Future configuration	Percentage of change
14 customers	Vehicle capacity ratio			+41.4%
	Cost of power supply			-5.7%
	Energy consumption			+100%
	Fuel consumption			-5.5%
	CO2 emission			-5.62%
	Total service time			-1.8%
	Cost per item			-5.2%

Customer density	Performance indicators	Current situation	Future configuration	Percentage of change
28 customers	Vehicle capacity ratio			+41.4%
	Cost of power supply			-7.12%
	Energy consumption			+100%
	Fuel consumption			-7.11%
	CO2 emission			-6.97%
	Total service time			-10.99%
	Cost per item			-5.4%
56 customers	Vehicle capacity ratio			+35%
	Cost of power supply			-7.29%
	Energy consumption			+100%
	Fuel consumption			-7.5%
	CO2 emission			-7.24%
	Total service time			-11.5%
	Cost per item			-5.32%
112 customers	Vehicle capacity ratio			+28.57%
	Cost of power supply			-11.8%
	Energy consumption			+100%
	Fuel consumption			-11.78%
	CO2 emission			-12.78%
	Total service time			-15.3%
	Cost per item			-5.9%

Table 5.1: Overview of performances for different node densities, for current situation and future configuration

The following sections provide a thorough analysis of the results for each demand distribution.

5.1.1 14 customers



(a) Routing solution current situation (b) Routing solution future scenario

Figure 5.1: Routing solutions of current situation and future scenario 14 customers

The network with 15 nodes is the smallest customer distribution, assigning the entire demand of one postcode in just one location. The network results to be fairly easy to visualise, with nodes widely spread across the delivery area. Figure 5.1 shows the comparison between the routing solution of the current situation with three vans and the future configuration with two vans and one drone. The complete solution of the implementations can be found in subsection I.3.1.

For the current situation, having only vans in the delivery fleet, customers are assigned rather equally to each van. This happens because vehicles have the same fixed and operational costs, and nodes are evenly spread among the delivery area. For what concerns the drone, the capacity limitation allows the flying vehicle to serve only one customer, since the combination of two or more customers will always lead to a demand of more than [redacted] products.

For what concerns the KPIs comparison, analysing the complete solution in Figure I.9 and Figure I.10 and using the formulas found in subsection 4.2.3, it is possible to retrieve the KPIs of Figure 5.2.

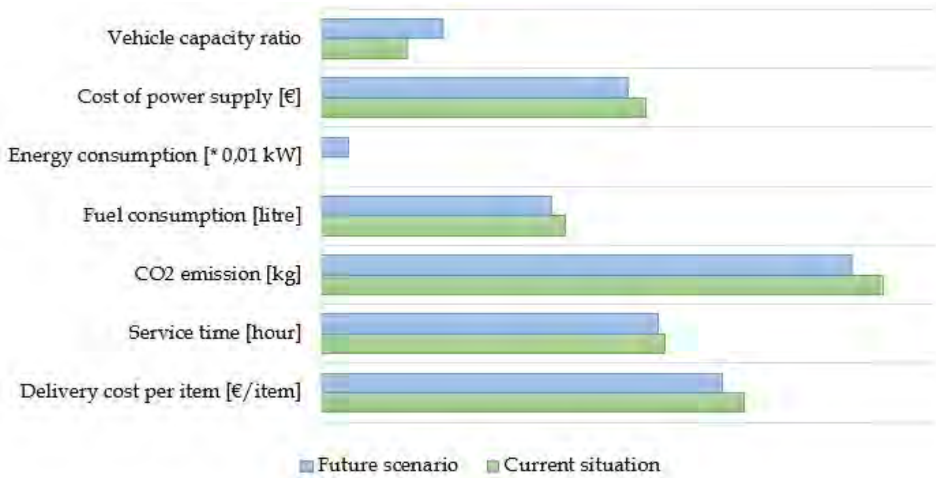
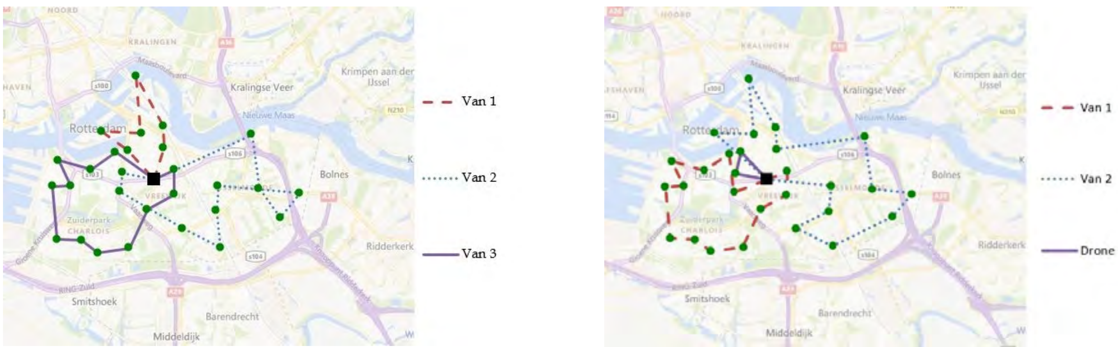


Figure 5.2: Comparison of Key Performance Indicators for 14 customers

Overall, the introduction of drones in the fleet brings a performance improvement. Costs slightly decrease, with a 5.2% decrease in cost per item and 5.7% decrease in power supply cost. Fuel consumption decreases by 5.5% with a reduction in CO2 emission of 5.62%. Energy consumption increases of 100%, due to the introduction of an electric vehicle. Service time slightly decreases from [redacted] to [redacted]. Vehicle capacity ratio largely increases, with a jump of 41.4%. The high difference that is observed in this KPI is due to the fact that, although demand remains unchanged, the fleet available has an overall smaller capacity; therefore, the utilisation rate must increase.

5.1.2 28 customers



(a) Routing solution current situation

(b) Routing solution future scenario

Figure 5.3: Routing solutions of current situation and future scenario 28 customers

Increasing the number of customer per postcode provides a more realistic network description. Demand is now spread randomly within a postcode, making sure that the total amount of demand per postcode remains unvaried. Figure 5.3 shows the comparison between the routing solution of the current situation and the future scenario. The complete solution of the implementations can be found in subsection I.3.2. Key Performance Indicators are then evaluated based on the results reported in Figure I.11 and Figure I.12.

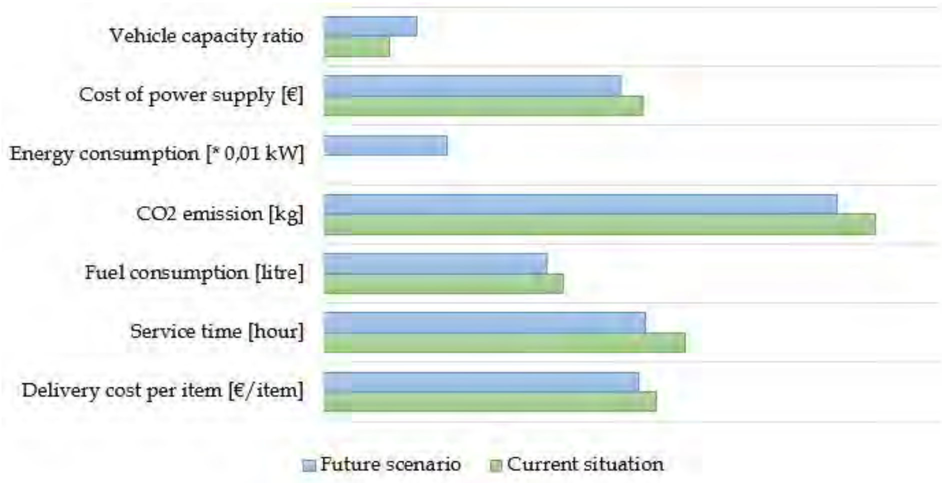
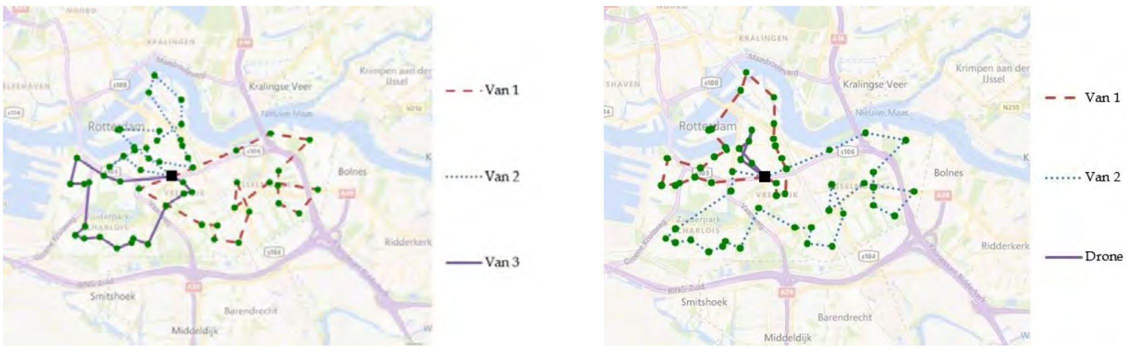


Figure 5.4: Comparison of Key Performance Indicators for 28 customers

Increasing the number of customers up to 28, shows the same positive trend for KPI improvements. Costs decrease of 5.4% per item and of 7.12% for the total power supply cost. Service time sees a large decrease, with a reduction of 10.99% in the future scenario, going from [redacted] for the whole operation to [redacted]. Fuel consumption decreases of 7.11%, with a decrease in CO2 emission of 6.97%; energy consumption increases of 100%. The increase in vehicle capacity ratio is the same as the solution with 14 nodes, and it amounts to 41.4%, reaching almost the full utilisation.

5.1.3 56 customers



(a) Routing solution current situation (b) Routing solution future scenario

Figure 5.5: Routing solutions of current situation and future scenario 56 customers

The map in Figure 4.2c shows a denser distribution of nodes within the delivery area, with each postcode divided into 4 destination points. Preserving the fixed demand per customer, the amount of products to be shipped is spread randomly within a postcode. The results of the model implementation are shown in Figure 5.5, where the routing sequence of the current situation is compared to the one of the future scenario. The complete output of the solver is found in subsection I.3.3. Now that the products to be shipped for each postcode are spread across multiple delivery points, the drone can serve more than one customer, being the demand per node consistently lower than the maximum allowed drone capacity. The relevant KPIs are reported in the bar chart of Figure 5.6.

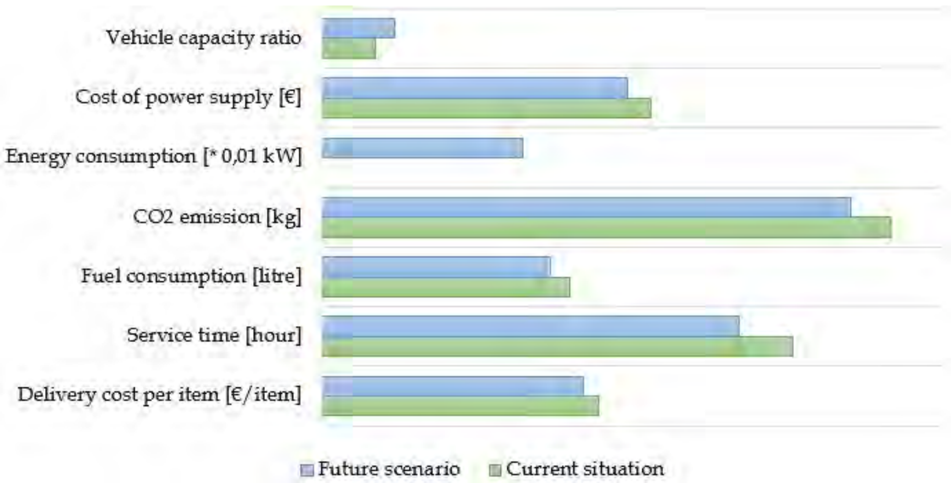


Figure 5.6: Comparison of Key Performance Indicators for 56 customers

In the future scenario, delivery cost per item decreases of 19 euro cent, 5.32% of the current cost. Also the operating cost decreases from [redacted] euro to [redacted] euro, equal to a 7.29 percentage points. The total time in the system decreases of 11.5% going from [redacted] to less than [redacted]. Fuel consumption decreases of 7.5%, with a corresponding decrease in CO_2 emission of 7.24%. Utilisation rate sees a slightly less increase with respect to the previous implementation, with a 35% rise, from [redacted] to [redacted].

5.1.4 112 customers

(a) Routing solution current situation

(b) Routing solution future scenario

Figure 5.7: Routing solutions of current situation and future scenario 112 customers

The last two implementations, with 112 customers, show a situation in which nodes are very dense, being each postcode divided into 8 destination points. This distribution is believed to be the one that most resembles reality, in which for each customer the associated demand is [redacted] products. Figure 5.7 shows the routing sequence of the current situation compared to the routing sequence of the future scenario. Number of nodes have been erased in order to make the map as clear as possible.

The complete calculation is found in subsection I.3.4. From the tables in subsection I.3.4 it is also possible to derive the most important KPIs for the case study, related to the division of demand among 112 customers. Figure 5.8 shows a comparison of the KPIs values of the current situation and future demand.

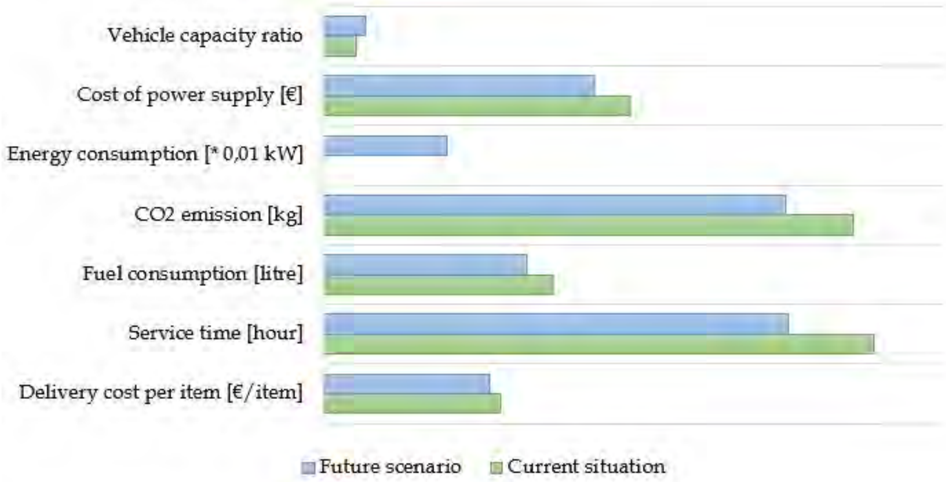


Figure 5.8: Comparison of Key Performance Indicators for 112 customers

With the increase of the number of customers, a greater improvement can be noticed. Costs of operations see a decrease of 5.9% for what concerns the cost per item and 11.8% for the cost of power supply. Service time shows a great improvement, with a reduction of 15.3%, equal to [redacted]. Fuel consumption and CO_2 emission also gain an interesting improvement, being 11.78% and 12.78% respectively lower in the future scenario compared to the current situation. Vehicle capacity ratio is not as improved as the previous implementations, although the introduction of one drone and the elimination of one van in the delivery fleet proves to bring 28.57% better vehicle load utilisation.

5.2. Sensitivity analysis

The aim of the sensitivity analysis is to study how changes in input parameters affect the values of performance indicators. Several implementations are run, and in each run only one parameter is changed. To obtain a trend of these input - output relationships, for each input parameter values are changed several times, and the resulting outputs are analysed accordingly.

The following paragraphs show the trend in cost per item, capacity ratio, service time and fuel consumption related to input parameters variations. To simplify the graphs and make them more readable, distance related KPIs (i.e. fuel consumption, CO_2 emissions and fuel cost) are represented by fuel consumption values, given the fact that they are all dependent on distance travelled and therefore have similar trends. Moreover, other potential future situations are assessed and compared with the future scenario analysed in this research, one with the fleet entirely composed by electric vehicles (electric vans and drones) and one with the fleet composed by only drones. In this way, the influence of the power supply mode and the vehicle fleet composition on Key Performance Indicators is assessed. Lastly, based on some ideas shared with the owner of the pharmacy BENU 't Slag on future logistic development, a scenario with multiple depots is briefly analysed. A KPI comparison between the situation with only 1 depot and the one with 5 depots is provided.

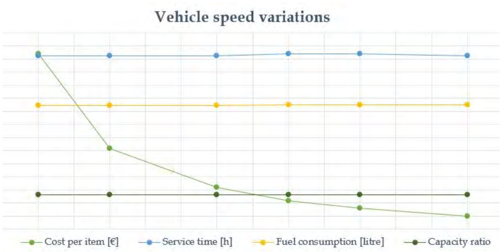
Changes in vehicle speed

In the model formulation, time related costs are embedded in distance cost, by transforming the time in the network into distance travelled using the average speed. Therefore, changing the vehicle speed entails a change in operational cost, given the fact that less or more kilometre can be travelled. Figure 5.9a shows the trend in cost per item, capacity ratio, service time and fuel consumption related to vehicle speed variations. The performance indicator that is mostly affected by vehicle speed variations is the cost per item, which considerably decreases by increasing vehicle speed. Service times and fuel consumption are slightly affected by vehicle speed variations, showing a small increase in the first one and decrease in the second one. Vehicle capacity ratio remains unaffected by variations of vehicle speed.

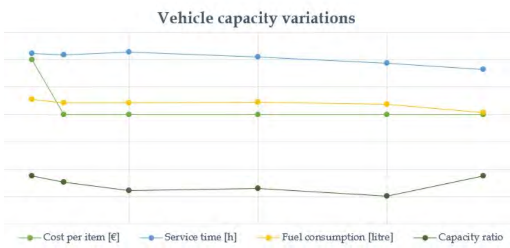
Changes in vehicle capacity
Given a total demand of [redacted] products and 3 vehicles available, vehicle capacity is varied from [redacted] unit (the minimum value below which the problem results not feasible) to [redacted] units per vehicle (a maximum value after which KPIs remain constant, with the exception of vehicle capacity ratio). Figure 5.9b shows the trend in cost per item, capacity ratio, service time and fuel consumption related to vehicle capacity variations. All KPIs are somehow affected by these changes: the cost per item decreases after a first increase in vehicle capacity, to remain constant higher values. As expected, capacity ratio values fluctuate depending on the number of vehicle used for deliveries: increasing the capacity brings a decrease in vehicle utilisation, to increase again once it is enough to eliminate one vehicle from the fleet (corresponding to [redacted] units per vehicle and then again to [redacted]).

Changes in distance limit
Variations in distance limits do not cause significant changes performance indicator values. With very restrictive values (from the minimum allowable value of 19 km to 25 km), a small decrease in cost per item, fuel consumption and service time is noticed, to settle to a constant value for bigger distances. Vehicle capacity ratio remains constant for all the distance limitations considered.

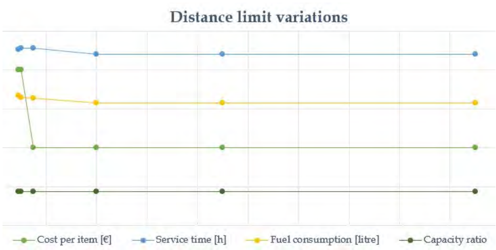
Changes in working time limit
Variations in working time limits do not cause any change in cost per item, service time fuel consumption and vehicle capacity ratio. The reason behind these results is that the time limit constraint for the van fleet is not as restrictive as other constraints, for example the capacity constraint. Therefore, provided that a minimum distance range is guaranteed, increasing this parameter does not bring any changes in the performance indicators.



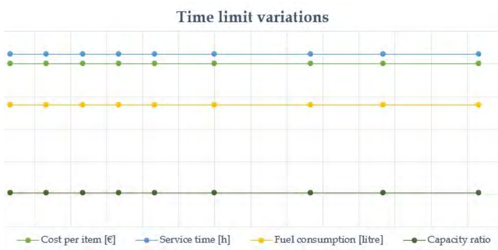
(a) Influence of vehicle speed



(b) Influence of vehicle capacity



(c) Influence of distance limit



(d) Influence of working time limit

Figure 5.9: Influence of input parameters on KPIs

5.2.1 Test scenarios on fleet composition and depot locations

This sub section shows the results of three test scenarios implemented in the context of the sensitivity analysis. The first test scenario concerns the use of only electric vehicles (EVs) in the delivery fleet, composed by two e-vans and one drone. This situation is compared with the future configuration of two vans and one drone, and the comparison is carried out with the demand distribution of 28 customers. The second test scenario considers a network entirely served by drones, compared with the future configuration of two vans and one drone. The third test scenario considers the same fleet composition of the second one, but with the introduction of 4 more depot locations cooperating with BENU 't Slag. Results for this multiple depot configuration are compared with the ones obtained with the fully drone network (test scenario 2), to see the extent to which adding depot locations benefits network performances. For both the second and the third test scenario, the comparison is carried out with the demand distribution of 112 customers. Table 5.2, Table 5.3 and Table 5.4 show an overview of the obtained results.

Performance indicators	**Future configuration (2 vans, 1 drone)**	**Test scenario 1 (2 e-vans, 1 drone)**	**Percentage of change**
Vehicle capacity ratio			–
Cost of power supply			-98.72%
Energy consumption			+2823.08%
Fuel consumption			-100%
CO2 emission			-100%
Total service time			+2.35%
Cost per item			+53.6%

Table 5.2: Overview of performances for test scenario with only EVs in comparison with the future configuration

Performance indicators	**Future configuration (2 vans, 1 drone)**	**Test scenario 2 (35 drones)**	**Percentage of change**
Vehicle capacity ratio			+11.1%
Cost of power supply			-98.59%
Energy consumption			+3284.61%
Fuel consumption			-100%
CO2 emission			-100%
Total service time			-27.4%
Cost per item			+1976.92%

Table 5.3: Overview of performances for test scenario with only drones in comparison with the future configuration

Performance indicators	**Test scenario 2 (35 drones, 1 depot)**	**Test scenario 3 (35 drones, 5 depots)**	**Percentage of change**
Vehicle capacity ratio			–
Cost of power supply			-33.3%
Energy consumption			-25%
Fuel consumption			–
CO2 emission			–
Total service time			-11.8%
Cost per item			–

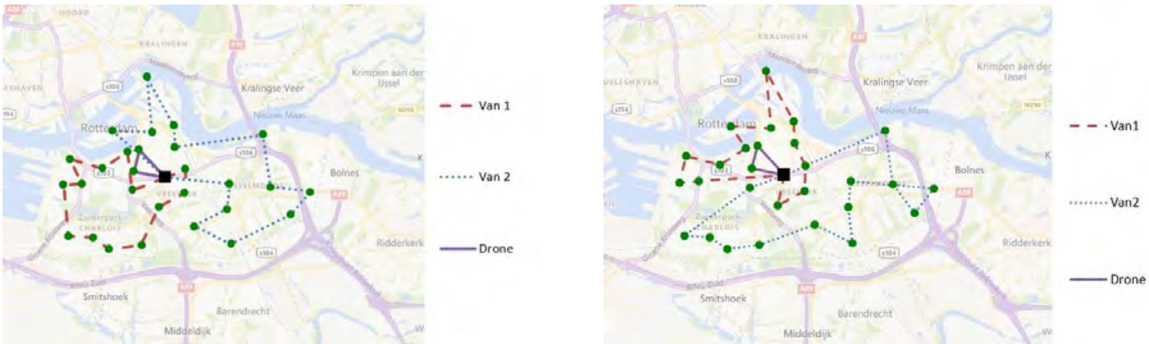
Table 5.4: Overview of performances for test scenario with multiple depot in comparison with one depot

Test scenario with only electric vehicles

In this test scenario, only electric vehicles (EVs) are used in the delivery fleet, which is now composed by 2 electric vans and 1 drone. A new cost model is developed, with the same components as in the one for the future scenario. The differences concern the cost related to the van fleet. The vehicle to be used in the fleet is the Mercedes-Benz eVito, which will become available in the coming months

(Mercedes-Benz, 2019a). The purchase cost is set to 70,000 euro, according to an estimation based on the current cost of a Mercedes-Benz Vito. The maximum range is set to 150 km, which is the distance that the vehicle will be able to perform with one charge (Mercedes-Benz, 2019a). Insurance cost is set to 1,470 euro/year, which refers to the average insurance cost for EVs MyEV. According to EVBox (2019), the incoming regulations might bring an incentive of zero annual taxes on EVs, hence this value is set to null in the cost model. Operational costs depend on the cost of energy and the energy consumption; knowing that a Mercedes-Benz eVito will be able to drive 90 km with 10kWh (Mercedes-Benz, 2019a) and the cost of power supply is 0.25 euro/kWh, the variable cost related to the power supply is set to 0.03 euro/km, which is summed to the 0.43 euro/km derived from the driver salary per kilometre (also present in the previous cost model). Annual costs, fixed cost and variable cost for this test scenario are reported in section 3.2.

The routing solution of a fleet composed only by EVs is shown in Figure 5.10, in comparison with the one found for the future scenario envisioned for the case study. Figure 5.11 shows a comparison of Key Performance Indicators for the envisioned future scenario with 2 vans and 1 drone and the testing scenario with 2 e-vans and 1 drone in the vehicle fleet. The situations that are compared refer to the one with 28 customers.



(a) Routing solution future scenario

(b) Routing solution test future only EV

Figure 5.10: Routing solutions of future scenario and test scenario with only EV

The routing solution for the drone fleet remains the same in the two scenarios object of comparison. Customers served by the fleet of e-vans are assigned according to a different sequence, although no major changes can be noticed. Vehicle capacity of e-vans is assumed to remain the same as non electric ones, hence the vehicle capacity ratio does not change between the two compared scenarios. For the energy consumption it is assumed that the consumption of e-vans is equal to 0.11 kWh (EnergyGuide, 2019), and the consumption for drones is 0.26 kWh (UAV, 2019). The total energy consumed for a day of operation is then of kW, almost 30 times higher than the scenario with non electric vehicles. With a fleet entirely composed by electric vehicles, CO2 emissions and fuel consumption are reduces to a null value, since no gasoline is needed to operate vehicles. Therefore, the total cost of power supply refers only to the energy cost, and is dropped to only euro per day of operation. Cost per item changes substantially, with an increase of 53.6%. Lastly, service time changes marginally, being only higher in the test scenario with EV only.

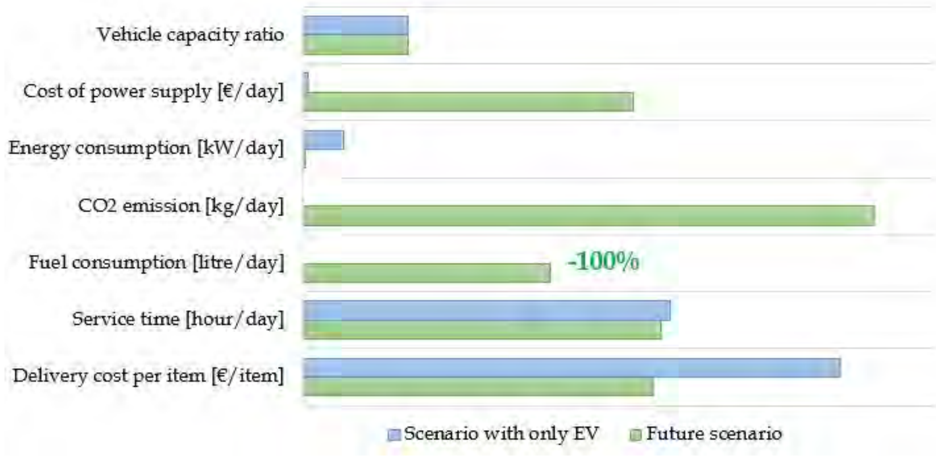


Figure 5.11: Comparison of KPIs for future scenario and test scenario with only EV

Test scenario with only drones in the fleet

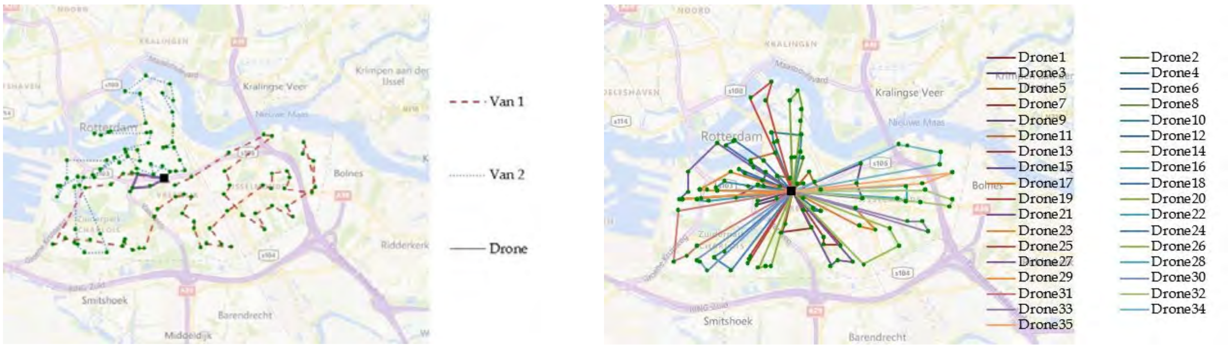
The aim of this test is to define how many vehicles would be needed in case of a fleet composed entirely by drones. For this purpose, the model is implemented with an unlimited amount of drones available. Demand is kept equal to the initial values and fixed and variable costs refers to the one found in the cost model for the future scenario (Table 4.2). After having found the total number of drones needed, a new cost model can be developed, in order to properly evaluate the KPIs for this testing scenario.

After performing several LNS iterations, the model found a non-feasible solution due to range limitation: with a maximum range of 4 km, postcode 3085 cannot be reached and has to be excluded from the home delivery service. To avoid this loss, UAV (2019) states that it is possible to increase the drone range up to 32 km at the expenses of payload capacity. With a range of 32 km and a drone capacity of products, a new implementation is run. Time constraint remains unchanged. Results of this implementation shows that the minimum number of drones needed to complete a daily operation is 35. With these information, a new cost model is developed. The following changes are applied:

1. All components related to the van fleet are set to zero.
2. 35 drones are purchased, therefore costs are multiplied by 35.
3. According to Vliet and Zaman (2019), one drone pilot can control up to 3 drones; therefore 12 drone pilots are needed. Consequently, the piloting area must be expanded to allow 12 people to work in it. Also the parking location must be rearranged, in order to make room for 35 drones. Labour cost in multiplied by 12, as well as the cost of drone license.
4. The expected yearly utilisation is set to 0 km and 0 hour for the van fleet. All the deliveries are carried out by the drones, for which a yearly utilisation of km and hour per drone is expected.
5. Distance related cost decreases to 0.1 euro/km due to the fact that each pilot can operate 3 drones, therefore the labour cost is 3 times smaller.

Referring to the cost model of section G.3 and to the changes mentioned above, a total annual cost of 363,590 euro was found, which determines a fixed cost of euro/trip and a variable cost of 0.10 euro/km. The extremely high increase in annual cost is due to the fact that 35 drones must be purchased and operated, with a consequent increase in number of drone pilots and piloting locations.

The routing solution of a fleet composed only by drones is shown in Figure 5.12, while Figure 5.13 shows a comparison of Key Performance Indicators for the envisioned future scenario with 2 vans and 1 drone and the testing scenario with only drones in the vehicle fleet. The situations that are compared refer to the one with 112 customers. In a situation in which only drones are considered, the indicators show an overall better performance. Vehicle capacity reaches full utilisation, even though the improvement is of only 10 percentage points. Environmentally speaking, the test scenario brings considerable improvements, dropping to 0 the CO2 emissions and the fuel consumption. Cost of power supply drops from [redacted] euro to only [redacted] euros, due to the fact that the energy cost is lower that the fuel cost and the consumption rate is less in electric vehicles. Service time also improves, going from [redacted] to [redacted], corresponding to a time reduction of [redacted] As expected the energy consumption largely increases, due to the introduction of a big number of electric vehicles. The delivery cost per item also experiences a steep increase, which is related to the higher annual cost associated with this test scenario.



(a) Routing solution future scenario

(b) Routing solution test only drones

Figure 5.12: Routing solutions of future scenario and test scenario with only drones

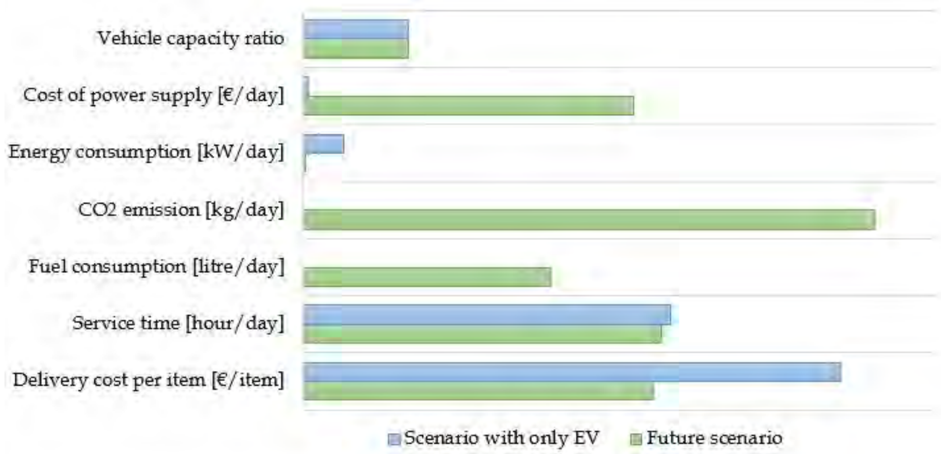
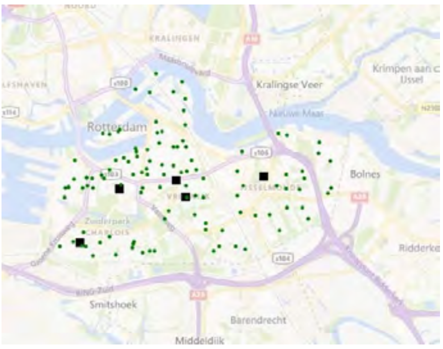


Figure 5.13: KPI comparison for future scenario and test scenario with only drones

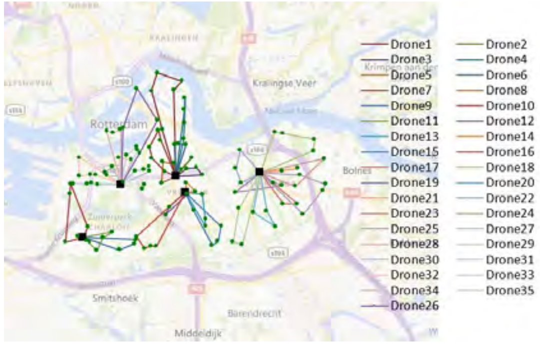
Test scenario with multiple depot locations

According to Frijmersum (2019), additional depot locations are likely to be included in the near future. For this reason, it is decided to provide a brief analysis of the influence of depot location on performance indicators. Two alternatives are assessed, both having a vehicle fleet composed by only drones (with the optimal amount of drones previously found). The difference is that in the first test scenario, vehicles start and end their trip just at the pharmacy Benu ’t Slag, while in the second test scenario starting and ending locations are increased up to 5 depot locations (including the pharmacy). The cost model is considered to be the same as the one for the test scenario with drones only, hence with a fixed cost of [redacted] euro per trip and a variable cost of 0.10 euro/km. Vehicle characteristics are also kept unchanged from that test scenario. Figure 5.14 shows the location of the 5 depots and the routing solution obtained from the model implementation.

Analysing the KPI comparison of Figure 5.15, it can be seen that some indicators do not change when the number of depots is incremented. Vehicle capacity ratio remains the same, due to the fact that



(a) Depots locations



(b) Routing solution

Figure 5.14: Locations and routing solutions for test scenario with multiple depots

the same demand and the same vehicle capacity is considered for the two scenarios. Same line of reasoning for the CO2 emission and fuel consumption: characterised by a fully electric drones fleet, both alternatives have zero emissions and zero fuel consumption. When multiple depots are introduced, vehicles can carry out their deliveries in a faster way, travelling a shorter distance. Therefore, a decrease in service time and cost of operations is noticed: adding four more depots reduces the service time by 11.8%, the energy consumption by 25% and the cost of power supply by 33.3%.

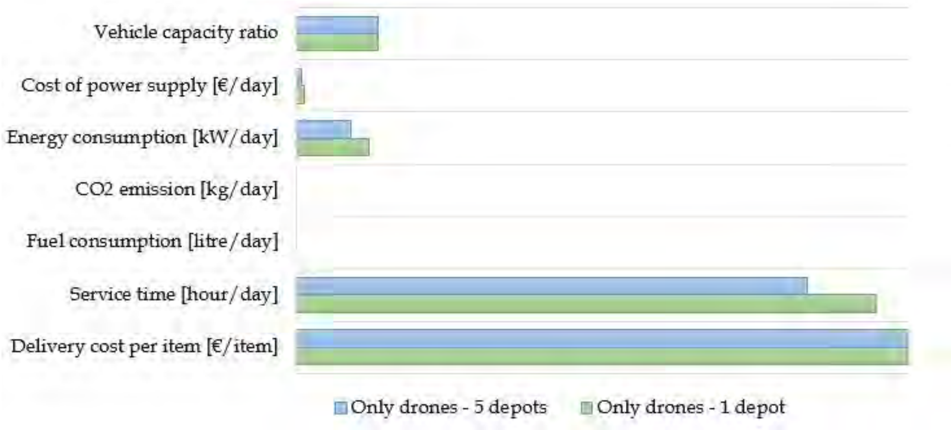


Figure 5.15: KPI comparison for test scenarios with only drones: 1 depot vs 5 depots

5.3. Comparison of alternatives

The comparison between the current situation and the future configuration is made according to the performance indicators and the design requirements. For the KPI comparison, four important criteria are assessed: costs associated with network alternatives, environmental benefits, service time and payload utilisation. The values are averaged among the solutions obtained for the implementation with 14, 28, 56 and 112 customers. Each alternative is then analysed according to the functional and non functional requirements of subsection 3.1.2, considering the extent to which they are satisfied.

5.3.1 Comparison based on Key Performance Indicators

Costs associated with network alternatives

To evaluate the cost savings brought by the introduction of drones in the vehicle fleet for home delivery of medical products, comparing the cost model of the current situation and the future configuration is not sufficient. It is indeed important to consider the different business models and the implications that follow the adoption of drones in the last-mile delivery process. For this reason, two different analysis can be made: one merely compares the costs associated with one day of operation in the current situation with the costs of the same operation in the future configuration. A second analysis considers the business model of adopting the future scenario alternative, characterised by the purchase of one drone and the sale of one van and all the implications that follow, evaluating the monetary benefit in terms of total annual cost.

The model output shows that the optimal fleet for the future situation is composed by two vans and one drone. Therefore, the analysis of annual costs for the business model is done considering the expenses associated with buying and operating a drone and the savings derived from selling a van. Purchase costs, drone license cost and parking location costs are divided by the depreciation time of 5 years. The selling price of a second hand van Mercedes Citan 108 cti, year 2015 with 55,000 km is retrieved from Mercedes-Benz (2019b). Table 5.5 shows the expenses and the savings associated with the two different network configuration and refers to the cost model of section G.1.

Component	**Current situation**		**Future configuration**	
	Amount	**Annual cost**	**Amount**	**Annual cost**
Vehicle purchase				
Vehicle sale				
Park location				
Human labour				
Drone license				
Insurance				
Taxes Operation costs				

Table 5.5: Annual cost comparison between current situation and future configuration

The total annual cost used for the business model is found using Equation 5.1. For the current situation a total of 63762.5 euro/year is found whereas for the future configuration the total amounts to 50,256.2 euro/year. This means that adopting the future configuration would bring a cost saving equal to 13,500 euro/year.

$$\begin{aligned} Annual\ cost = {} & vehicle\ purchase - vehicle\ sale + park\ location + human\ labour \\ & + drone\ license + vehicle\ insurance + vehicle\ taxes + operation\ costs \end{aligned} \tag{5.1}$$

For what concerns the daily costs of operations, performance indicators show that with the introduction of drones in the vehicle fleet, a reduction of euro/item is noticed for the delivery cost per item and a reduction of euro/day for the cost of power supply.

Environmental benefits

Environmental benefits are compared evaluating the CO2 emission, the fuel consumption and the energy consumption in each network configuration. With the removal of one van from the vehicle fleet and the introduction of one electric vehicle, the total distance travelled by road vehicles decreases, leading to a consequent decrease in CO2 emission and fuel consumption, but an increase in energy consumption. As expected, CO2 emissions decrease on average of grams per day of operation, fuel consumption is reduced of litres a day and energy consumption increases of Watt per day.

Service time

Service time is the time that each vehicle spends to complete its tour, summed over all vehicles. It indicates the total time spent in the system, to conclude the daily deliveries. Drones are faster than vans, and most importantly are not bounded by the physical infrastructure. As expected, the adoption of the future scenario alternative would reduce the total service time of minutes.

Payload utilisation

Payload utilisation is calculated as the ratio between the used capacity and the available capacity. Total demand is kept unchanged between the two network alternatives, being equal to [redacted] products per day. For what concerns the total vehicle capacity, van capacity is assumed to be [redacted] units whereas drone capacity only [redacted] units, meaning that the current situation has a maximum available capacity of [redacted] products while in contrast the future scenario only [redacted] products. As expected then, payload utilisation reaches almost 100% in the future scenario, with an increase of 25.75 percentage points.

5.3.2 Comparison based on functional and non functional requirements

The functional and non functional requirements object of comparison are the one stated in subsection 3.1.2. For each requirement, a green v indicates that the requirement is satisfied whilst a red x indicates that the network alternative does not comply with it.

Requirement	Current situation	Future configuration
Products are delivered to the intended customer	v	v
Products are delivered within the arranged time	v	v
Feasible vehicles are assigned to each customer	v	v
Vehicle utilisation complies with regulations	v	v
Solution lowers the total cost of operations	x	v
Solution decreases the total time spent in the system	x	v
Solution provides a maximised vehicle utilisation	x	v

Table 5.6: Comparison based on functional and non functional requirements

Functional requirements are all satisfied in each network alternatives. Being mandatory attributes for the system to function, it is a sign that both alternatives are feasible in practice. Most of the non functional requirements are satisfied by the future scenario, meaning that the introduction of drones provides a better alternative, having the qualities that define an optimal system.

5.4. Conclusion

In this chapter the results of the optimisation model are analysed and discussed. The routing sequence for each implementation is displayed using maps, and the current situation is compared with the future scenario. Model outcomes are also used to calculate Key Performance Indicators, so that the comparison analysis can be carried out under an economic perspective, but also under environmental, time savings and payload utilisation perspectives. It is then possible to answer the fifth and last research sub question:

What network alternative is the most promising in the case of last-mile logistic of medical products for home deliveries?

The introduction of drones in the vehicle fleet brings an overall improvement in the cost performance of the home delivery logistics. Costs are reduced of 5.45% for item delivered and 8% for the power supply, with a saving of respectively [redacted] euro per item and [redacted] euro per day of operation. The associated business model, characterised by the purchase of one drone and the sale of one van, shows that on a yearly base the cost savings associated with the adoption of the future scenario are a little bit more than [redacted] euro, which is around 12.5% of the total annual cost of the two network configurations. This reduction is justified by the low purchase cost of a drone compared to the selling price of one used van, and also by the low operational costs of vans compared to the operational savings that terminating one van brings.

Environmentally speaking, the introduction of drones brings substantial changes in the emission of carbon dioxide and in fuel consumption. In fact, in the future scenario one diesel powered van is replaced with a fully electric powered drone, meaning that the total distance travelled by van is reduced and consequently CO2 emission and fuel consumption are also reduced. Quantitatively, the environmental benefits amount to [redacted] grams of CO2 reduction and [redacted] litres of diesel per day of operation, equal to respectively 8.15% and 7.97% improvements.

The third performance indicator is the service time, i.e. the time needed by the whole vehicle fleet to carry out all the scheduled deliveries. Drones can travel at a faster speed (assumed as double the average speed of a van) and can reach any point by travelling at a bird flight distance (which is the distance that connects two points with the shortest straight line that a plane would cover). Consequently, delivering products to a set of customers using a drone takes less time than serving the same amount of customers using a van. On an average service time of [redacted], the average reduction amounts to [redacted], equal to 11.8% of the initial time.

The last performance indicators refers to the payload utilisation, namely the ratio between the capacity used and the total available capacity. This indicator shows great improvement, reaching almost a full utilisation in the future scenario. This results from the fact that eliminating one van and introducing one drone decreases the total available capacity from [redacted] to [redacted] products in total. Given the fact that the demand amounts to 105 products per day, vehicles must be used in a more efficient way and loaded almost to their full capacity.

The chapter is concluded with a sensitivity analysis, that shows the influence that changes in model inputs have on the model outputs and thus on the performance indicators. Furthermore, other potential future scenarios are tested, referring to a situation in which only EVs are used (e-vans and drones) and one in which the fleet is entirely composed by drones.

Results of the sensitivity analysis show that the inputs that mostly affect the performance indicators are the vehicle speed and vehicle capacity. Changing the vehicle speed brings changes in the variable costs of the fleet, since it affects the time that vehicles are in the system and consequently the salary of the drivers/drone pilot. Vehicle capacity mostly influences the capacity ratio, which fluctuates until it reaches the full utilisation once the vehicle capacity equals the total daily demand. These fluctuations depend on the fact that increasing vehicle capacity decreases payload utilisation, until a certain threshold is reached and one vehicle can be discarded. Same trend is followed a second time until full utilisation is reached. Distance limit and working time limit provide slight or no changes in performance indicators.

At last, three test scenarios are explained and compared with the future scenario of the case study. Analysing the situation in which all vehicles are electric (fleet composed by 2 e-vans and 1 drone), substantial differences in the cost components are found. The cost per item increases from [redacted] euro to [redacted] euro, meaning that each item is 56.6% more expensive when transported with a fully electric fleet. This results from the high investment costs of buying a complete new fleet of 2 e-vans and 1 drone. On the other hand, the cost of power supply decreases enormously, from [redacted] euro to only [redacted] euro, due to the switch from fuel- to energy- powered vehicles. From an environmental perspective, the benefits are extremely positive, reducing the CO2 emission and the fuel consumption to zero, while keeping low the energy consumption. The second situation that is tested is the scenario in which only drones are operated in the vehicle fleet. This test run provides the minimum amount of drones that are needed in a fully-drone scenario, or at least the number of trips that are needed to operate a full day of deliveries. Results show that 35 drones must be operated, which brings consequent high investment and exploitation costs, increasing the value of the cost per item (reaching almost [redacted] euro per item delivered). The last test involves again a scenario with a homogeneous drone fleet composition, but the previous alternative with 35 drones and 1 depot is compared to the one with 35 drone and 5 depots randomly located in the delivery area. With the addition of four more depot location, the distance travelled and the service time were both reduced, allowing for a time saving of [redacted] (equal to 11.8% of the total service time) and a cost saving of [redacted] euro (equal to 33.3% of the total cost of supply).

6
Conclusions and further recommendation

This research focused on the feasibility assessment of introducing drones in the last-mile logistic process of medical product delivery, with an application to the case study of BENU Apotheek 't Slag. After a thorough description of the system and the current home delivery process, a future scenario alternative was chosen among several proposed scenarios, to be used further on in the network comparison. Theories on last-mile delivery and transport network optimisation were discussed and the most suitable approach was chosen to carry out the feasibility assessment. A conceptual model was created, to create an abstraction of the system and allow for a mathematical formulation of the problem. Alternatives were then modelled using an adaptation of the well known Vehicle Routing Problem and the results were compared. This chapter concludes the research, by answering the sub questions and the main research question of chapter 1 and by providing a discussion of the results and some further recommendation for future research studies.

6.1. Conclusions

The main objective of the research was to assess the feasibility of operating a home delivery service that includes drones in the vehicle fleet, providing a comparison of performances with the current logistic operations in use. Based on the hypothesis that drones provide a feasible fleet addition for the last-mile logistic process when added to the conventional transportation means that are currently in use, a study was conducted on the modelling techniques that can be implemented to optimise a transport system, focusing specifically on the last-mile network. The Vehicle Routing Problem proved to be a valid model formulation, with some adaptations complying with drone specifications and requirements. Results for the current situation were compared to the one obtained for the future scenario. This section provides the answer for the main research question, by first answering the five sub questions.

6.1.1 Main characteristics of B2C last-mile delivery process

The first sub question concerns the logistics of last-mile delivery and it is formulated as follows:

What are the main characteristics of a B2C last-mile delivery process?

Throughout a literature study, characteristics and challenges encountered by the last-mile delivery service are assessed. Four logistics decisions define this process, from the starting point to the final place of delivery. The first decision concerns the location from which products are shipped, which might be warehouses, depots or retail shops. Then the second decision regards the identification of delivery destination, i.e. the place where product are consigned. Common places are usually pick up points, clustering points and customer's home. Once the delivery destination is set, the means of collecting product must be arranged. In case of clustering points, products can be collected through reception boxes, collection points or post offices. For home deliveries, collection might be attended or unattended. Lastly, the agreements on the final consignment of products must be arranged, e.g. pin code security in reception boxes, or neighbours pick ups for unattended home deliveries.

For what concerns the challenges faced by the last-mile delivery sector, the main causes that hamper its effectiveness and efficiency are high costs of operations, traffic congestion and environmental damage.

Studies have shown that the last-mile leg is the most expensive part of the delivery process, counting up to 75% of the total cost of the logistic process. Moreover, the most used vehicles for last-mile delivery are vans and small trucks, which cause not only traffic congestion, especially in densely urbanised areas, but also air pollution.

6.1.2 Main stakeholders involved in the case study

The second sub question refers to the actors involved in the research study of last-mile delivery and introduction of drones in the delivery fleet. It is tailored to the case study associated with the research and it is formulated as follows:

Who are the main stakeholders involved in the last-mile logistic process, in relation to the case study?

Stakeholders are defined as individuals or organisations that are actively involved in a project, can express their interest and opinions and have a pre-arranged power on important decisions. For what concerns this research and the case study of BENU 't Slag, the following stakeholders are identified:

1. BENU 't Slag: it is the retail store from which deliveries are operated. Their interest is to provide a fast and reliable service, yet maintaining costs of operations as low as possible and avoid loss in profit and customers' expectations. Provided that regulations and laws in force allow for this technology to take place, they have the final say on whether to adopt it.
2. BENU Apotheek franchising: being the company that administrates all the BENU pharmacies across the Netherlands and provides the medicines, their interest and power is similar as the ones for BENU 't SLag.
3. Delivery companies: external companies, such as the current Farma Clean and Service, have the interest in investing on new technology and fleet components for the near future. Their interest is in cost savings and delivery contract stipulation.
4. Customers of BENU 't Slag: people that usually buy and benefit from the home delivery service want to have a fast, cheap and reliable delivery service, without additional expenses or product damage. Their influence mainly concerns customer loyalty.
5. Population of Rotterdam: people that live in the nearby area might be annoyed by the congestion and pollution caused by delivery vans, and at the same time worried for the introduction of flying drones in their neighbourhoods.
6. Municipality of Rotterdam: legislators that give the green light on the use of drones for last-mile delivery in the city of Rotterdam. Their interest is to operate according to the laws, guaranteeing the best service to the population.
7. Other pharmacies in Rotterdam: their interest is on fair competition, and to maintain their loyal customers. They do not have influence on the final realisation of the project, but might be interest to adopt the same technology in order not to see a decrease in customers.

Each stakeholder is compared to the others based on their power and interests. The result is the power-interest matrix of Figure 2.8.

6.1.3 Comparative analysis of last-mile delivery transport networks

The third sub question investigates the Key Performance Indicators and the data that need to be retrieved for comparing transport network alternatives, followed by an analysis of the different design methodologies for transport network assessment. The question is formulated as follows:

What are the main KPIs, data and design methodologies for a comparative analysis of last-mile delivery transport networks?

The performance indicators to be used in the network comparison analysis concern costs, service time, environmental parameters and vehicle capacity. After a literature study and a series of interviews with relevant stakeholders, the following list of Key Performance Indicators is complied, together with the related data that must be retrieved:

- Delivery cost per item: average number of deliveries per day; cost of storage area; cost of handling equipment; cost of parking location; purchase cost of vehicles; license to operate a drone; ATM purchase and fees for outdoor sale; human labour (van drivers and drone pilots); operation management costs; insurance cost of vehicles; regional taxes per vehicle type; operational costs of vehicles; financial costs.
- Average service time: average speed for vehicle type; average loading and unloading time for vehicle type.
- Fuel and energy consumption: fuel consumption of vans; energy consumption of drones.
- CO2 emission: CO2 emission per distance travelled per vehicle type.
- Vehicle capacity used versus available capacity: maximum allowed payload for vehicle type; average used payload for vehicle type.

For what concerns the mathematical description of transport network problems, two main formulations are found in literature: the Travelling Salesman Problem and the Vehicle Routing Problem. The first one refers to a simulation approach that finds the shortest path that connects a set of nodes, for which the order of visits is not important. The second one refers to an optimisation approach which defines the optimal tour given a set of nodes to be visited and a fleet of vehicles, such that each node is visited once and only once by just one vehicle and the costs of operations are minimised. The main substantial differences between the TSP and the VRP are the fleet composition and the vehicle capacity restriction: the VRP is proved to be most suitable when more vehicles are included in the fleet and each of them has a maximum allowed capacity. For this reason, the feasibility assessment of drones as additional vehicle for last-mile deliveries was carried out using the VRP formulation, with the required adaptations for the considered case study. For the definition of the constraints and therefore the boundaries of the design, a list of functional and non functional requirements was made.

- Functional requirements: medical products must be delivered to the intended customer; medical products must be delivered within the intended arranged time; the model must assign a feasible vehicle to the trip, based on delivery characteristics; the chosen alternative must comply with existing regulations.
- Non-functional requirements: the chosen alternative should lower the total cost of the delivery process; the chosen alternative should minimise the total time spent on the network; the sequence of chosen alternatives should provide a maximised vehicle utilisation.

6.1.4 Adaptation of model framework for home deliveries

Once the design methodology to formulate the transport network is chosen, the fourth sub question relates to the adaptations that are needed in order to address specifically the case study. The formulation of this sub question is as follows:

How to adapt the chosen design methodology for last-mile delivery networks to fit the case study requirements?

Starting from the classical Vehicle Routing Problem formulation, to define which adaptations are needed it is first important to understand what new constraints are added when including drones in the vehicle fleet. When vans and drones are included, the VRP becomes a heterogeneous fleet problem, with two vehicle types, each of them having their own cost components and vehicle specifications. For this reason, in the objective function, costs must be divided per fleet component, by adding the subscript k (related to vehicle type) to the total cost c_{ij} and including it into the summation over k. Moreover, drones have a hard constraint on maximum range and maximum flight time; therefore, two constraints (number 7 and 8 of the following list) are added from the basic VRP formulation, concerning the technical and spatial limitations of drones.

OF	$min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m} c_{ijk} * x_{ijk}$		
ST	$\sum_{k=1}^{m} y_{ik} = 1$	$1 \leq i \leq n$	(1)
	$\sum_{k=1}^{m} y_{ik} = m$	$i = 0$	(2)
	$\sum_{i=1}^{n} q_i * y_{ik} \leq Q_k$	$1 \leq k \leq m$	(3)
	$\sum_{j=0}^{n} x_{ijk} = y_{ik}$	$0 \leq i \leq n, 1 \leq k \leq m$	(4)
	$\sum_{i=0}^{n} x_{ijk} = y_{jk}$	$0 \leq j \leq n, 1 \leq k \leq m$	(5)
	$\sum_{i \epsilon S} \sum_{j \epsilon S} x_{ijk} \leq \lvert S \rvert - 1$	$S \subseteq 1, ..., n,\ 1 \leq k \leq m$	(6)
	$\sum_{i=0}^{n} \sum_{j=0}^{n} t_{ijk} \leq T_k$	$1 \leq k \leq m$	(7)
	$\sum_{i=0}^{n} \sum_{j=0}^{n} x_{ijk} * d_{ij} \leq R_k$	$1 \leq k \leq m$	(8)

Table 6.1: Mathematical formulation adapted from the VRP

1. Each customer i is visited by only one vehicle k
2. Each vehicle k must come back to the depot
3. The demand at each node i should not exceed the vehicle capacity.
4. The number of vehicles leaving the pharmacy is the same as the number entering the pharmacy
5. Same for constraint number 4
6. Sub-tour prohibition, which forbid solutions consisting of several disconnected tours
7. The total time from i to j using vehicle k must not exceed the maximum utilisation time T_k
8. The distance covered by a vehicle must not exceed the maximum range R_k

The decision variable x_{ijk} assigns to each vehicle k a routing sequence, being x_{ijk} equal to 1 if customer j is visited after customer i with vehicle k. The second decision variable y_{ik} assigns one vehicle k to one customer i, guaranteeing that each customer is visited once and only once by only one vehicle. The solution approach that was used to implement the model is an open source spreadsheet solver specific for the VRP, developed by Erdoğan (2017). It uses a Local search Neighbourhood algorithm, which tries to find an optimal or quasi-optimal solution by means of iterations, finding in each step an improved solution in the neighbourhood of the current one, for which costs are minimised. The algorithm stops when a local optimum is reached.

6.1.5 Most promising network alternative for the last mile logistics of medical products

The final sub question relates to the comparison analysis between the current situation, in which deliveries are carried out with a homogeneous vehicle fleet composed by 3 delivery vans, and the future scenario, in which drones are added to the fleet. Its formulation is as follows:

What network alternative is the most promising in the case of last-mile logistic of medical products for home deliveries?

Results of model implementation are the fleet allocation and customer sequence (matrix x_{ijk}), the distance travelled per vehicle d_k, the driving time per vehicle t_k, the number of stops per vehicle, the number of packages transported by each vehicle for each stop and the cost of operation per vehicle c_k. These outputs were then used as input parameters to calculate the KPIs for the network alternative comparison, using the following equations:

$$Delivery\ cost\ per\ item = \sum_k c_k/n_{deliveries} \quad [euro/item] \tag{6.1}$$

$$Service\ time = \sum_k t_k \quad [hours] \tag{6.2}$$

$$Fuel\ consumption = \sum_k d_k * 5/100\ with\ k \in van\ fleet \quad [litres] \tag{6.3}$$

$$CO_2\ emission = \sum_k d_k * 115\ with\ k \in van\ fleet \quad [g] \tag{6.4}$$

$$Energy\ consumption = \sum_k t_k * 0.26\ with\ k \in drone\ fleet \quad [kW] \tag{6.5}$$

$$Cost\ of\ power\ supply = 1.33 * FC + 0.1024 * EC \quad [euro] \tag{6.6}$$

$$Vehicle\ capacity\ ratio = \sum_k (Q_{used,k}/Q_{available,k})/n_{vehicles} \quad [\%] \tag{6.7}$$

Four different implementations were run, varying the number of customers from 14, to 28, 56 and then 112. Lower an upper bounds were chosen based on the geographical area served by the pharmacy and the demand pattern: 14 postcodes are served, with a demand that varies from [redacted] products per postcode. Therefore, the first implementation considers only one customer per postcode, while the last considers 8 customers per postcode. Increasing customer density would have led to several customers with zero demand, hence it was decided to stop the implementations after 112 customers. Figure 6.1 shows a comparison of performance indicators for the current situation and the future scenario. Values are averaged across the 4 different customer densities.

Figure 6.1: Comparison of KPIs for current situation and future scenario

Comparing the KPIs for a day of operation, the introduction of drones in the home delivery fleet brings an overall improvement. Benefits can be noticed in the cost components, with a reduction of 5.60% in cost per item and 5.85% in cost of power supply. Environmentally speaking, the benefits are even higher, with a reduction of 8.60% in fuel consumption and 9.00% in CO2 emissions. The average service time is reduced by 12%, amounting to a total time saving of [redacted] minutes. Reducing the available capacity brings a substantial change in the vehicle capacity ratio, with an increase of 37.15% in payload utilisation. The only performance that is drastically worsened is the energy consumption, which increases of [redacted] Watt, equal to 100% more than in the current scenario. This result is totally expected, since in the current fleet there are no EVs whereas in the future scenario a fully electric drone is introduced.

Comparing the business model for the two alternatives, substantial cost savings were noticed. Adopting the future scenario not only means that a new drone must be purchased, but also that a delivery van can be sold. Combining the expenses of buying and operating a drone with the cost savings of selling and quitting daily operations of a delivery van, it was found that including drones in the delivery fleet allows for a reduction of [redacted]

6.1.6 Benefits for the pharmaceutical sector

After having answered the 5 sub questions, it is possible to provide an answer to the main research question, that was formulated as follows:

How can the pharmaceutical sector benefit from the introduction of drones for the last-mile logistic process, in combination with the current means of transport?

Throughout the research, several problems of the current last-mile transportation means have been addressed. The main challenges that were defined consisted in cost reduction and congestion and pollution diminution. Two design alternatives were elaborated and tested to understand the extent to which the pharmaceutical sector can benefit from the adoption of a heterogeneous fleet composed by vans and drones, and hence answer the research question. Optimise these two situations provided some interesting results in terms of cost ad time savings and environmental benefits. Referring to the case study of BENU 't Slag, it was estimated that with the adoption of the envisioned future scenario, the pharmacy could potentially save [redacted] euro a year (based on a 5 year depreciation period), equal to 12.5% of the total annual costs. Based on the assumption of an average amount of [redacted] deliveries per day, the cost per item is reduced by [redacted] euro, equal to 5.60% of the initial price per package delivered. Routes were found to be faster, decreasing the total service time of [redacted] or by 12.05%, suggesting that more customers could potentially be served and the geographical area expanded. The introduction of flying vehicles and the consequent reduction of road vehicles brings indisputable improvements under an environment perspective: CO_2 emissions are reduced by 9.00% for a daily operation, and less vehicles are driving in the urban area, decreasing the amount of traffic congestion. Besides the improvement in vehicle capacity ratios, the highest gains were found in the service time indicator, meaning that the performance that most improve is the total time in the system. Considering that the case study referred to the home delivery of medical products, improving the service time is more beneficial than increasing cost savings, given the fact that it is more important to provide a fast and reliable distribution rather than as cheap as possible.

6.2. Discussion of the results

Although the results of the research showed a clear predisposition towards the adoption of drones as means of transport for home deliveries, some aspects are worth to mention.

First of all, the results obtained refer to the case study of BENU 't Slag, and the performance indicators refer to the cost model specifically developed for the pharmacy concerned. Cost components highly depend on the average number of deliveries per day and on the distance between nodes. Input data are either assumed or obtained from the pharmacy. Nonetheless, it is believed that results can be extended for similar case studies, for which research could potentially produce similar or better results.

Speaking of data availability, it is important to mention that a lot of assumptions were made, especially on cost components and demand distribution. Real data pertaining the case study were used for the total demand and for the area in which BENU 't Slag operates the home delivery service. The exact number of costumers and their precise location was not made available by the pharmacy; therefore, the node distribution was made randomly withing the 14 postcodes, trying to cover as much area as possible. The demand distribution was also spread across nodes in a random way. Changing the demand allocation produces a different routing solution and a different associated cost. Although noticeable, these variations were not substantial and similar results were produced.

For what concerns the solution approach for the implementation method, two important manipulation were operated. For what concerns the variable costs, the Excel Spreadsheet Solver that was used to implement the Vehicle Routing Problem did not account for time related costs, but only distance related costs. To overcome this drawback and still include the human labour cost (expressed in euro/hour) and the energy cost (expressed in euro/hour as well), these two costs were converted into distance costs (expressed in euro/km) using the average vehicle speed. Calculating how many hours are needed to travel 1 kilometre, and multiplying this value by the hourly cost, it is indeed possible to obtain the time related components expressed in euro/km. The second manipulation concerned the distance computation method and the average vehicle speed used in the implementations. Vans and drones are inherently different, especially in terms of average speed and path followed for going from origin A to destination B. The assumptions made on vehicle speed assigned an average speed of 35 km/h for the van fleet and 70 km/h for the drone fleet. The distance computation method for vans was the Bing Map real distance, which calculate the real distance between two points, following the real existing infrastructure and the road regulations that are applied. For the drone, the birdflight distance computation was used, that calculates the shortest straight line that a plane would cover. Unfortunately, the Spreadsheet Solver allows for only one distance computation per implementation, and just one vehicle speed can be inserted. For this reason, for the future scenario assessment, two implementations were run, one with distance and speed characteristics of vans and one with distance and speed characteristics of drones. Results were then assembled together so that the route is still feasible and capacity and node constraints are still respected.

Lastly, it is worth to mention that results provide a routing solution that assigns one tour per vehicle per day, meaning that each vehicle carries out only one round of deliveries every day. The service time per van in the case of 112 customers (hence the case with the highest service time) spans from [redacted] to [redacted] for the current situation and from [redacted] to [redacted] for the future scenario. Given that the total working time window is 9 and a half hours (from 8AM to 5:30PM), it could be also possible to use the same van for carrying out two delivery rounds. In any case, two different drivers must still be employed, due to labour restrictions that do not allowed drivers to work more than 6 hours without interruptions.

6.3. Further recommendations

Due to the limited amount of time for this research, the comparison analysis was conducted only between two alternatives, with a brief analysis of other potential future scenarios. Moreover, as discussed previously, some assumptions and modifications were applied to the model and the solution approach. Therefore, this chapter contains some general recommendation regarding the different scenarios and the potential different model implementations and solution approaches. Moreover, given the promising results, some recommendation specifically tailored for BENU 't Slag and for the BENU Apotheek franchising are provided.

General recommendation

Once results showed that the introduction of drones would bring substantial improvements in the logistic operations of last-mile delivery for the pharmacy Benu 't Slag, several scenarios alternatives were hypothesised, to check the extent to which different network configurations would provide different performance indicators. A fully-drone scenario, a fully-EVs scenario and a multiple depot scenario were suggested. First results showed that a homogeneous fleet of only drones brings a considerable increase in cost per item amounting to [redacted] euro per product delivered. Environmental benefits are undoubtedly interesting, with a drop of CO2 emission and fuel consumption down to zero. Same environmental results can be obtained with a fully electric heterogeneous fleet composition, with 2 e-vans and 1 drone. Moreover, with 2 e-vans and 1 drone, cost per item can be considerably reduced, as well as the cost of power supply. Lastly, the test scenario with multiple depot showed that, in comparison with the situation where only one depot is arranged, service time can be reduced by 12% and cost of power supply by 33%. Therefore, the main recommendation for further research is the implementation of the scenario with a fully electric homogeneous fleet composition, with multiple depots. The choice of avoiding a fleet composed only by drones and keeping road based vehicles with drivers carrying out deliveries is also justified by the delivery agreements of BENU 't Slag. Twice a week, drivers consign several packages that are meant to fit in the mail box, without the customer having to collect them in person. If BENU wants to maintain this service, it is believed that a homogeneous fleet of drones is not feasible.

For what concerns the implementation method, further research can be extended including solution approaches that can account for multiple distance computations and average vehicle speed in the same implementation setup. Examples are the Simulated Annealing or the Genetic Algorithm implemented using Matlab or Python. Comparing the results obtained with the one of this research, might provide a better insight on the feasibility assessment of drones for last-mile logistics. Moreover, it is recommended to undertake some practical test as soon as regulations will allow drones to fly.

Under a technical perspective, it might be interesting to further investigate on some technical characteristics of the vehicle fleet. As an example, fuel consumption was assumed to be static, fixed at 5 litres/100km. In reality, this value changes dynamically based on vehicle speed and traffic congestion (i.e. if the vehicle needs to stop and re start the engine several times). Another characteristic that might be worth of investigation, is the effect of weather condition on drone flight performances, e.g. how wind or rain might affect the possibility of drones to reach customers locations.

Recommendation for BENU 't Slag and the BENU franchising

Based on the results obtained in this research, it is recommended for Benu 't Slag to include drones in their delivery fleet, as part of near future investments. This new technology cannot be adopted yet, due to regulations that impose restrictions on flying vehicle. However, European regulations are about to change in the coming months, and drones will be soon introduced in delivery logistics.

In the context of the multiple depot scenario, one practical recommendation for the pharmacy is to implement a tracking system that registers customers locations and their corresponding demand. As it is now, data on product demand are only available on a monthly basis, and are not divided per customer. This tracking system not only keeps records of the amount of products that leaves the pharmacy, but also of their final destination. By doing so, it is possible to define the demand pattern in a more precise way. Although this system might encounter some privacy issues, it would be a valid tool to arrange the multiple depots in an optimal way, so that starting locations can be positioned close to areas with high concentration of customers or high demand.

6.4. Personal reflections

Now that my time as a student is almost concluded and I finished the research for my Master's thesis, it is time for some personal reflection.

Looking back on when I started this project, I can say that it was surprisingly easy to find a pharmacy that was interested in a collaboration and willing to help me. Studying the feasibility of drones as delivery vehicles for medical products was my first idea, so I was really enthusiastic when the opportunity of BENU 't Slag came up. Although they provided me with some real data, they were not enough to carry out a thorough research. Consequently, I had to formulate several of assumptions, especially on customer distribution and cost associated with the delivery process. I tried to remain as much close to reality as possible, yet of course some discrepancy might be found if a complete set of real data were to be used.

Right after the mid-term meeting in January I struggled with some health issues which inevitably delayed my research. Fortunately my supervisors were really understanding, and let me fully recover before starting again with my work. Regardless, I managed to finish with a very small delay on my initial plan, working very hard in the following months.

The biggest step to overcome was the formulation of the mathematical problem and the choice of the solution approach. After many consultations with my supervisors and some other professors at the TU Delft, I chose for the VRP, but the solution approach was still unknown. I first tried to implement the optimisation problem with Matlab, encountering some problems. I was able to run some simple VRP problems, but I couldn't visualise the results in the way I was imagining, with the routing sequence on top of the map of Rotterdam. After many trials, I found the VRP Spreadsheet Solver that I used in this research, and I could finally implement the model in the correct way. After having found the correct approach, the analysis continued fast and smooth.

Almost at the end of my research I had a very interesting brainstorm with all my supervisors. A lot of ideas came out of that meeting, such as using electric vehicles, adding mode depot locations and so on. All of them were very interesting and I sort of regretted having so little time left and not being able to implement and analyse all these engaging alternatives. I tried my best and I managed to include a small investigation on EVs and multiple depot configuration, which may be the starting point for further research.

Overall, I can say that this whole experience was really formative and helped me understand that the research career is what I want to pursue. I really enjoyed working on my own research, with all the ups and downs of the process. I must also thank my supervisors for that, who always pushed me to make my own choices and trust my decisions. I hope that the outcome of my research will see practical applications, improving the quality of medical product home deliveries with a faster, more reliable and cheaper service.

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A
Costs associated with last-mile delivery

Costs associated with last-mile delivery depend mainly on the geographical location of delivery, the market density, the physical transport infrastructure and the delivery agreements.

Geographical area and market density

The geographical area and the market density are two of the most important aspects of last-mile delivery. The size of the area, its population and the delivery demand, jointly determine the shipment method, the delivery feasibility and the most suited vehicle to be used. A clear distinction is made between urban areas and rural areas. According to the definition provided by the National Geographic, an urban area is the region surrounding a city, in which the density of human structures (e.g. houses, commercial building, transport infrastructure) is relatively high (NationalGeographic, 2011). In the same way, areas with different market density can be classified. Operational decisions and related costs are then based on the area of shipment and on the market segment: travelling several kilometres for delivering one package in a rural area far away from the depot centre might result in higher operational costs compared to the shipment of several parcels in an urbanised space, given the same number of kilometres travelled. Last-mile economy is indeed driven by route density and drop size. A high number of deliveries over a short period of time or distance result in lower cost per delivery compared to one single delivery over long distances. A study conducted on the differences in last-mile delivery costs in urbanised area and in rural area (Gevaers et al., 2014), showed that shipping a product to a densely populated area (i.e. more than 1500 inhabitants/km2) can be up to 65% less expensive than shipping the same product to a rural area (i.e. less than 50 inhabitants/km2). In this way, efficiency is limited when shipping into rural areas. Figure A.1, adapted from Gevaers et al. (2011), shows the relation between the number of customers in the delivery area and the average mile travelled per costumer.

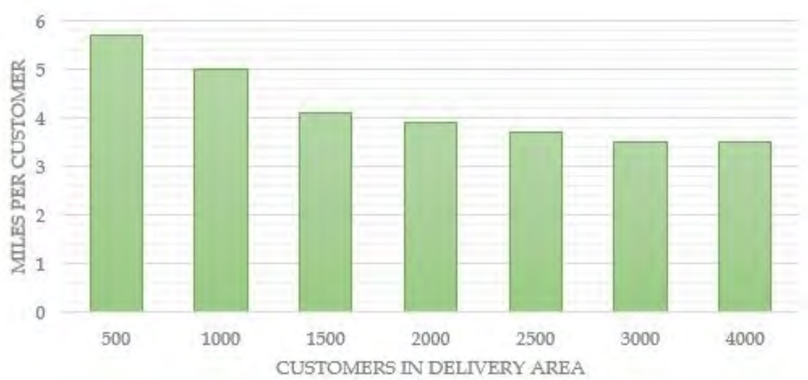


Figure A.1: Effect of consumer density on miles travelled

As can be seen from the figure, the number of miles is inversely proportional to the number of customers. This is mainly given to the fact that when several customers are clustered together in the same shipment area, an optimised route is found, that do not necessarily impose a return to the warehouse after every shipment, minimising thus the kilometres travelled. Customer density highly affects costs of last-mile delivery due to the dichotomy between cost of delivery and cost of shipment. While the first is unaltered for every type of service (i.e. most of the time is a free service provided by the company that sells the product), the latter depends on infrastructure conditions, congestion, distance to be travelled and service agreements (Gevaers et al., 2011).

Infrastructure limitation
Infrastructure limitation is one of the conditions that mostly curbs the last-mile delivery process, and it concerns several aspects. When talking about infrastructure limitations, one can refer to different categories of limitation, based on the geographical area of interest. Areas are commonly divided into urban areas and rural areas, depending on population density and structural composition. The main challenges that are faced in urban areas are related to congestion. High population density, urbanised living and concentration of offices and shops create a large transport demand. The offer, i.e. infrastructure capacity, rarely increase proportionally with demand. Consequently, roads are becoming more and more crowded, causing congestion and long waiting times. This is particularly relevant in the delivery sector, where congested roads lead to delayed shipment, cost inefficiency and customer dissatisfaction. Some attempt to reduce the impact of congestion have been made introducing e-cargo bikes for last-mile delivery in replace of the classical modes of transport (Schliwa et al., 2015). For what concerns rural areas, the main issue connected to infrastructure limitation is the lack of adequate connection between the depot and the delivery points (i.e. customers' house). In this sense, the efficiency and effectiveness of the last-mile logistic process is hindered by inaccessible areas and poor infrastructure maintenance.

Delivery agreement: time of delivery
Time of delivery refers to the shipment agreement that defines in advance a time window in which the delivery must take place (Gevaers et al., 2009). The main reason behind a predefined time window is to avoid trips in which the delivery is not successful due to the customer not being at home. In that case, the courier will have to return again, adding extra costs for the same shipment. On the other hand, in the case that a delivery window is agreed upon, route efficiency might be hampered by the fixed sequence of shipment. In that case, indeed, routes are not optimal and do not follow the shortest possible path but are bound by the different pre-arranged time of delivery (Gevaers et al., 2009). Consequently, allowing for a pre-determined time delivery window concerns a trade-off between the minimisation of the number of trips and the optimisation of route efficiency. Figure A.2 shows the effect of delivery window on the average miles per customer in urbanised areas. With the relaxation of the time window, a decrease in average miles per customer is observed.

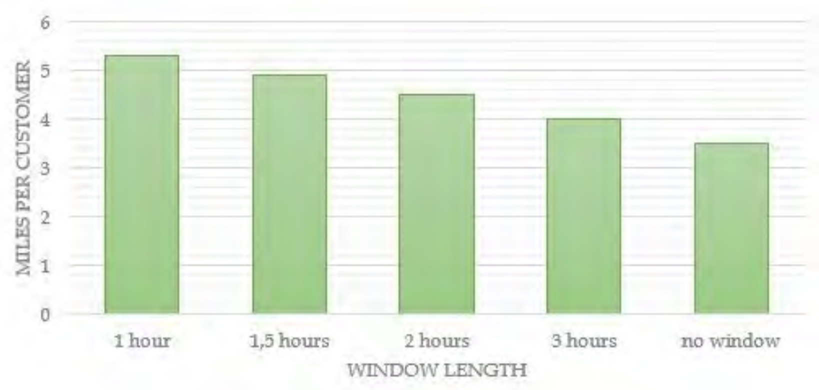


Figure A.2: Effect of delivery window on miles travelled

In some cases, a pre-arranged time of delivery might lead to the so-called "ping-pong effect", implying a significant raise in driven kilometres and associated costs. Figure A.3 shows a simulation of a delivery round without time windows (left-hand side) and with time windows (right-hand side), conducted by Boyer et al. (2005).

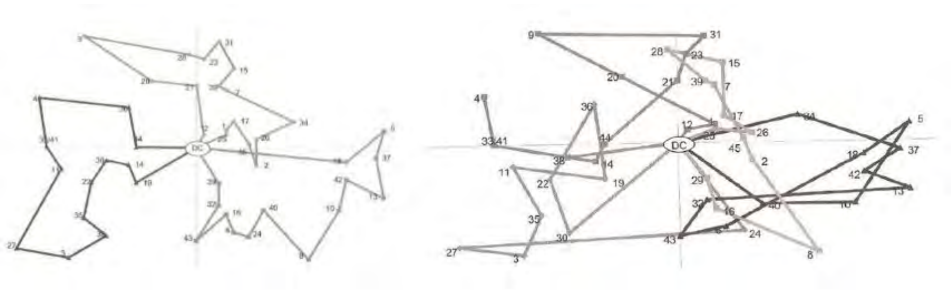


Figure A.3: Simulation of a delivery round without TW and with TW

As a first comparison, the disparity between the efficiency of these two simulations is easily noticeable. In the case of no time window provided, the optimal route is found through the shortest path as defined in the Vehicle Routing Problem (VRP) by Fisher and Jaikumar (1978). When a time window is defined, an extra synchronisation constraint must be added, which bound the nodes to be visited according to the scheduled deliveries. In this case the optimal route is found using the Vehicle Routing Problem with Time Window (VRPTW) as defined in Solomon (1987).

B

Network alternatives

B.1. Demand distribution

BENU ’t Slag operates home deliveries in 14 postcodes, with an average daily distribution of products (Frijmersum, 2018). Demand is spread across postcodes according to their size and their house units.

Table B.1: Weighted distribution of daily deliveries across postcodes

B.2. Scenario description

Referring to the description of subsection 2.3.1, this section provides arguments for and against each proposed scenario, with potential improvements or deterioration compared to the current situation. Each scenario is based on potential development of the delivery service provided by the pharmacy, and it is strictly related to the case study of BENU ’t Slag.

Scenario 1 - no changes applied

In the future situation no changes are made compared to the current state. This first scenario suggests to not apply any changes with respect to the current situation, keeping the 3 vehicles and the ATM, not expand the current area of delivery and the available fleet.

Arguments for:

1. No initial investments on new vehicle or on new technologies;
2. No investments on information campaign for new technology and delivery changes.

Arguments against:

1. Deliveries might increase with the population growth (WorldPopulationReview, 2018).

Scenario 2 - drones only

All deliveries are carried out via drones, with a total elimination of the current fleet of vans. The area of delivery is expanded due to the elimination of infrastructure limitation.

Arguments for:

1. Improvement in the emission, with a completely electric-powered fleet;
2. No need of organising two different categories of vehicles;

Arguments against:

1. All deliveries must be attended, for the drone to drop off correctly the products;
2. Interruption of the pre-packaged medications delivered twice a week;
3. Decrease in customer satisfaction;
4. High investment on new fleet

Scenario 3 - speedy deliveries
A fleet of drone is purchased only to take care of the speedy deliveries. Whenever an urgent delivery is requested, a drone is used instead of a van, which can in this way continue with the scheduled deliveries and avoid any change of route.

Arguments for:

1. Speedy deliveries can be carried out without affecting the route of other vehicles, eliminating the costs associated with these adjustments.

Arguments against:

1. It is expensive to buy a new fleet of vehicles only for one specific type of deliveries that might or might not take place;
2. Most likely low return on investment.

Scenario 4 - hybrid van and drone deliveries
A drone is attached to the roof of the van and acts as a sidekick to the van, so that drone and van can split the deliveries, while the drone can transport light weights and can recharge on the roof.

Arguments for:

1. Deliveries can potentially be completed in a shorter time.

Arguments against:

1. Very expensive investment, both on drones and on new vans to accommodate drones on;
2. Difficult to coordinate two different vehicles for the same shipments.

Scenario 5 - combination of vans and drones
Introduction of a new fleet of drones that cooperate with the existing vans. Deliveries are carried out based on an optimised system that minimises costs and assigns the most suitable vehicle.

Arguments for:

1. Vehicle selection can be optimised based on the characteristics of the delivery;
2. Existing vehicles do not need to be replaced or renovated.

Arguments against:

1. Initial investment on a new vehicle category.

C

History and characteristics of drones and use in last-mile delivery

C.1. History of drones

Drone applications started in the mid of the 19th century, for war fighting purposes, when Austrian forces sent some incendiary balloons to attack the city of Venice in July 1849 (Buckley, 1998). The fast pace of technology that characterised the last century, allowed for a continuous improvement and maturing of available UAVs. The military field has remained the biggest market share, in which autonomous or remote-controlled aerial vehicles are used as capable fighting machines that eliminate the risk to aircrews. In recent years, UAVs have been used for other purposes, such as transport of vital resources in emergency situations or parcel delivery. Several prototypes have been tested, with great results in term of cost savings and safety. On the other hand, people acceptance of drones has not increased in parallel with technology progress. The main issue is related to the fact that in the past, drones have been exclusively used for military purposes, as defence and attack devices. For this reason, drones are still seen as "killer robots" rather than potential delivery vehicles, hampering the acceptance amongst most of the population (Franke, 2015). The following paragraphs contain a brief overview of the main sectors in which drones have found potential applications, from the beginning of their use to recent days.

Military use

The first use of UAVs for war fighting purposes dates to 1849, when the Austrian army used an unmanned aerial vehicle as a balloon carrier to launch 200 incendiary balloons at the city of Venice (Buckley, 1998). Since the early 20th century, innovations started to take place, allowing for improvements in flight characteristics and performances. UAVs were used for training military personnel, gaining increasing popularity especially during World War 1 (Shaw, 2013). The first description and attempt of powered UAVs as made by A.M. Low in 1915, followed by Nikola Tesla in 1916 (Dempsey, 2010). With the addition of electricity to these vehicles, different armies started to adopt them for their military strategies. Germany used UAVs to train antiaircraft gunners and to fly attack missions starting from 1935. UAVs remained mainly remote-controlled aircraft for the following 20 years, since they started to be automated, without requiring a remote pilot during the Vietnam War in 1955 (Kenneth, 1997). Other examples of military use are found in the Yom Kippur War of 1973, when the Israeli government sent anti-aircraft missiles (Saxena, 2013) and developed the first UAV with real time surveillance as air defences against the Syrian army in the Lebanon war of 1982 (Azoulai, 2011), with the result of no pilots downed (Levinson, 2010). The maturation and miniaturisation of applicable technologies in the 1980's and 1990's captured the attention of the US military sector, interested in cheaper and more capable fighting machines which do not require a pilot and hence cause no risk to aircrews. UAVs were extensively used during the Gulf War in 1991, as surveillance vehicles and armaments carriers.

Emergency and medical purposes

The key factor in emergency situations is time. Being not bounded to physical transport infrastructure, having a relatively high speed and the capability of flight in a straight line between two points, drones have been proved to be useful when it comes to save lives. A study conducted by the European Resuscitation Council in 2015 shows that a prompt intervention of less than 10 minutes in the case of accidental drowning is crucial for having a successful outcome (Truhlář et al., 2015). In those situations, a drone that transmits live videos can be used to monitor beach environments and provide the accurate location of a possible drowning victim. Moreover, delivery drones can be used to provide life-buoys, cardiopulmonary resuscitation and automated external defibrillator (Claesson et al., 2017). Regarding the restricted time window in which medical products should be delivered, researches were conducted on several potential application of UAVs in the medical field. UAVs have been found efficient to deliver medical products that are perishable or not easy to stock in big quantities, such as blood products, (e.g. platelets, plasma and red cells), but also anti venom to hospitals and remote areas (Thiels et al., 2015). Other potential applications of drones for medical purposes concern the transport of vaccines in low- and middle-income countries (Haidari et al., 2016). Modelling the vaccine supply chain for the Gaza province, in Mozambique, they found that implementing a drone system could increase vaccine availability and decrease costs, once the high capital investments are overcome.

Transport
The state of research on drone delivery is still on its early stages. Practical trials have already been carried out by leader companies in the delivery sector, such as Amazon, Alibaba and Google (Agatz et al., 2018). Drones used for these trials were equipped with multi-propeller, being able to carry parcels of 2 kilograms for more than 20 kilometres. In 2014, the American company AMP Electric Vehicles together with the University of Cincinnati Department of Aerospace Engineering, developed a combined mode of truck and drone for last-mile delivery (Wohlsen, 2014). The challenges faced under a transportation planning perspective concerned both an assignment problem and a routing problem. The first one relates to the allocation of one vehicle (drone or truck) to a specific customer; the latter seeks for an optimal sequence of visits. The Aerospace Industries Association (AIA) forecasts that within 20 years, a large amount of cargo drones will be introduced in the market. Investments in research and development will rise from a few hundred millions USD to 4 billion USD by 2028 and 30 billion USD by 2036 (Warwick, 2018).

Civilian use
Civilian market refers to the use of drones for photography, surveillance, path recognition, racing and advertising purposes. The biggest portion of this business is controlled by the Chinese company DJI, which owns more that 75% of the entire market, with a 11 billion USD forecast for the year 2020, followed by the French company Parrot, with a 110 million USD global sales (Chavers, 2018).

C.2. Classification of drones

Drones can be categorised by their performance characteristics, such as weight, wing span, range, maximum altitude, speed, production costs and engine types, but also according to their purposes (Hassanalian and Abdelkefi, 2017). The following tables provide an overview of three different classifications, made according to different characteristics and purposes.

Purpose	Description
Target and decoy	Simulation of enemy aircraft or missile
Reconnaissance	Battlefield intelligence
Combat	Attack vehicle for high-risk missions
Logistics	Cargo delivery
Research and development	Improvements of UAV technologies
Civil and commercial	Agriculture, aerial photography, data collection

Table C.1: UAVs classification according to their purpose

C.3. Drone characteristics

When defining the characteristics of an autonomous vehicle, one of the most important aspects to look at are the vehicle system and the level of automation. The following paragraphs provide a description of the components that form a UAV, followed by the communication modules that can be used between the vehicle and the system and the level of automation.

Category	Altitude [m]	Range [km]
Hand-held	600	2
Close	1500	10
NATO type	3000	50
Tactical	5500	160
MALE	9000	200
HALE	9100	Indefinite

Table C.2: UAVs classification according to their range and altitude

Category	Weight [kg]
Micro air vehicles	Less than 0.001
Miniature UAVs	Less than 25
Heavy UAVs	More than 25

Table C.3: UAVs classification according to their weight

Components

Unmanned Aerial Vehicles are part of a bigger system (the Unmanned Aerial System), which controls a series of vehicles and provide data and communication with the ground service. The body of an UAV is composed by sensors, actuators and a computing power, all powered by an energy supplier. These components are in communication with each other, as well as with the entire system through a communication module. Figure C.1 provides a visual explanation of these relations. Unmanned Aerial Vehicles are usually part of an Unmanned Aerial System, with which they repeatedly communicate. All the components are positioned in an aircraft body, which is essentially similar to an aircraft body with no cockpit area and no windows (Fingas, 2016). The computing power was initially composed by analogue controls, then replaced with micro controllers, systems on a chip or single-board computers in more modern UAVs. System on a chip refers to a circuit that integrates all components of an electronic system, which can include destination- and application- specific routing. Single-board computers on the other hand, refer to complete computers that are built on a single circuit board. The energy supplier differs according to the dimension of the UAV. For big vehicles, conventional aircraft engines are used. For smaller vehicles, lithium-polymer batteries are used, which require less maintenance, a more environmentally friendly supply and a quieter flight (Brown, 2011). Sensor technology is important in order to connect the vehicle to the physical system. This connection is made through sensors and actuators. Sensors are devices that translate physical phenomena into electrical signals, whereas in opposition, actuators are devices that convert electrical signals into physical phenomena (Wilson, 2005). Unmanned aerial vehicles are equipped with different sensors and actuators. Among the sensor devices, position and movement sensors provide information about the vehicle state; exteroceptive sensors provide external information (e.g. distance measurements); exproprioceptive sensors compare internal and external states (Floreano and Wood, 2015). To avoid collisions and to assure the minimum space separation with external objects, non-cooperative sensors are used (Fasano et al., 2015). Non-cooperative sensors identify unknown targets without establish any communication with them, by comparing the position of the observed object with a database of potentially dangerous targets, determining the closest match (López-Rodríguez et al., 2015). Actuator devices are usually present in the form of digital electronic speed controllers. The interaction of sensors and actuators might follow an open loop or a closed loop control architectures. Open loop control systems do not provide any feedback from the sensor data, furnishing only the control signal that is required (e.g. faster, slower, left, right, up, down). In opposition, closed loop control systems incorporate to the control signal a sensor feedback to adjust the movement of the vehicle in a more precise manner (Bristeau et al., 2011).

Automation levels

The term automation refers to the ability to perform a sequence of tasks without human intercession, only relying on current state and sensing (ISO, 2012). The level of autonomy depends on the type of vehicle and on the intended use. As far as small UAVs are concerned, three possible levels of increasing

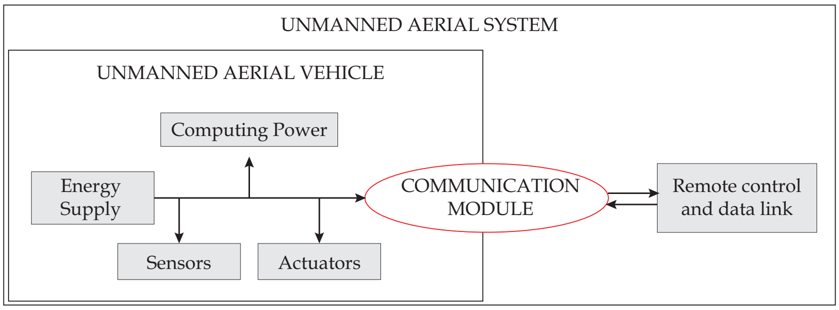


Figure C.1: UAV components

autonomy have been defined in Floreano and Wood (2015):

1. Sensor – motor autonomy: this type of autonomy translates human commands into control signals. Instructions such as reach a certain altitude, perform circular trajectory or maintain position are converted into control signals such as pitch, roll, yaw angle or speed.

2. Reactive autonomy: vehicles equipped with a reactive autonomy system can compare internal and external states, being thus able to maintain the current position in the presence of external perturbations or change the trajectory based on potential hazards, adverse weather conditions and whatnot. They can also interact with other moving objects and perform autonomous take-off and landing.

3. Cognitive autonomy: this last and highest level of autonomy characterises vehicles that can learn from the surrounding environment, meaning that they can perform simultaneous localisation and mapping, resolve conflicting information, plan for battery recharge and recognise objects.

According to the previous enumeration of the autonomy level, Table C.4 shows the features of UAVs related to the three different level of automation. Per level of automation, it is defined whether exteroceptive sensors are present, the level of computational load, whether a supervision is required, the level of readiness and which UAVs can be equipped with that autonomy (Floreano and Wood, 2015).

	Sensors	**Computation**	**Supervision**	**Readiness**	**Drone type**
1	None or few	Little	Yes	Deployed	All types
2	Few	Medium	Little	Partly deployed	Fixed wing
3	Several	High	None	Not yet deployed	Rotorcraft

Table C.4: Features of UAVs related to their automation level

The basic principle of autonomy is that control is achieved through a hierarchy of the system. The vehicle behaviour is decomposed into manageable states with known transitions. Different algorithms are then used to compute these system states and define the motion of the vehicle. The most used algorithms concern path planning, trajectory generation and trajectory regulation. Path planning defines the optimal path according to the mission objectives and the system constraints. Trajectory generation defines the control manoeuvre that must be adopted in order to follow the predefined path. Trajectory regulation provides the constraints to the vehicle motion, allowing for some tolerance. Possible algorithms that can be used for this hierarchical planning are tree search algorithm and genetic algorithm (Çekmez et al., 2014).

C.4. Drones for last-mile delivery

The state of research on drone delivery is still on its early stages. Practical trials have already been carried out by leader companies in the delivery sector, such as Amazon, Alibaba and Google (Agatz et al., 2018). Drones used for these trials were equipped with multi-propeller, being able to carry parcels of

2 kilograms for more than 20 kilometres.

In 2014, the American company AMP Electric Vehicles together with the University of Cincinnati Department of Aerospace Engineering, developed a combined mode of truck and drone for last-mile delivery (Wohlsen, 2014). The challenges faced under a transportation planning perspective concerned both an assignment problem and a routing problem, relating to the allocation of one vehicle (drone or truck) to a specific customer the first; and the optimal sequence of visits the latter.

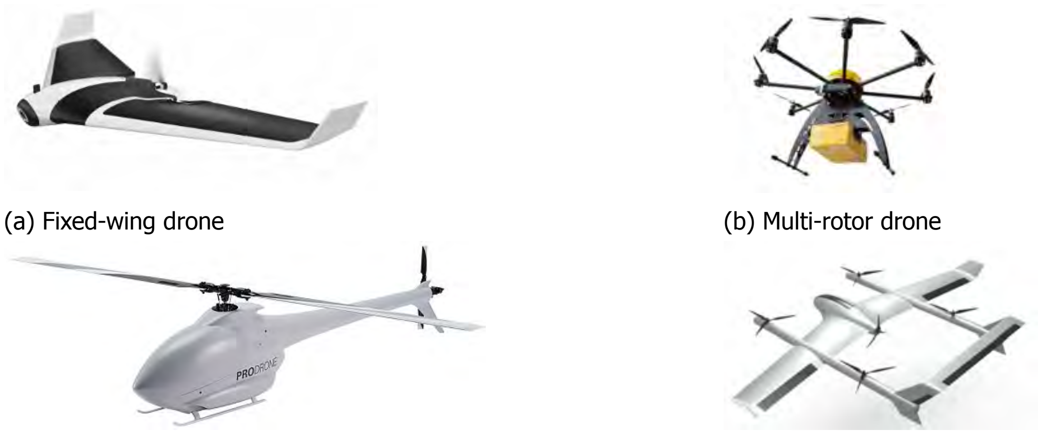
The Aerospace Industries Association (AIA) forecasts that within 20 years, a large amount of cargo drones will be introduced in the market. Investments in research and development will rise from a few hundred millions USD to 4 billion USD by 2028 and 30 billion USD by 2036 (Warwick, 2018)).
Different drones can be used for package deliveries. So far, two categories may be distinguished for drone delivery: fixed wing drones and rotorcraft drones (King, 2017). Among rotorcraft drones, multi rotor and single rotor drones can be found (Chapman, 2016). According to Chapman (2016), a third category of drones can be defined: fixed-wing hybrid drones.

Fixed-Wing drones have predetermined fixed aerofoil, which allows the drone to fly by means of forward airspeed, generated by forward thrust. The thrust is achieved by an internal combustion engine or, for electric drones, by an electric motor. Fixed wing drones have a simple structure, compared to other types of drones, which allows for less complicated maintenance and more efficient aerodynamics. These two factors ensure a lower cost for operational time and longer flight duration at higher speed. Moreover, the payload that these drones can carry is higher than other drone configurations. On the other hand, the disadvantages of fixed wing drones lie on the fact that they need a runway or a launcher for take-off and landing, and, while flying, they constantly need air moving over their wings. As a result, they might not be suitable for deliveries with dismal pick up and drop off areas, or in the case that the drone needs to stay stationary for a long period of time.

Rotorcraft drones are characterised by the presence of a rotor composed by two or three rotor blades that whirl around a fixed mast. The rotor provides the thrust needed to generate lift, making it unnecessary for the drone to have constant air movement. This means that the drone can stay in a standstill position for a certain period. The advantage brought by the rotor blades is the fact that they allow for vertical take-off and landing, without the need of a designated runway. On the other hand, they need a more complicated maintenance due to the greater mechanical and electronic complexity, which is translated into higher operation costs. Moreover, the speed and the flight range are lower than fixed wing drones. Multi-Rotor drones are characterised by the presence of more than one rotor blades. They have a limited endurance and speed; therefore, they are not suited for long distances (thus they might be not suitable for rural areas). Energy-wise they are considered to be inefficient, for they require a lot of energy only for fighting gravity. The allowed payload depends highly on the time range the drone must fly: with a max range of 20-30 minutes, the maximum payload is reduced to the one of a small camera. For higher payload, the flight time is considerably reduced (Chapman, 2016). Single-Rotor drones are characterised by only one rotor to hold them up, plus a tail rotor to control their heading. Given the presence of only one rotor blade, single-rotor drones are more efficient than multi-rotor drones. Moreover, compared to the other typology they can carry higher payloads. The downside is their high costs and vibration when flying, making then not suitable for fragile packages (Chapman, 2016).

Fixed-Wing Hybrid drones are fixed-wing drones that can land and take-off vertically. Their design is similar to the one of existing fixed-wing drones, with the addition of vertical motors bolted on. Their testing started during 1950's, with disastrous results. Recent technologies like modern autopilots, gyros and accelerometer are opening new possibilities for fixed-wing hybrid drones, making them feasible for package deliveries (Chapman, 2016). An example of fixed-wing hybrid drone is the self-flying delivery drone proposed by X Development in their X Wing Project for drone delivery of food, medical supplies and home delivery (XDevelopment, 2018). The most important characteristics that make this type of drone interesting from a last-mile delivery perspective, is the fuel efficiency, high precision and increased safety. Being completely powered by an electric system, they can fly up to 120 km/h on a maximum height of 120 meters, safely delivering the package to the intended destination (XDevelopment, 2018).

The following paragraph provides an overview of the advantages, disadvantages and applications of



(a) Fixed-wing drone

(b) Multi-rotor drone

(c) Single-rotor drone

(d) Fixed-wing hybrid drone

Figure C.2: Types of drones for last-mile delivery

the different types of drones mentioned above.

Fixed-wing drones

- Advantages: long endurance, large coverage, fast flying speed.
- Disadvantages: launch needs quite some space, expensive to purchase, vertical take-off and landing not possible.
- Applications: aerial photography, pipeline inspection.

Multi-rotor drones

- Advantages: accessibility, ease of use, vertical take-off and landing.
- Disadvantages: short flying times, small payload capacity.
- Applications: aerial photography, aerial inspection.

Single-rotor drones

- Advantages: long endurance, heavy payload capability, vertical take-off and landing.
- Disadvantages: dangerous because of the rotors, hard to pilot, expensive.
- Applications: aerial laser scanning.

Fixed-wing hybrid drones

- Advantages: vertical take-off and landing, long endurance flight.
- Disadvantages: still in development.
- Applications: deliveries

D

Flying with drones: insights on Dutch regulations

Drones are classified as airborne objects, and as such they fall within aviation laws. Being a recent innovation technology, regulations on drones are still on an early phase. New procedures will be applied a year from now, which makes it important to state what is nowadays in force and what will be implemented in the near future.Figure D.1 shows the map of The Netherlands with the outlines of the areas in which flying a drone is allowed (Rijksoverheid, 2018).

Figure D.1: Outline map flying with drones

Heliports, microlight fields, hang-glider fields and glider fields are denoted with an H, M, S and G respectively. Forbidden zones are highlighted in red, limited zones in orange and Natura 2000 zones in green. Natura 2000 zones refer to protected areas in which rare and threatened species are bred and kept safe (EuropeanCommission, 2018). It can be easily noticed that the amount of airspace in which flying a drone is permitted is quite restricted. Most of the airspace area is indeed already claimed by airports for passenger transport. In areas in which flying a drone is allowed, the current regulation sets a limit of 500 meters as maximum distance that can be flown (which corresponds to the sight distance).

Current regulations on drone use

As stated by the Ministry of Infrastructure, general rules regarding the authorisation to fly a drone are as follows (Rijksoverheid, 2018): drones can be flown only in daylight and up to a maximum of 120 meters high; drones cannot be flown above crowds, contiguous buildings, roads, railways, industrial and port areas; drones must give priority to aeroplanes, helicopters, floats, free balloons and airships. When using a drone for business purposes, the drone user must hold a flying permit, to ensure the safety of the flight and to minimise the risk of accidents, both in the air and on the ground (Rijksoverheid, 2018). Companies flying drones need a RPAS Operator Certificate (ROC). Light ROCs refer to drones up to 4 kilograms, whereas normal ROCs are intended for bigger drones, with a weight higher than 4 kilograms and a wider flying range.

Future regulations on drone use

To get insights on future regulations of drone transportation, interviews have been conducted throughout the research process. On the 7th of December an interview with Jeroen Bartelse, innovation manager of Achmea, was conducted. On the 27th of March 2019, a collective interview with Arjan van Vliet, innovation manager for the Ministry of Infrastructure and Water Management in Den Haag and Patrique Zaman, founder of Avy.

Regulations regarding flying drones are about to change in the coming years. The space in which will be allowed to fly a drone will increase, changing thus the aspect of the map in Figure D.1. Provided that drones remain within a height of 150 meters, the restriction will be limited only to the vicinity of airports. The range will also be extended, discarding thus the limitation of remaining within the sight distance of 500 meters (Bartelse, 2018). To implement these changes, new regulations will be created, both at a National and European level, involving the Dutch government and the European Aviation Safety Agency. Referring to Figure D.1, with future regulations it will be possible to fly over green zones (Natura 2000), provided that no take-off or landing procedures will be operated there, and that the noise produced by the drones is not disturbing nearby areas. Moreover, drones will be allowed to fly also on red zones, with special permissions based on risks and safety approaches, apart from military zones, royal houses and in line with airport runways (Vliet and Zaman, 2019).

D.1. Economy and insurance policies for drone use

To insure a vehicle means to know the risks associated with the use of that specific vehicle. When it comes to new technologies like drones, the risks are not known to the company that insures the object. Therefore, the first step for the insurance company is to bear the economic risk. After a time period of operation, the actual risks of flying a drone are known, allowing the company to define a specific cost for a specific drone. One of the biggest risks that can be associated with flying a drone, is linked to the possibility of the drone falling on the ground and injure a person. In that case, not only the merchandise that was delivered need to be reimbursed, but also the costs related to the gravity of the injure must be considered (e.g. in the case that the person injured is not able to work anymore, that person must be paid for the rest of his life). One way of reducing costs of insure a vehicle, is to reduce the risks associated to it and/or the severity of the injuries. An example that can be investigated when insuring a drone, is the installation of parachutes in the vehicle to mitigate the damage caused by a crash with the ground (Bartelse, 2018).

Different options are available when insure a fleet of drones for last-mile delivery: insure the whole fleet of drones over a time period, insure only one single drone over a time period or insure one single drone per single trip. According to Bartelse (2018), the third option is the preferred one, since it allows the company to adapt the insurance cost based on the delivery characteristics. The insurance cost depends indeed on several aspects and adapting this cost to each single trip may lead to substantial savings. These aspects are:

- Size and weight of the drone;
- Weather conditions during flight operations, e.g. wind category in which the drone is allowed to fly (in the case it can fly with very adverse conditions, the insurance cost might be higher);
- Value of the package to be transported and related content (i.e. if heavy drug is transported, the risk is higher);
- Territory over which the drone is flying. Flying over the sea leads to lower costs than flying over a densely populated area.

To properly consider each of the aforementioned aspects, it is necessary to insure one single drone per single flight. Weather conditions, value and content of the package and flown area change in every delivery, leading to potentially different insurance costs (Bartelse, 2018).

E

Stakeholder analysis

The most effective way of carrying out a stakeholder analysis is through the elaboration of a stakeholder matrix. Based on the metric of comparison, several matrices can be found in literature. The following paragraphs provide a brief description of the different elements of comparison that are related to each stakeholder matrix.

Ability - View matrix
This matrix maps the stakeholders' ability to impact the project and their view (positive or negative) on it, and it is also called business process management matrix. First proposed by Jeston and Nehlis (2014), it is used in project management to understand who is important for the engagement strategy and who could be a helpful assistant, who will be the leader and sponsor of the project. Figure E.1a shows an example of this matrix configuration.

Importance - Commitment matrix
This matrix, also called Stakeholder Influence grid, was proposed by Milosevic and Martinelli (2003) and it maps the level of commitment of each stakeholder compared to the importance of their support. Depending on their position on the grid, as portrayed in Figure E.1b, stakeholders are divided into Cheerleader, Strong Believer, Conscientious Objector and Fully On-Board.

Power - Support matrix
This type of analysis relates the power of every stakeholder to their support on the project. It was first introduced by Paul Roberts and its results are used to identify who is critical to a project's success. Depending on their position on the grid (Figure E.1c), stakeholders are divided into Hecklers, Supporters, Terrorists and Promoters. In the case that the top half of the grid is empty or with only few Members, it might be a sign that the project does not have sufficient sponsorship authority.

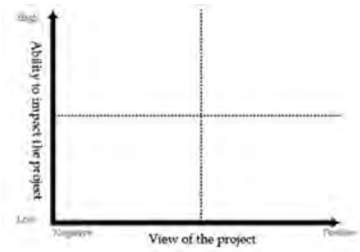
Power - Interest matrix
This analysis technique was first introduced by Eden and Ackermann (1998) and it focuses on the stakeholders who have an interest in a project and the power to strategically affect it. As can be seen in Figure E.1d, actors with the highest interest and the highest decision power are the Leaders and are the ones that play a significant role in the project management. Players are the stakeholders that despite the low interest, they have a high decision power; they must be considered in the planning phase and accordingly convinced.

Support - Importance matrix
Developed by Nutt (2002), this matrix arranges the actors in a grid according to their level of support and importance to the project. On the x axis, stakeholder importance is rate from 1 to 10, whereas on the y axis, the intensity of their expected opposition or support position is rated from 1 to 5. Figure E.1e shows an example of this matrix configuration.

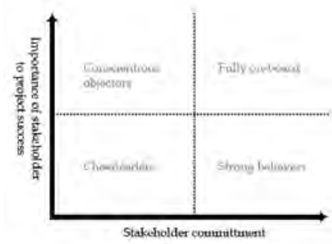
Influence - Interest matrix
The Influence – Interest matrix, developed by OGC (2007), measures stakeholders' influence and interest using a scale of high, medium or low, allocating thus each actor in one of the 9 possible square (Figure E.1f). Based to their position, stakeholders are classified according to their role in the project management: Key Players, Active Consultation, Maintain Interest and Keep Informed.

Attitude - Knowledge matrix

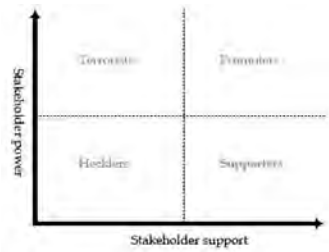
Elaborated by Turner (2016), the Attitude – Knowledge matrix assesses stakeholders' knowledge on a project and their attitude. For each actor, it is stated if it is ignorant or aware of the importance of the project, based on their knowledge, and whether it is in support or in opposition of it, based on their attitude. This matrix helps to define the measures to inform and/or change the attitude of specific stakeholders. An example is found in Figure E.1g.



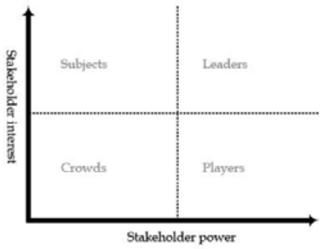
(a) Ability - View



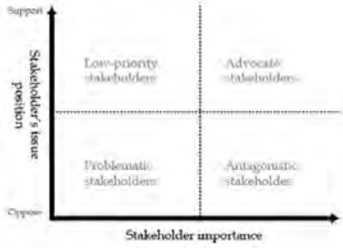
(b) Importance - Commitment



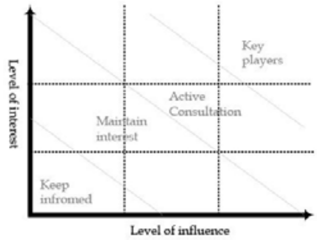
(c) Power - Support



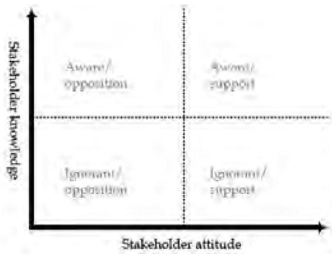
(d) Power - Interest



(e) Support - Important



(f) Influence - Interest



(g) Attitude - Knowledge

Figure E.1: Stakeholder matrices

E.1. Construction of the Power – Interest matrix

To describe the stakeholders involved in the project, it is decided to use the Power - Interest matrix from Eden and Ackermann (1998). The construction of the matrix begins with the definition of the people involved in the project. The following paragraph provides a list of actors, followed by the analysis of their tasks, interests, fears and influence. The actors involved in the process are:

1. BENU 't Slag: pharmacy that will introduce the fleet of drones in their home delivery service.
    - Task: provide the medicines;
    - Interest: provide a fast and reliable service, maintaining costs low;
    - Fear: loss in profit and customers' expectations;
    - Influence: if allowed, final decision whether to use drones or not.
2. BENU Apotheek franchising: the company that administrates all the BENU pharmacies across the Netherlands.
    - Task: provide the medicines;

- Interest: provide a fast and reliable service, maintaining costs low;
- Fear: loss in profit and customers' expectations;
- Influence: if allowed, final decision whether to use drones or not.

3. Delivery company Farma Clean and Service: the external company that provides the delivery service. Being the provider of vans, the company might be interested in investing in a fleet of drones for the near future.
   - Task: deliver medicines, deliver operation management, provide the fleet;
   - Interest: cost savings;
   - Fear: loss of delivery contracts, increase in expenses, loss in revenue;
   - Influence: can decide to rescind the contract.
4. Customers of BENU 't Slag pharmacy: people that usually buy their medical products from BENU 't Slag and that regularly have their products delivered at home.
   - Task: buy and receive the products;
   - Interest: have a fast, cheap and reliable delivery service;
   - Fear: addition of delivery price, damage of the products;
   - Influence: customer loyalty.
5. Population of Rotterdam: people that live in Rotterdam but currently buy their medical products in another pharmacy (that might or might not be part of the BENU franchising).
   - Task: -;
   - Interest: -;
   - Fear: nuisance and pollution caused by the delivery vehicles;
   - Influence: -.
6. Municipality of Rotterdam: legislator that gives the green light on the use of drones for last-mile delivery in the city of Rotterdam.
   - Task: provide regulations and policies;
   - Interest: operate according to the law, guarantee the best service to the population of Rotterdam;
   - Fear: loss in population trust;
   - Influence: decide whether or not flying with drones is permitted.
7. Other pharmacies in Rotterdam: other pharmacies that might or might not be part of the BENU franchising.
   - Task: provide medicines to other customers;
   - Interest: fair competition;
   - Fear: decrease in customers number due to a better service of BENU 't Slag;
   - Influence: -.

The second step involves the creation of two comparative matrices, one comparing each stakeholder based on their power, and one comparing them based on their interest. If a stakeholder has more power or interest than another stakeholder, a value of 1 is assigned; for equal power or interest, a value of 0.5 is assigned and, a value of 0 is assigned when the first stakeholder has less power or interest than the second one. For each stakeholder, a total value of power and a total value of interest is then assigned adding up their results. These total values will then be used to allocate the stakeholder in the power – interest matrix. In both matrices, values are read column-wise, therefore the actor in the column is compared with the actor in each row. The last row provides the total value of power and interest for each stakeholder.

Comparative matrix for stakeholder's power

Power	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	-	1	0	0	0	1	0
(2)	0	-	0	0	0	1	0
(3)	1	1	-	0	0	1	0
(4)	1	1	1	-	0.5	1	1
(5)	1	1	1	0.5	-	1	0.5
(6)	0	0	0	0	0	-	0
(7)	1	1	1	0	0.5	1	-
Total	**4**	**5**	**3**	**0.5**	**1**	**6**	**1.5**

Table E.1: Comparative matrix for stakeholder's power

Comparative matrix for stakeholder's interest

Interest	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	-	0.5	0.5	0	0	0	0
(2)	0.5	-	0.5	0.5	0	0	0
(3)	0.5	0.5	-	0	0	0	0
(4)	1	0.5	1	-	0	0	0
(5)	1	1	1	1	-	1	0.5
(6)	1	1	1	1	0	-	0
(7)	1	1	1	1	0.5	1	-
Total	**5**	**4.5**	**5**	**3.5**	**0.5**	**2**	**0.5**

Table E.2: Comparative matrix for stakeholder's interest

Combining the results obtained from the previous matrices, it is possible to obtain the power – Interest matrix shown in Figure E.2.

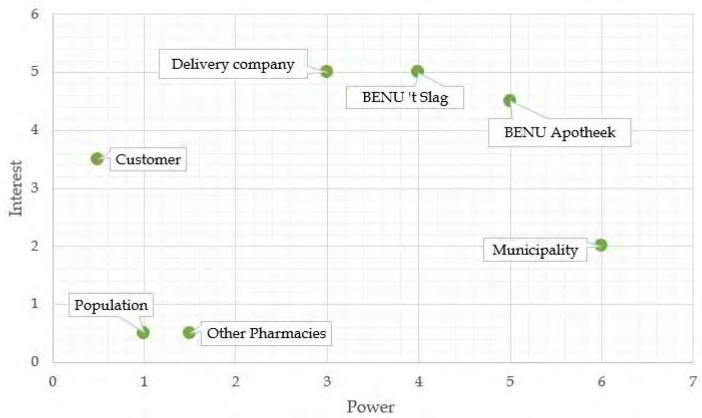


Figure E.2: Power - Interest matrix

F

Optimisation theories for last-mile delivery networks

In literature, several research studies can be found that elaborate different approaches for transport network optimisation. The starting point is to define a conceptual model that best represents an abstraction of reality. Given a set of location to be visited, the most common model formulations in operation research are the Travelling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP). For what concerns model implementation, several techniques are currently used, mostly depending on the size of the model. The following sections provide an overview of the mathematical models used in transportation research and the computer models that are mostly used to implement them.

F.1. Mathematical models for transport network optimisation

F.1.1 The Travelling salesman problem

The TSP is a non-deterministic problem within combinatorial optimisation, used in operation research to find the shortest path that connects a set of nodes, for which the order of visit is not important. It takes its name from the analogy of a salesman who, given a set of destinations, must visit each one of them starting from a certain node and ending at his starting location. The goal of the problem is to minimise the total length of the tour. The mathematical formulation of the TSP, shown in Table F.1, is found in Dantzig (2016). In this formulation, the objective function is to minimise the cost of visiting each node. The decision variable x_{ij} refers to the binary integer value that returns 1 if the path goes from node i to node j and zero otherwise. The combinatorial model involves n cities and it only allows path solutions that visit each node once and only once and that define a tour, i.e. a return to the initial node (Jenses, 2004). This type of path is called Hamiltonian path, with the specific characteristic that the start node is the same as the end node.

OF	$min \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} * x_{ij}$		
ST	$min \sum_{i=1}^{n} x_{ij} = 1$	$1 \leq j \leq n$	(1)
	$min \sum_{j=1}^{n} x_{ij} = 1$	$1 \leq i \leq n$	(2)
	$x_{ij} \geq 0$	$1 \leq i \leq n, 1 \leq j \leq n$	(3)

Table F.1: Mathematical formulation of the TSP

Adaptations of the TSP

Adaptations of the TSP that include drones in the vehicle fleet are found in Murray and Chu (2015) and Agatz et al. (2018). The following paragraphs provide a short description of these adaptations.

The Flying Sidekick TSP model adaptation considers a set of nodes that must be served at least once and only once by either a truck or a drone. In this configuration, drone and truck depart together from the depot and can either travel in tandem (with the drone transported by the truck) or independently, carrying out their deliveries simultaneously. This configuration is particularly useful when the average distance between the depot and the nodes to be served is higher than the drone's range. Solutions are found using heuristic approaches. Referring to the study conducted by Murray and Chu (2015), Figure F.1 provides a comparison between a truck-only network (left-hand side) and a tandem network (right-hand side) as described in the Flying Sidekick TSP. The gains in travel time are displayed in Figure F.2. The reduction is not very significant, with a return to the depot that is anticipated by only few minutes.

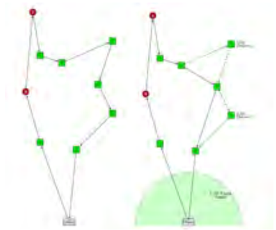


Figure F.1: Conventional truck-only mode compared to FSTSP (Murray and Chu, 2015)

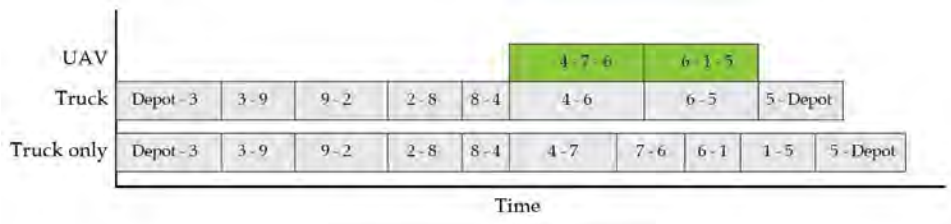


Figure F.2: Travel time gains using FSTSP. Adapted from Murray and Chu (2015)

In the case that the depot is in a convenient position with respect to the nodes to be served (i.e. within the flight range of the fleet of drones), the TSP can be modified into the PDSTSP (Parallel Drone Scheduling Travelling Salesman Problem). In the PDSTSP, a single delivery truck and a fleet of drones depart and return, with the truck serving customers along a TSP route and the drones serving customers directly from the depot. Being part of two different networks, no synchronisation is needed between van and truck. As in the previous formulation, solutions are found using heuristic approaches. Referring to the study conducted by Murray and Chu (2015), Figure F.3 provides a comparison between a truck-only network (left-hand side) and an asynchronous truck-drone network (right-hand side) as described in the Parallel Drone Scheduling TSP. In this formulation, the gain in travel time (Figure F.4) is much more visible compared to the FSTSP previously described. When compared to the FSTSP, the results of Murray and Chu (2015) show how the PDSTSP performs better compared to the FSTSP in terms of travel time gains.

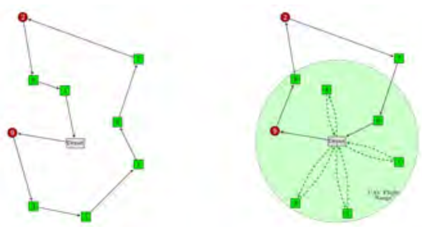


Figure F.3: Conventional truck-only mode compared to PDSTSP (Murray and Chu, 2015)

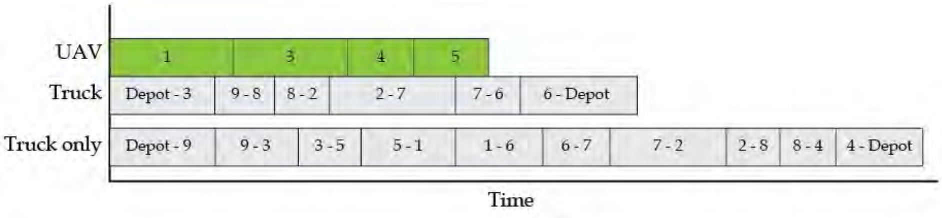


Figure F.4: Travel time gains using PDSTSP. Adapted from Murray and Chu (2015)

An evolution of the previous modification was proposed by Agatz et al. (2018), who based their formulation of the TSP Drone on the formulation of the Flying Sidekick TSP (FSTSP) of Murray and Chu (2015). In their paper of 2016, they claim that the FSTSP did not bring optimal solutions due to the mixed-integer formulation of the problem. Therefore, they proposed an integer formulation of the TSP for drone network (TSP Drone, or simply TSP-D), solved both with a greedy partitioning heuristic and with an exact partitioning algorithm.

F.1.2 The Vehicle Routing Problem

The Vehicle Routing Problem (VRP) is a combinatorial optimisation and integer programming problem, which generalises the TSP. The goal of the VRP is to define the optimal tour given a set of nodes and a fleet of vehicles, such that each node is visited at least once and only once, and the costs of operations are minimised. Another objective function that is commonly used in delivery network optimisation is the minimisation of the total number of vehicles needed to serve all customers (Toth and Vigo, 2002). The mathematical formulation of the VRP, shown in Table F.2, refers to the one provided by Fisher and Jaikumar (1978).

OF	$min \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} * x_{ij}$		
ST	$\sum_{k=1}^{m} y_{ik} = 1$	$1 \leq i \leq n$	(1)
	$\sum_{k=1}^{m} y_{ik} = m$	$i = 0$	(2)
	$\sum_{i=1}^{n} q_i * y_{ik} \leq Q_k$	$1 \leq k \leq m$	(3)
	$\sum_{j=0}^{n} x_{ijk} = y_{ik}$	$0 \leq i \leq n, 1 \leq k \leq m$	(4)
	$\sum_{i=0}^{n} x_{ijk} = y_{jk}$	$0 \leq j \leq n, 1 \leq k \leq m$	(5)
	$\sum_{i \epsilon S} \sum_{j \epsilon S} x_{ijk} \leq \lvert S \rvert - 1$	$S \subseteq 1, ..., n,\ 1 \leq k \leq m$	(6)

Table F.2: Mathematical formulation of the VRP

The objective function is to minimise the cost of the tour, by providing the cheapest possible sequence of nodes to be visited. The decision variable x_{ijk} can assume the value of 1 if customer j is visited immediately after customer i by vehicle k, and 0 otherwise. The variable y_{ik} defines whether customer i is visited with vehicle k. The capacity of the vehicles is limited by constraint 3, in which q_i indicates the demand at each node visited by vehicle k and Q_k the capacity of vehicle k. Constraint 6 guarantees that not sub tours are generated. A visualisation of the VRP is provided in Figure F.5.

Adaptations of the VRP

The VRP can be extended including more constraints to the model formulation. Examples of extensions that can be found in literature are:

- VRP with pick-up and delivery (VRPPD): goods are first moved from the retail shop to pick-up points and then to the delivery locations;

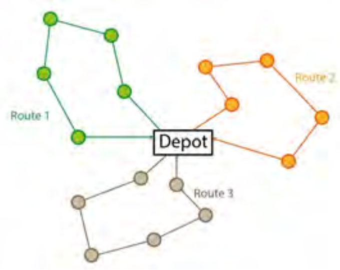


Figure F.5: Division of nodes into different routes for the VRP

- VRP with last in first out (VRPLIFO): the VRPPD is extended with another restriction that the first item to be delivered must be the last one that was picked up. This is usually used when the loading and unloading time at the delivery location is limited;
- VRP with multiple trips (VRPMT): vehicles are allowed to do more than one route in their tour;
- Open VRP (OVRP), vehicles do not have to return to the initial node (depot or retail store);
- VRP with time windows (VRPTW): used when deliveries have pre-arranged times for the delivery visit;
- Dynamic VRPTW (DVRPTW): extension of the VRPTW in which two types of customers are defined, the known customers and the new customers. Known customers refers to the ones that are already planned in the delivery schedule, while new customers refer to the one that call in and must be inserted in the existing route (Block, 2016);
- Capacitated VRP (CVRP), used in the case that the vehicles have a limited capacity.

Interesting for this research are the DVRPTW and the CVRP. In the case of mixed drone and van delivery, the decision of which vehicle to use depends also on the size of the package. Drones have a limited capacity, and can mostly deliver one package at a time, going back to the pharmacy before starting another delivery service. Furthermore, the fact that there can be situations in which an urgent delivery must be carried out, a dynamic model should be considered. In this extension of the VRP, the new node is added in the existing route and within a short time period a new route is computed (Block, 2016).

One other adaptation that can be found in literature is the VRP with heterogeneous fleet of vehicle (HVRP), as defined by Baldacci et al. (2008). In this variant, different types of vehicles are available for the deliveries, characterised by different capacities and different costs. In this sense, assignment decisions and routing decisions are optimised; the assignment model determines which vehicle of the available fleet will serve which customer; the routing model determines the sequence in which the customers assigned to each vehicle are visited. The model output provides an optimised set of routes with the most efficient vehicle to be used. The model description was first formulated in Li et al. (2007), and the suggested solution method in Taillard (1999).

F.1.3 Comparison between TSP and VRP and selected model formulation

The choice on which optimisation model to use and, in specific, which adaptation, is made based on the characteristics of the new transport network of combined vans and drones. Table F.3 shows a comparison of the model adaptations previously described. For each characteristics of the new network, it is assessed whether the model can account for it.

In the Vehicle Routing Problem, a set of nodes is given, each having a known service demand (which on a general case might be pick-up demand or delivery demand) as well as a set of vehicle with fixed capacity available to satisfy the service demand. The objective is to assign nodes to vehicles and specify the route order for each vehicle, maintaining the total cost of operation at minimum (Nelson et al., 1985). In case of unlimited vehicle capacity, given a set of *m* vehicles, the Vehicle Routing Problem problem is referred to as the m-Travelling Salesman Problem. The main substantial difference between the VRP and the TSP is then in the vehicle capacity restriction.

	TSP			VRP		
Characteristics	**FSTSP**	**PDSTSP**	**TSPD**	**DVRPTW**	**CVRP**	**HVRP**
New network	v	v	v	v	v	v
Restricted fleet	v	v	v	v	v	v
Non-sync fleet	x	v	x	x	x	v
Dynamic nature	x	x	x	v	x	x
Heterogeneity	x	v	v	x	x	v
Different veh costs	v	v	v	x	x	v
Different veh capacity	x	x	x	x	v	v
Vehicle restrictions	x	x	x	x	x	x

Table F.3: Comparison of the optimisation models and their adaptations

Selected model formulation

Given the network requirements for the case study of BENU 't Slag, the model formulation of the VRP is chosen, with the adaptation of heterogeneous vehicle fleet and capacity and working time restrictions.

The Vehicle Routing Problem can be described using graph theory, with a partition of the nodes of the network into nodes set and arcs set, with the aim of finding the optimal sequence of nodes visit such that each node is visited, demand does not exceed vehicle capacity, cost is minimised and each vehicle starts and ends its tour at the depot (Pop et al., 2011).

Let $G = (V', A)$ be a directed graph, where $V' = \{0, 1, 2, ..., n\}$ is the set of $n + 1$ vertices and $A = \{(i, j) \mid i, j \in V,\ i \neq j\}$ is the set of arcs. To each arc (i, j) a non-negative cost c_{ij} and a non-negative travel time t_{ij} is associated. Each customer i requires a supply of q_i units from the depot 0, which is satisfied using a fleet of m vehicles type k of capacity Q_k. A route is defined as a least cost elementary cycle $R = (0, i_1, i_2, ..., 0)$ of graph G, starting and ending at the depot, in such a way that the total demand of visited customers does not exceed vehicle capacity. The total cost of route R is equal to the cost of the solution of the VRP having the set R of vertices.

F.2. Model implementation for the VRP

To implement the mathematical formulation of the Vehicle Routing Problem, several approaches can be used. The VRP belongs to the category of NP-complete problems, a *class of computational problems for which no efficient solution algorithm has been found* (EnciclopediaBritannica, 2019). For this reason, exact algorithms can be used to obtain true optimal routes only up to 30 nodes. In case of more than 30 nodes, heuristic algorithms must be used (Nelson et al., 1985).

F.2.1 Exact algorithms for VRP implementation

An example of exact algorithm is the Branch-and-Bound algorithm. Being firstly introduced in 1960 by Ailsa Land and Alison Doig, the BnB algorithm is used to solve discrete and combinatorial optimisation problems, using a systematic enumeration of candidate solutions by means of state space search (Land and Doig, 2010). The iterations are seen as forming a tree, which branches represent subsets of the solution set. At each iteration, feasible sets are broken up into successively smaller subsets, for which the upper and lower bounds of the objective function are calculated and used for discard certain subsets from further consideration, in case they cannot produce a better solution than the best one already found (Van Essen, 2017).

F.2.2 Heuristic algorithms for VRP implementation

Several types of heuristic algorithms are found in literature. Pop et al. (2011) define two types of heuristic algorithms to solve the Vehicle Routing Problem: constructive heuristics and improvement heuristics.

Constructive heuristics. Constructive heuristics gradually build a feasible solution, while minimising the solution cost.The construction method is based either on the nearest, the farthest or the cheapest neighbour, depending on the criteria used for the selection method. In all cases, constructive heuristics can fail to provide the best optimal solution, given the greedy nature of their algorithms.

Improvement heuristic. Improvement heuristics aim to obtain a feasible solution upgrading the previous one obtained, by changing the sequence of edges within or between vehicle routes. Improvements come from a neighbourhood search process, for which each route is associated with a neighbourhood, and better solutions are sought within that specific neighbourhood. Examples of improvement heuristics are the 2-opt, 3-opt, etc. In the first case, two connections are deleted in the network, to create other two sub-tours. The different ways of reconnecting the edges are then analysed, and the optimum one is chosen. The same process is repeated for an other pair of connections, until all possible combinations have been analysed. For what concerns 3-opt algorithm, the same procedure is followed, analysing three connections per time instead of two.

F.2.3 Metaheuristic algorithms for VRP implementation

Metaheuristic algorithms are a category of modern heuristics that are used for generate or select the best heuristic method to solve an optimisation problem, providing a sufficiently good solution in case of imperfect information or limited computation capabilities (Balamurugan et al., 2015). Global optimal solution is not guaranteed, given the fact that this type of solution approach relies on assumptions about the optimisation problem to be solved (Blum and Roli, 2003). Furthermore, to find a sufficiently good solution in case of imperfect information, metaheuristics implement a stochastic optimisation, generating a random set of variables and solving the problem for that specific set; in this way, the solution is highly dependent on the chosen variables, which contributes to the reasons why global optimal solution is not guaranteed (Bianchi et al., 2009).

According to Laporte et al. (2000), six types of metaheuristics can be used to solve the VRP: Simulated Annealing (SA), Deterministic Annealing (DA), Tabu Search (TS), Genetic Algorithm (GA), Ant System (AS) and Neural Networks (NN). For what concerns SA, DA and TS, starting from the initial solution x_1, each iteration t is characterised by a starting solution x_t and provides a new solution x_{t+1}, which belongs to the neighbour $N(x_t)$ of the starting solution x_t. Cost improvements are not guaranteed, thus the model developer must check for cycle solutions. Genetic algorithm takes its name from the genetic evolution of species; it considers at each iteration a population of solutions derived from previous iterations by combining their best elements and getting rid of the worst. Ant system is a probabilistic constructive approach that finds the optimal path to be followed through graph theory, inspired by the behaviour of real ants (Monmarché et al., 2010). In each iteration, several new solutions are created as a result of information gathered at previous iterations. Lastly, neural networks are a learning mechanism that base their solution on previous results, gradually adjusting the outcome values or implementation mechanism until an acceptable solution is reached. Implementation mechanism are searching rules are specific to the optimisation problem that is considered.

G

Cost model of different alternatives

In this research, the development of a cost model is carried out to define the costs associated with each network alternative, to help analyse the feasibility of introducing drones in the last-mile logistics of the pharmaceutical sector.

In this model, costs are divided into investment costs and exploitation costs and are assessed on a yearly scale. Investment costs relate to the amount of money spent for the expenditure needed to operate the network. To translate these amounts into yearly costs, a depreciation period of 5 years is defined. Exploitation costs refer to all the components that contribute to the final expenses based on the utilisation rate. A third element is added to the total annual costs, referred to as "other costs". In this category are included all the components for which insufficient data are available as well as the cost components which contribute is extremely low compared to the overall cost.

Investment costs

- Storage area: area of the pharmacy where products ready to be delivered are stored. Its cost is calculated assuming that a tot% of the total pharmacy area is dedicated to the storage unit (Numbeo, 2019);
- Handling equipment: machinery needed to assist the drivers during loading procedures. An example of handling equipment is the two-wheeled trolley found in LiftingEquipment (2019);
- Drone piloting area: small office dedicated to the drone operations, where the drone pilot can remotely fly the drone. Its cost is calculated assuming that a tot% of the total pharmacy area is dedicated to the storage unit (Numbeo, 2019);
- Parking location: place where vans are parked when not in service and loaded before staring the delivery visits. The cost is defined by assuming that each van occupies a total of 7.2 m^2 (Mercedes-Benz, 2018), and needs the same amount for loading (Numbeo, 2019);
- Cost of purchasing a van: list price of the van currently used (Mercedes-Benz, 2018);
- Cost of purchasing a drone: list price of X8 Long Range Cargo Drone (UAV, 2019);
- License to operate: for certain categories of drones, a flying license is required from the remote pilot. In this case, given the size and the permitted payload, the person responsible for drone operations must hold a plying license (UAVCoach, 2019);
- ATM purchase: cost of purchase and installation of a built-in/ through the wall ATM machine (CostOwl, 2019).

Exploitation costs

- Fees for outdoor sale: when an ATM machine is installed, companies have to pay a monthly fee to be able to sell their product outdoor, directly to customers (CostOwl, 2019);
- Van driver: hourly salary of a delivery driver, retrieved from Glassdoor (2019);
- Drone pilot: hourly salary of a drone pilot, estimated after the interview with Vliet and Zaman (2019);

- Operation management: cost of a route and fleet planner. For this cost element, the average yearly salary of a transportation planner is considered (Payscale, 2019);
- Insurance cost of vans: cost of insuring one van Mercedes Citan 108 cti (Mercedes-Benz, 2018);
- Insurance cost of drones: cost of insuring a drone. According to UAVCoach (2019), drones can be either insured on an annual base or on-demand. For a 1 million in liability, prices range between 440 – 700 euro/year for a commercial insurance or 4.40 – 8.80 euro/hour for an on-demand drone insurance. Given the expected utilisation of a drone (1 hour per day, see Table G.1), it is believed that a commercial yearly insurance is less expensive;
- Tax on van purchase: each vehicle registered in the Netherlands is subjected to a taxation fee. According to Belastingdienst (2019), for a vehicle with diesel engine this tax fee is equal to 37.7% of the net list price plus 273 euro;
- Tax on drone purchase: given the lack of data on drone tax fees, it is assumed that the same percentage of net list price that is applied for van's taxation is also applied on drones. Therefore, drone tax fee is considered to be equal to the 37.7% of the total purchase cost of the drone;
- Operational costs for vans: cost of fuel consumption. It is assumed an average value of 1.33 euro/litre for the diesel price (GlobalPetrolPrices, 2019) and a consumption rate of 5 litre/100km (Mercedes-Benz, 2018);
- Operational costs for drones: cost of energy consumption. It is assumed an average value of 0.1024 euro/kW for the electricity price (MainEnergie, 2019) and a consumption rate of 0.26 kW/h (UAV, 2019);
- Financial costs: costs pertaining the interests on the loan. For a financial loan of an amount bigger than 50,000 euros, with a payment depreciation of less than 7 years, the current interests are set to 7.75% (FitSmallBusiness, 2019).

To calculate the total value for the operational costs of drones and vans, some assumptions are made regarding the vehicle utilisation. For the first situation, when only vans are used for delivery and no ATM machine is provided, it is assumed a total of 6,300 km per van per year, and a corresponding total of 630 hours per van per year. After the introduction of the ATM machine, the new value for the yearly kilometre travelled is found using the monthly price paid by the pharmacy to the delivery company. Before the introduction of the ATM, the pharmacy paid a fixed amount of 10,218 euro per month to the company that provides the home deliveries; after the introduction of the ATM, this amount was reduced to 9,705 euro per month. Therefore, it can be assumed that a 5% reduction on the distance travelled occurred as a consequence of the ATM installation. A new value of 5,985 km per van per year is assumed, with a corresponding value of 598 hours per van per year. For what concerns the drone utilisation, the assumed values are retrieved from the drone space and time limitations (UAV, 2019); consequently, a yearly amount of 1,008 km and 252 hours of flight time is considered. These values are visually summarised in the table below.

Table G.1: Vehicle utilisation for the 3 analysed situations

G.1. Cost models for different alternatives

Figure G.1: Cost model before the introduction ATM, fleet of vans

Figure G.2: Cost model after the introduction of ATM, fleet of vans

Figure G.3: Cost model after the introduction of ATM, fleet of vans and drones

G.2. Cost model for scenario with only electric vehicles

Figure G.4: Cost model for test scenario with only EVs

Table G.2: Comparison of fixed and variable costs for test scenario with only EVs

G.3. Cost model for scenario with only drones

Table G.3: Vehicle utilisation for the test scenario with only drones

Figure G.5: Cost model for the test scenario with only drones

Table G.4: Fixed and variable costs for test scenario with only drones

H

Solution approach with VRP Excel spreadsheet solver

Current situation

Figure H.1: VRP spreadsheet Solver Control for 14 node implementation

Figure H.2: VRP spreadsheet locations for 14 node implementation

Figure H.3: VRP spreadsheet vehicle characteristics for 14 node implementation

Future scenario

Figure H.4: VRP spreadsheet Solver Control for 14 node implementation with drones

Figure H.5: VRP spreadsheet vehicle characteristics for 14 node implementation with vans and drones

Model verification

Figure H.6: VRP spreadsheet Solver Control for code verification test

Figure H.7: VRP spreadsheet location for code verification test

Figure H.8: VRP spreadsheet vehicle characteristics for code verification test

Figure H.9: VRP spreadsheet node location for calculation verification test

I

Solutions of model verification, validation and implementation

This chapter contains the solutions of the model verification, model validation and model implementation. Output values of the Excel Solver are copied directly from the spreadsheet, thus have the same visualisation interface. Cells characterised with a black background are fixed and will not change varying the initial inputs. Cells with a light blue background show the routing sequence of customers. To satisfy constraint 2 of the model formulation (see Table 6.1), each sequence must end with a visit back to the depot (BENU 't Slag). Cells with a yellow background refer to the output of the model, and provide the values that are used for the KPIs evaluation. In case a non-feasible solution is found, the visual feature of the model provides an orange frame for the routing sequence in the map and a red background for the cells in the solution table.

I.1. Model verification

The following sections provide the results of the model verification. Verification tests consist in code verification and calculation verification. For the first one, computational results on benchmark instances provide the code developer test, to check whether the code of the model returns acceptable results, whereas a sample implementation of a Vehicle Routing Problem for 10 cities in the United Kingdom provides the model developer test, to check whether the implementation made by the modeller is correct. For the calculation verification, numerical results obtained with the Excel Spreadsheet solver are compared with analytical results obtained with the Farthest Insertion Heuristic algorithm.

I.1.1 Code verification

Code developer test

Figure I.1 shows the results on benchmark instances that can be found in Erdoğan (2017). Results for seven implementations of the CVRP and seven implementation of the DCVRP using the Excel Spreadsheet Solver are compared with best known solution values.

Instance	Number of	Fleet size	Vehicle	Distance	Best known	VRP Spreadsheet Solver			
name	customers		capacity	limit	solution value	Average	Average gap	Best	Best gap
vrpnc1	50	5	160	N/A	524.61	**524.61**	**0.00%**	**524.61**	**0.00%**
vrpnc2	75	10	140	N/A	835.26	840.67	0.65%	**835.26**	**0.00%**
vrpnc3	100	8	200	N/A	826.14	841.05	1.80%	831.28	0.62%
vrpnc4	150	12	200	N/A	1028.42	1052.22	2.31%	1040.81	1.20%
vrpnc5	199	17	200	N/A	1291.29	1341.19	3.86%	1323.08	2.46%
vrpnc6	50	6	160	200	555.43	556.77	0.24%	**555.43**	**0.00%**
vrpnc7	75	11	140	160	909.68	913.13	0.38%	**909.68**	**0.00%**
vrpnc8	100	9	200	230	865.94	876.40	1.21%	**865.94**	**0.00%**
vrpnc9	150	14	200	200	1162.55	1181.77	1.65%	1170.81	0.71%
vrpnc10	199	18	200	200	1395.85	1435.27	2.82%	1415.02	1.37%
vrpnc11	120	7	200	N/A	1042.11	1047.82	0.55%	1047.61	0.53%
vrpnc12	100	10	200	N/A	819.56	821.29	0.21%	821.29	0.21%
vrpnc13	120	11	200	720	1541.14	1565.01	1.55%	1554.51	0.87%
vrpnc14	100	11	200	1040	866.37	886.41	2.31%	869.96	0.41%

Figure I.1: Computational results on benchmark instances (Erdoğan, 2017)

Model developer test

The results for the code verification of the test implemented with the 10 locations in the United Kingdom are here displayed with the model output interface of the Excel Spreadsheet Solver. Solutions obtained are compared with the ones provided in Erdoğan (2017), to check whether implementing the same optimisation problem with the same input values provides similar, if not equal, results.

Total net profit:	-1572,24							
Vehicle:	V1 (Minibus)	Stops:	4	Net profit:	-407,93			
Stop count	Location name	Distance travelled	Driving time	Arrival time	Departure time	Working time	Profit collected	Load
0	Depot	0,00	0:00		08:00	0:00	0	0
1	Customer 10	95,06	1:14	09:14	09:14	1:14	0	0
2	Customer 3	212,25	2:35	10:35	10:35	2:35	0	0
3	Customer 7	342,79	3:53	11:53	11:53	3:53	0	0
4	Depot	407,93	4:48	12:48		4:48	0	0
5								

Vehicle:	V2 (Minibus)	Stops:	3	Net profit:	-292,44			
Stop count	Location name	Distance travelled	Driving time	Arrival time	Departure time	Working time	Profit collected	Load
0	Depot	0,00	0:00		08:00	0:00	0	0
1	Customer 4	128,38	1:30	09:30	09:30	1:30	0	0
2	Customer 5	159,33	1:58	09:58	09:58	1:58	0	0
3	Depot	292,44	3:30	11:30		3:30	0	0
4								

Vehicle:	V3 (Midibus)	Stops:	2	Net profit:	-267,78			
Stop count	Location name	Distance travelled	Driving time	Arrival time	Departure time	Working time	Profit collected	Load
0	Depot	0,00	0:00		08:00	0:00	0	0
1	Customer 6	107,17	1:21	09:21	09:21	1:21	0	0
2	Depot	214,23	2:43	10:43		2:43	0	0
3								

Vehicle:	V4 (Midibus)	Stops:	5	Net profit:	-604,09			
Stop count	Location name	Distance travelled	Driving time	Arrival time	Departure time	Working time	Profit collected	Load
0	Depot	0,00	0:00		08:00	0:00	0	0
1	Customer 8	154,89	1:47	09:47	09:47	1:47	0	0
2	Customer 1	193,86	2:23	10:23	10:23	2:23	0	0
3	Customer 2	237,82	3:05	11:05	11:05	3:05	0	0
4	Customer 9	380,58	4:41	12:41	12:41	4:41	0	0
5	Depot	483,27	5:56	13:56		5:56	0	0
6								

Vehicle:	V5 (Bus)	Stops:	0	Net profit:	0,00			
Stop count	Location name	Distance travelled	Driving time	Arrival time	Departure time	Working time	Profit collected	Load
0	Depot	0,00	0:00		08:00	0:00	0	0
1								
2								

Figure I.2: Output of code verification for model development

I.1.2 Calculation verification

Customer locations that are used for the calculation verification are randomly chosen between the 14 ones served by the pharmacy. The chosen locations are postcodes number 3085, 3078, 3077, 3083 and 3072 with a demand of 8, 7, 8, 9 and 6 products respectively.

From Google Maps real distances, it is possible to compute the distance matrix between each node in the network, shown in Table I.1, for which values are expressed in kilometre. Using the equation $cost_{ij} = distance\ cost * distance_{ij}$ the cost matrix is computed using the distance matrix and the distance cost values (Table I.2). These inputs are used in both calculation techniques in the verification test: numerical results are obtained with the VRP Excel Spreadsheet Solver, whereas analytical results are obtained with the Farthest Insertion Heuristic algorithm.

	D	1	2	3	4	5
D	0.00	2.35	3.45	10.15	1.96	2.99
1	3.44	0.00	5.23	11.40	3.25	4.53
2	5.30	5.16	0.00	3.71	5.63	5.12
3	7.92	6.81	3.16	0.00	11.11	7.54
4	1.77	3.08	5.22	12.07	0.00	2.86
5	2.98	5.54	5.05	11.75	2.98	0.00

Table I.1: Distances between nodes for calculation verification test

Table I.2: Cost between nodes for calculation verification test

VRP Excel Solver

The solution of nodes sequence and the associated cost are displayed in Figure I.3, showing the Excel interface output of the numerical calculation verification. The outputs of the VRP Excel Spreadsheet solver provide a total cost of operation equal to euro, with the node sequence to be visited being D - 2 - 3 - 1 - 4 - 5 - D (visualised in Figure I.4. The total time spent on the network is equal to , and the total distance covered is km.

Figure I.3: Output of calculation verification using the Excel Spreadsheet Solver

Figure I.4: Routing solution for calculation verification using the VRP Excel Solver

Farthest Insertion Heuristic algorithm

The first step to implement the FIH algorithm is define the cost matrix. The cost matrix is based on the distance matrix, according to the equation for the total cost of operation $cost_{ij} = dixed\ cost + distance\ cost * distance_{ij}$. Distance matrix and cost matrix are found in Table I.1 and Table I.2 respectively. Using the cost matrix as input, it is possible to proceed with the algorithm iteration. Table I.3 shows the steps for the iterations. Each cell contains the distance (in kilometre) between the selected node of the iteration and each node in the network. The distance in the matrix is chosen according to the minimum distance present in the column, in other words $d_{ij} = min(d_{ij,iter}; d_{ij,iter-1})$. The node corresponding to the highest distance is selected for the next iteration.

Table I.3: Farthest Insertion Heuristic algorithm iterations

For iterations 3 to 6, the insertion of the node is based on the cost minimisation criterion. Being i and j the initial nodes, the selected node k is inserted such that $d_{ik} + d_{kj} - d_{ij}$ is minimal. Figure I.6 shows a visual representation of the cost minimisation criterion, where the bottom vertices of the triangles indicate the existing nodes and the top vertex indicates the node to be inserted.

The output of the Farthest Insertion Heuristic algorithm provides a total cost of operation equal to [redacted] euro, with the node sequence to be visited being: D - 2 - 3 - 1 - 4 - 5 - D. The routing solution is visualised in Figure I.5.

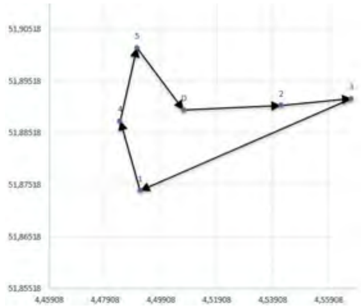


Figure I.5: Routing solution for calculation verification using FIH algorithm

(a) Minimisation criterion iteration 3

(b) Minimisation criterion iteration 4

(c) Minimisation criterion iteration 5

(d) Minimisation criterion iteration 6

Figure I.6: Minimisation criterion for Farthest Insertion Heuristic algorithm

I.2. Model validation

I.2.1 Extreme condition test

The solution of node sequence, fleet allocation and associated costs for the extreme condition validation test are displayed in Figure I.7 and Figure I.7. In case a feasibility issue is reported, a warning sign with orange background is displayed, and the not feasible values are marked with a red background cell. This is the case for the extreme condition test with parameters approaching to infinity, for which the capacity of the given fleet is not enough to transport the mandatory delivery.

Parameters set to zero

As expected, total cost of operation is equal to zero, and the vehicle fleet is reduced to only 2 vans, with most of the deliveries carried out by the first van.

Figure I.7: Output of model validation - extreme condition test with parameters set to zero

Parameters approaching infinity
Not feasible values are found due to capacity restriction, with a very high cost of operations.

Figure I.8: Output of model validation - extreme condition test with parameters approaching infinity

I.3. Model implementation

The following sections provide the results of the model implementation. Results are divided per customers density, firstly with 14 delivery points, then 28, 56 to eventually finish with 112. For each demand distribution, output values for the current situation are followed by the output values for the future configuration.

The total cost of operations is found in the upper left corner of the table. For each vehicles, the number of stops and the total cost is provided, together with the distance travelled, the driving time and the total service time.

I.3.1 14 customers

Current situation

Figure I.9: Output of model implementation for current situation, 14 customers

Future configuration

Figure I.10: Output of model implementation for future configuration, 14 customers

I.3.2 28 customers

Current situation

Figure I.11: Output of model implementation for current situation, 28 customers

Future configuration

Figure I.12: Output of model implementation for future configuration, 28 customers

I.3.3 56 customers

Current situation

Figure I.13: Output of model implementation for current situation, 56 customers

Future configuration

Figure I.14: Output of model implementation for future configuration, 56 customers

I.3.4 112 customers

Current situation

Figure I.15: Output of model implementation for current situation, 112 customers

Future configuration

Figure I.16: Output of model implementation for future configuration, 112 customers

I.4. Sensitivity analysis

Sensitivity analysis aims to find the influence of input parameters on Key Performance Indicators. In the following paragraphs the results of the analysis are explained, linking changes in vehicle speed, vehicle capacity, distance limit and working time limit to the delivery cost per item, the average service time, the fuel consumption and the vehicle utilisation.

I.4.1 Influence of vehicle speed

The first set of runs consists in varying the average vehicle speed. Table I.4 shows the output values obtained after 6 implementations with 6 different values of average speed. Figure I.17 shows the trend of each KPIs related to vehicle speed variations.

Veh. speed	Cost per item	Service time	Fuel cons.	Utilisation
10 km/h				
20 km/h				
35 km/h				
45 km/h				
55 km/h				
70 km/h				

Table I.4: Influence of vehicle speed on KPIs

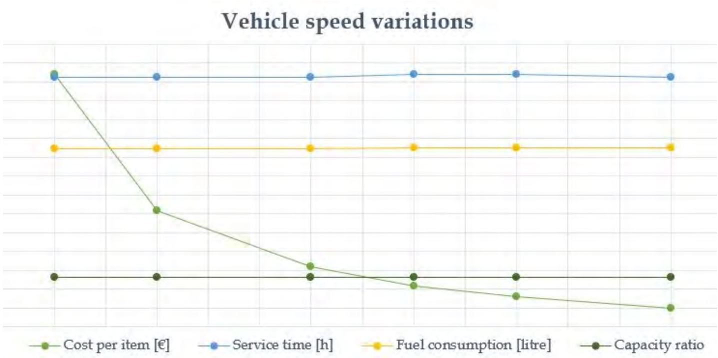


Figure I.17: Influence of vehicle speed on KPIs

I.4.2 Influence of vehicle capacity

This second set of runs consists in varying the average vehicle capacity. Table I.5 shows the output values obtained after 6 implementations with six different values of vehicle capacity. Figure I.18 shows the trend of each KPIs related to vehicle capacity variations.

Veh. capacity	Cost per item	Service time	Fuel cons.	Utilisation
35 units				
40 units				
50 units				
70 units				
90 units				
105 units				

Table I.5: Influence of vehicle capacity on KPIs

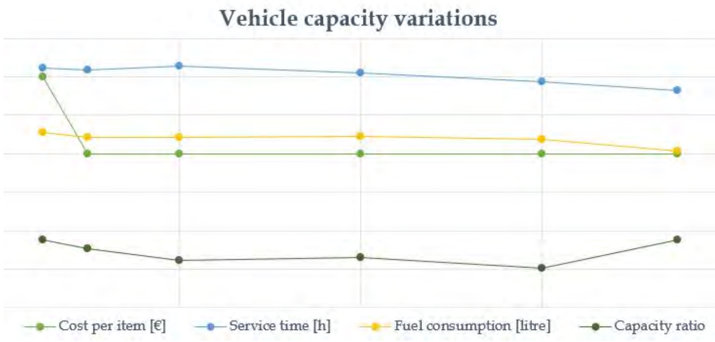


Figure I.18: Influence of vehicle capacity on KPIs

I.4.3 Influence of distance limit

The third set of runs consists in varying the distance limitation. Table I.6 shows the output values obtained after 6 implementations with six different values of distance limit. Figure I.19 shows the trend of each KPIs related to vehicle capacity variations.

Max distance	Cost per item	Service time	Fuel cons.	Utilisation
19 km				
20 km				
25 km				
50 km				
100 km				
200 km				

Table I.6: Influence of distance limit on KPIs

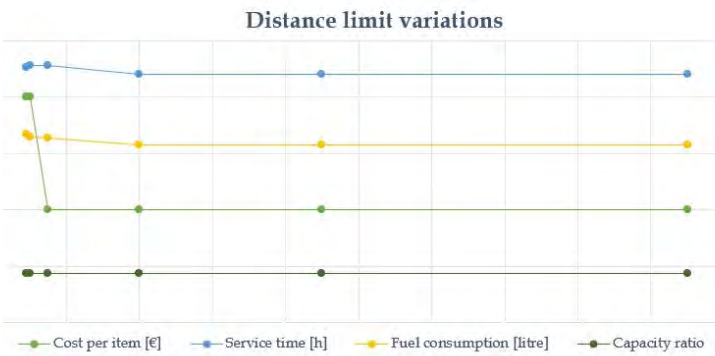


Figure I.19: Influence of distance limit on KPIs

I.4.4 Influence of working time limit

The last set of runs consists in varying the working time limitation. Table I.7 shows the output values obtained after 9 implementations with nine different values of time limit. Figure I.20 shows the trend of each KPIs related to vehicle capacity variations.

Working time	Cost per item	Service time	Fuel cons.	Utilisation
90 minutes				
120 minutes				
150 minutes				
180 minutes				
210 minutes				
260 minutes				
340 minutes				
400 minutes				
480 minutes				

Table I.7: Influence of working time limit on KPIs

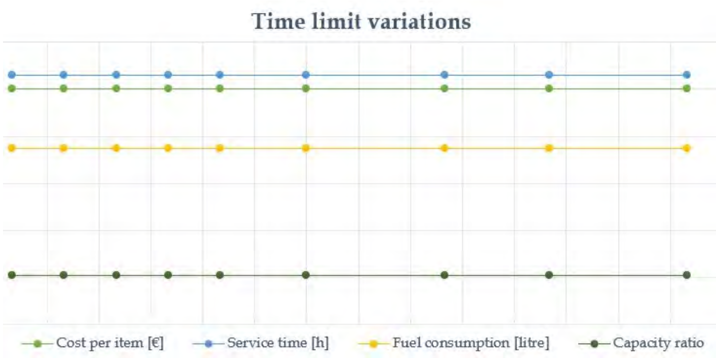


Figure I.20: Influence of working time limit on KPIs

J
Scientific Academic Paper

This chapter contains the scientific academic paper that was written as part of the documents for the graduation process. It was decided to keep it in the original format.

Introduction of drones in the last-mile logistic process of medical product delivery:
A feasibility assessment for the case study of Benu ’t Slag

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Abstract

The term last-mile delivery refers to the final leg of a business-to-customer service, in which a product is shipped from a depot to a final destination point by means of land transportation, such as vans and small trucks. Although they provide a common and easy way to consign products, companies are striving for new transport technologies to reduce congestion problems, infrastructure limitations and air pollution. Recently, a valid alternative to road-bounded vehicles that is has gained attention is the adoption of drones in the delivery fleet. Drone applications range from military training, surveillance, path recognition and shipment of perishable products in emergency situations. Research on drones as delivery vehicles is still on its early stages, with some practical trials carried out by leader companies such as Google and Amazon. However, the application of drones in the pharmaceutical sector, and specifically for home deliveries of medical products, has not been investigated yet. To gain new insights into the feasibility of introducing drones in the delivery fleet composition, drone applications were studied for the delivery operations of the pharmacy BENU t Slag, in Rotterdam. Two scenario alternatives were tested using the Vehicle Routing Problem (VRP) formulation and a Large-scale Neighbourhood Search (LNS) algorithm was implemented to estimate the performance indicators associated with each scenario. Performances were then analysed through a comparative analysis. Conclusively, indicators were found to improve the delivery performance when drones are included in the fleet composition, with gains in environmental aspects, service time and delivery costs. Results provide important information for further research on the implications of using drones in the pharmaceutical sector. Moreover, results are also useful for BENU t Slag, providing a valid feasibility assessment of using drones for their home delivery operations.

Keywords

Drones, Large-scale Neighbourhood Search algorithm, last-mile delivery, medical products, network optimisation, pharmaceutical sector, Vehicle Routing Problem.

Introduction

The term last-mile delivery refers to the final leg of a business-to-customer service, in which a product is shipped from a depot to a final destination point (Gaevers, et al. 2014). Last-mile logistics are generally operated by road transportation means, such as vans and small trucks. The growing demand of home deliveries is increasing the number of vans on the road, leading to traffic congestion and air pollution (ITV 2018). Together with congestion and environmental impact cutbacks, cost reduction is a big challenge faced by the last-mile sector. Studies have shown that the last-mile leg is the most expensive part of the delivery process, accounting up to 75% of the total cost of the logistic chain (Gaevers, et al. 2011).

To provide a faster and more cost-efficient home delivery service, companies are now striving for new technologies. With specific attention to urban areas and densely populated neighbourhoods, the aim of recent studies was to find feasible alternatives to vans, so that less or smaller vehicles are introduced in the daily traffic, to reduce congestion, speed up the delivery process and potentially save on operational costs. According to Gruber, et al. (2014) a valid alternative is represented by electric cargo bikes, which, in urban areas and for small distances, can deliver packages to the end user in a fast and reliable way, avoiding traffic congestion and increasing accessibility. Another option introduced by Agatz, et al. (2018) is the adoption of drones in the delivery fleet, to provide consignments from a depot to customer’s home, reducing congestion and pollution and overcoming the problem of infrastructure limitation.

Although several studies have been conducted regarding drones utilisation, especially in aerial photography, surveillance and path recognition, their application in the pharmaceutical sector, and specifically for home deliveries of medical products, has not been investigated yet.

The research question that is intended to answer with this study is:

How can the pharmaceutical sector benefit from the introduction of drones for the last-mile logistic process, in combination with the current means of transport?

To gain new insights into the feasibility of introducing drones in the delivery fleet composition, this research utilises the Vehicle Routing Problem (VRP) optimisation technique to analyse and compare two different network alternatives.

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The first alternative refers to the current situation, in which medical products are delivered using three vans with three corresponding drivers, each of them loading the products at the pharmacy and visiting a pre-defined set of customers. The second alternative envisions the future scenario, in which drones are introduced in the heterogeneous fleet composition cooperating together with vans. Drones are piloted remotely from the pharmacy and work in a non-synchronised way with vans, meaning that each vehicle has its own set of customers and its own delivery route. A Large-scale Neighbourhood Search (LNS) algorithm was used to implement the VRP and examine the performance indicators associated with the two design alternatives. Conclusively, several indicators were found to be improved after the introduction of drones in the fleet composition, especially in terms of service time and CO2 emission.

Literature review

The last-mile delivery sector. Last-mile delivery refers to the final process of a business-to-customer (B2C) service, and addresses the logistic operations from a depot to the end user. According to Gavaers, et al. (2009), important logistic decisions must be taken upon consignments, being the identification of the starting point and delivery destinations, the means through which customers can collect the products and the delivery agreements on time of shipment and return policies. Starting points of deliveries might be warehouses, depots or retail shops. Commonly, delivery destinations are pick up points, clustering points and customer's home.

The main causes that hamper the effectiveness and efficiency of the last-mile delivery sector are high costs of operations, traffic congestion and environmental damage. Studies have shown that the last-mile leg is the most expensive part of the delivery process, counting up to 75% of the total cost of the logistic process (Gaevers, et al. 2011). Moreover, the most used vehicles for last-mile delivery are vans and small trucks, which cause not only traffic congestion, especially in densely urbanised areas, but also air pollution. In light of these challenges, companies are striving for new technologies, in order to provide a faster, more cost efficient and greener delivery service (Agatz, et al. 2018).

In the context of urban areas, electric cargo bikes proved to be an efficient alternative to trucks, addressing the problem of congestion and limited-access areas (Gruber, et al. 2014). Cargo bikes can use a much denser road network, being able to run in both directions even on one-way roads. For what concerns accessibility, delivering packages with electric bikes will help the shipment of products in limited- or no-access zones, such as pedestrian zones. Moreover, the fact that less parking space is required, it becomes easier to deliver in areas with narrow streets, without causing congestion or excessive roadblock (Reiter, et al. 2014). A very recent alternative that has been proposed to solve congestion, pollution and infrastructure limitation, is the use of Unmanned Aerial Vehicles (UAVs), or mostly referred as drones (Agatz, et al. 2018). Drones are fast and can operate without a human driver, saving thus time on congested road and having a low cost per kilometre. On the other hand, given the small size of a drone and the payload limitation, there is an upper limit to the size of the package to be delivered. Moreover, the battery-powered system, causes the drone to have a limited range. Nonetheless, the Aerospace Industries Association (AIA) forecasts that within 20 years, a large amount of cargo drones will be introduced in the market. Investments in research and development will rise from a few hundred millions USD to 4 billion USD by 2028 and 30 billion USD by 2036 (Warwick 2018).

Drone applications. Drone applications started in the nineteenth century, when the Austrian army used an unmanned aerial vehicle as a balloon carrier to launch 200 incendiary balloons at the city of Venice (Buckley 1998). Later on, during World War 1, UAVs were used for training personnel (Shaw 2013). The Vietnam war in 1955 (Kenneth 1997), the Lebanon war in 1982 (Azoulai 2011) and the Gulf war in 1991, adopted drones for surveillance purposes and as armament carriers. Nowadays, drones are mainly used for photography, surveillance, path recognition, racing and advertisement purposes (Chavers 2018). Studies have also been conducted on the applicability of drones in emergency situation. Being not bounded to physical transport infrastructure, having a relatively high speed and the capability of flight in a straight line between two points, drones have been proved to be useful when it comes to save lives. Truhlář, et al. (2015) proposed the use of drones to monitor beach environments, to increase the survival rate of drowning victims. Their research was followed by a study from Claesson, et al. (2017) on how to use drones to provide cardiopulmonary resuscitation and automated external defibrillator in those drowning emergency situations. Other potential applications of drones for medical purposes concern the transport of vaccines in low- and middle-income countries (Haidari, et al. 2016). Modelling the vaccine supply chain for the Gaza province, in Mozambique, they found that implementing a drone system could increase vaccine availability and decrease costs, once the high capital investments are overcome.

The state of research on drone delivery is still on its early stages. Practical trials have already been carried out by leader companies in the delivery sector, such as Amazon, Alibaba and Google (Agatz, et al. 2018). In 2014, the American company AMP Electric Vehicles together with the University of Cincinnati Department of Aerospace Engineering, developed a combined mode of truck and drone for last-mile delivery (Wohlsen 2014). The concept is that while the delivery truck visits a set of locations to make delivery, a drone simultaneously visits another set of locations, returning to the truck after each delivery, to pick up another package. In this way, the benefits of trucks (long range, high payload capacity) are combined with the benefits of drones (high speed and high accessibility), to provide an efficient and cost-effective delivery service.

Transport network assessment. Last-mile delivery is a transport network problem in which products are shipped from a depot to a set of customers, using a fleet of vehicles. The logistics of these deliveries should be such that the cheapest option is selected, providing thus an optimal tour that starts and ends at the depot and visits all the scheduled customers. Given a set of locations, the most common model formulations in operation research are the Travelling Salesman Problem (TSP) and the Vehicle Routing Problem

(VRP). The TSP formulated by Dantzig (2016), aims to find the shortest path that connects a set of nodes, for which the order of visit is not important. The VRP, firstly formulated by Fisher, et al. (1978), can be seen as a generalisation of the TSP. The goal is to define the optimal tour given a set of nodes and a vehicle fleet composition, such that each node is visited at least once and only once and total costs of operations are minimised. The main substantial differences between the TSP and the VRP are in the vehicle fleet composition and the vehicle capacity restriction, with the latter being able to account for a heterogeneous fleet composition, with each vehicle having a different capacity (Nelson, et al. 1985).

Adaptations of the TSP that include drones in the vehicle fleet are found in Murray, et al. (2015). The Flying Sidekick TSP (FSTSP) model adaptation considers a set of nodes that must be served at least once and only once by either a truck or a drone. In this configuration, drone and truck depart together from the depot and can either travel in tandem (with the drone transported by the truck) or independently, carrying out their deliveries simultaneously. This configuration is particularly useful when the average distance between the depot and the nodes to be served is higher than the drones range. In the case that the depot is in a convenient position with respect to the nodes to be served (i.e. within the flight range of the fleet of drones), the TSP can be modified into the Parallel Drone Scheduling Travelling Salesman Problem (PDSTSP). In this adaptation, a single delivery truck and a fleet of drones depart and return, with the truck serving customers along a TSP route and the drones serving customers directly from the depot. Being part of two different networks, no synchronisation is needed between van and truck. According to the results of Murray, et al. (2015), the gain in travel time is much more consistent in the PDSTSP compared to the FSTSP.

In summary, previous studies show that drones have caught the attention of researchers. Investments in research and development of drone use and capabilities will increase in the near future, paving the way for the introduction of drones in last-mile deliveries.

Methodology and data description

The objective of this study was to determine how can the pharmaceutical sector benefit from the introduction of drones for the last-mile logistic process, in combination with the current means of transport. To do so, a comparative analysis was carried out between two different scenarios, one referring to the current situation and one to the future plan for home delivery logistics.

1. Scenario 1: deliveries are operated with three delivery vans and three corresponding drivers, that pick up the products from the pharmacy storage area, carry out their scheduled consignments and conclude their tour back to the pharmacy.
2. Scenario 2: a heterogeneous vehicle fleet in operated, composed by vans and drones which carry out home deliveries in a parallel way, each vehicle visiting it own set of customers, starting and ending at the pharmacy.

The choice to adopt a parallel utilisation of vans and drones in a non-synchronised way was supported by the study of Murray, et al. (2015), which proved the PDSTSP to be more efficient than the FSTSP. Moreover, the area covered by the delivery service was not such as to justify synchronised operations.

Data on the current situation were obtained from the pharmacy involved in the case study. Vehicle fleet composition, delivery service characteristics and demand distribution inputs correspond to the information regarding the current home delivery operations of BENU 't Slag, part of BENU Apotheek franchising, located in Rotterdam. For what concerns drone specifications, values were retrieved from UAV System International (2019), and referred to the x8 long range cargo drone, depicted in Figure 1b. Drone maximum capacity was assumed based on the prototype showed in Figure 1a. The box was developed by a team of students from the faculty of Mathematics and Applied Science of the University of Leiden and presented during the Drones in the City Event organised by The Future Mobility Network that took place in Katwijk on the 31st of January.

(a) Box prototype

(b) Drone prototype

Figure 1. Drone delivery features

Input parameters are divided into vehicle characteristics, fleet characteristics, labour restriction, delivery agreements and product demand. More specifically, parameters that are inserted in the model are as follows (sensitive data omitted):

Vehicle characteristics

- Average van speed = 35 km/h
- Average drone speed = 70 km/h
- Fixed and distance costs of van = –
- Fixed and distance costs of drone = –
- Distance limitation for vans = 560 km
- Distance limitation for drones = 3.2 km
- Flight time limitation for drones = 1 hour
- Van capacity = 50 products
- Drone capacity = 7 products

Fleet characteristics

- Number of vehicle types current situation = 1
- Number of vans current situation = 3
- Number of vehicle types future scenario = 2
- Number of vans future scenario = 2
- Number of drones future scenario = 1

Labour restriction

- Working time limit for van drivers = 6 hours

Delivery service characteristics

- Number of depots = 1

- Number of customers = –
- Service time for products drop off = –
- Distance between customers = –

Demand

- Product demand for each customer = [–]

Alternatives were tested using the Vehicle Routing Problem formulation. For what concerns the cost function (Equation 1), fixed and variable components were calculated developing two cost models, one for each scenario alternative.

$$c_{ijk} = fixed\ cost_k + distance_{ij} * distance\ cost_k \quad (1)$$

Drones have strict limitations on distance range and time of flight, which depend on the energy consumption rate and the charging potentials (e.g. how many kilometres can be flown with one charge). For this reason, the classical formulation of the VRP as introduced by Fisher, et al. (1978) was adapted to include the range and time constraints for the drone fleet, but also to account for the heterogeneity of the fleet in the objective function, adding the subscript k to the cost component c_{ijk}, so that costs can be differentiated per vehicle type. The VRP problem was formulated as follows:

$$\text{OF} \quad min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m} c_{ijk} * x_{ijk}$$

$$\begin{array}{lll}
\text{ST} \quad 1. & \sum_{k=1}^{m} y_{ik} = 1, & 1 \leq i \leq n \\
2. & \sum_{k=1}^{m} y_{ik} = m, & i = 0 \\
3. & \sum_{i=1}^{n} q_i * y_{ik} \leq Q_k, & 1 \leq k \leq m \\
4. & \sum_{j=0}^{n} x_{ijk} = y_{ik}, & 0 \leq i \leq n \\
 & & 1 \leq k \leq m \\
5. & \sum_{i=0}^{n} x_{ijk} = y_{jk}, & 0 \leq j \leq n \\
 & & 1 \leq k \leq m \\
6. & \sum_{i \epsilon S} \sum_{j \epsilon S} x_{ijk} \leq |S| - 1, & S \subseteq 1, ..., n \\
 & & 1 \leq k \leq m \\
7. & \sum_{i=0}^{n} \sum_{j=0}^{n} t_{ijk} \leq T_k, & 1 \leq k \leq m \\
8. & \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ijk} * d_{ij} \leq R_k, & 1 \leq k \leq m
\end{array}$$

The objective is to minimise the cost of the tour, by providing the cheapest possible sequence of nodes to be visited. The decision variable x_{ijk} assumes the value of 1 if customer j is visited immediately after customer i by vehicle k, and 0 otherwise. The variable y_{ik} defines whether customer i is visited with vehicle k. Constraint 1 sets that each customer i must be visited at least once, and only once by just one vehicle k. Vehicle are bounded to return to the depot by constraint 2, 4 and 5. The capacity of the vehicles is limited by constraint 3, in which q_i indicates the demand at each node visited by vehicle k and Q_k the capacity of vehicle k. Constraint 6 guarantees that not sub tours are generated. Constraint 7 refers to the flight time constraint, indicating that the total time from i to j using vehicle k must not exceed the maximum utilisation T_k. Constraint 8 concerns the distance limitation, imposing that the distance covered by a vehicle must not exceed the maximum range R_k.

The outputs that will come out of the model are the fleet allocation, the customer sequence and the vehicle allocation.

Fleet allocation and customer sequence

- Binary $n * n * k$ matrix with customer visit sequence and vehicle allocation

Vehicle allocation

- Distance travelled per vehicle d_k [km]
- Driving time per vehicle t_k [hour]
- Working time per vehicle wt_k [hour]
- Number of stops per vehicle n_{stops} [-]
- Initial loading per vehicle $Q_{used,k}$ [products]
- Cost of operations per vehicle c_k [euro]

After having implemented the model, output parameters were used as inputs to calculate the Key Performance Indicators for the current situation and the future scenario. Alternatives are assessed based on the delivery cost per item (DC), the service time (ST), the fuel consumption (FC), the CO2 emissions, the energy consumption (EC), the cost of power supply (PS) and the payload capacity (PC). Based on the type of van used, CO2 emission rate for the van fleet was assumed to be 115 g/km, whereas the fuel consumption was averaged to 5 litres/100km (Mercedes-Benz 2018). For the fuel price, the average amount for the year 2018 was considered, equal to 1.33 euro/litre (Global Petrol Prices 2019). Based on the drone characteristics, energy consumption was fixed to 0.26kW/h (UAV System International 2019) and the energy price was set to 0.1024 euro/kW (Main Energie 2019). Key Performance Indicators were then found using the following equations:

$$DC = \sum_k c_k / n_{del} \ \ [euro/item] \quad (2)$$

$$ST = \sum_k t_k \ \ [hours] \quad (3)$$

$$FC = \sum_k d_k * 5/100 \ with \ k \in van \ fleet \ \ [litres] \quad (4)$$

$$CO_2 = \sum_k d_k * 115 \ with \ k \in van \ fleet \ \ [g] \quad (5)$$

$$EC = \sum_k t_k * 0.26 \ with \ k \in drone \ fleet \ \ [kW] \quad (6)$$

$$PS = 1.33 * FC + 0.1024 * EC \ \ [euro] \quad (7)$$

$$PC = (\sum_k Q_{used,k} / Q_{available,k}) / n_{vehicles} \ \ [\%] \quad (8)$$

Solution approach

Many solution approaches are available for solving the Vehicle Routing Problem. For this case study it was decided to use an open source spreadsheet solver specific for Vehicle Routing Problems, developed by Erdoğan (2017). Alternatives were tested using a Large-scale Neighbourhood (LNS) algorithm, a type of constructive heuristic algorithm that tries to find a near optimal solution by means of iterations, finding in each step an improved solution in the neighbourhood of the current one, for which costs are minimised (Ahuja, et al. 2002). Given an instance I of a combinatorial optimisation problem and a finite large set X

of feasible solutions, a function $c : X \to \mathbb{R}$ is defined, that maps from a solution to its cost. Being this a minimisation problem, the aim of the algorithm is to find a solution $x*$ such that $c(x*) \leq c(x) \forall x \in X$. A neighbourhood of a solution $x \subseteq X$ is defined as $N(x) \subseteq X$, with N being a function that maps a solution to a set of solutions. With this definition of neighbourhood, a solution x is locally optimal with respect of a neighbourhood N if $c(x) \leq c(x') \forall x' \in N(x)$. A neighbourhood search algorithm starts from an initial solution x as input and gradually improves this solution computing $x' = argmin_{x'' \in N(x)} \{c(x'')\}$, which finds the cheapest solution x' in the neighbourhood of x. If an improved solution x' is found, for which $c(x') < c(x)$, the algorithm performs the update $x = x'$. The algorithm then continues searching for an improved solution in the neighbourhood of the new solution x and it stops when a local optimum x is reached.

Initial information such as the number of customers, the geographical location and the available fleet were stored in the Solver Console. Details on each customer (locations, time window, service time and demand) were then inserted in the Location sheet. Based on the address of each customer, the model computed automatically the geographical coordinates. These coordinates were then used in the Distances sheet, where the distances between each customer (included the depot) were computed according the GIS map of the considered area. Data on the available fleet, such as cost parameters, capacity, time and range limits, were inserted in the Vehicle worksheet. Costs associated with each vehicle were retrieved from the cost model and divided into fixed costs and operational costs. Based on all the input inserted, the model provided the optimal number of vehicles to be used, the sequence of visits, the cost associated with each vehicle, the distance and the time travelled by each vehicle and the total cost of operation. Furthermore, locations and routes could be visually inspected in the visualisation worksheet, where the tour for each vehicle was placed upon the map from the GIS web service.

Two important manipulation were operated. For what concerns the variable costs, the Excel Spreadsheet Solver did not account for time related costs, but only distance related costs. To overcome this drawback and still include the human labour cost (expressed in euro/hour) and the energy cost (expressed in euro/hour as well), these two costs were converted into distance costs (expressed in euro/km) using the average vehicle speed. Calculating how many hours are needed to travel 1 kilometre, and multiplying this value by the hourly cost, it was indeed possible to obtain the time related components expressed in euro/km. The second manipulation concerned the distance computation method and the average vehicle speed used in the implementations. Vans and drones are inherently different, especially in terms of average speed and path followed for going from origin A to destination B. The assumptions made on vehicle speed assigned an average speed of 35 km/h for the van fleet and 70 km/h for the drone fleet. The distance computation method for vans was the Bing Map real distance, which calculates the real distance between two points, following the real existing infrastructure and the road regulations that are applied. For the drone, the Birdflight distance computation was used, that calculates the shortest straight line that a plane would cover between two points. Unfortunately, the Spreadsheet Solver allowed for only one distance computation per implementation, and just one vehicle speed could be inserted. Running the model first with the Bing Maps computation and vehicle speed of 35 km/h and then with the Bird flight computation and vehicle speed of 70 km/h, results for distance and time travelled were on average respectively 37% and 65% higher in the first run. Therefore, the inability of the solver to use two different distance computations in the same implementation might have brought biased results, assigning less customers to the drone route. For this reason, for the future scenario assessment, two implementations were run, one with distance and speed characteristics of vans and one with distance and speed characteristics of drones. Results were then assembled together so that the route is still feasible and capacity and node constraints are still respected.

To quantify the credibility of the model, verification and validation tests were performed. In the procedure of developing the model, the role of verification and validation is to define the comparison between experimental outcome and simulation outcome, providing thus an estimation of the model accuracy (Thacker, et al. 2004). For this reason, a code verification and a calculation verification were performed, to ensure that the computer model accurately implemented the mathematical formulation. Moreover, an extreme condition validation test was also executed, to compare the simulation outcome and the experimental outcome on a quantitative level and define the extent to which the model accurately represents the real world.

Code verification is a two-step procedure that is carried out both by the code developer and the model developer. To test the solution algorithm, a known problem was run with the VRP Excel Solver and the solutions obtained were compared with the best know solutions. The benchmark data set used in his research was the one provided in Christofides (1981), containing data about Capacitated VRP and Distance Constrained VRP. The best known solution values are then compared to the solutions obtained with the VRP Excel spreadsheet solver. For what concerns the model developer part, an example of a real world situation was run with pickups and deliveries with 1 depot and 10 customer locations spread in the United Kingdom, made available by Erdoğan (2017). The calculation verification test was performed considering a sub-problem of the initial one, with just 5 customers and one van. Numerical results obtained with the VRP Excel Spreadsheet Solver were compared to analytical results using the Farthest Insertion Heuristic algorithm, to find the numerical error induced by the computer model. Lastly, the extreme condition test was carried out by setting all the input parameters to their extreme values. Two situations were run: one with parameters set to zero and one with parameters approaching infinity.

Verification results showed that the code is properly written, with a 0.6% average gap on best known VRP solutions and a 0.15% gap on model development. Model calculation also performed well, with a very small gap of 0.016% between numerical and analytical calculations. Moreover, the model proved to be valid, with the extreme condition test giving expected results both in a qualitative and quantitative way.

Discussion of results

Results were reported in terms of routing solutions, in which the routing sequence for each vehicle was visualised on top of the map of Rotterdam. Tables containing the routing sequence, total number of stops, distance travelled, service time, vehicle loading and cost of operations for each vehicle resulted from the model implementation. With these model outputs, a KPI comparison was conducted and results were provided using bar charts. Performance values were expressed in terms of day of operation, with the exception of delivery cost per item, which is specific for each item delivered. In this way, the comparative analysis could be carried out under an economic perspective, but also under environmental, time savings and payload utilisation perspectives.

For the fleet composition of the future scenario, the optimal number of vehicles was found after the first model run. Given a fleet composed by several vans and several drones, the model assigned operations to one drone and two vans. Cost models were then updated with the new fleet composition, and a new implementation was run, with input parameters complying with the optimal vehicle fleet.

Figure 2. Routing solution current situation

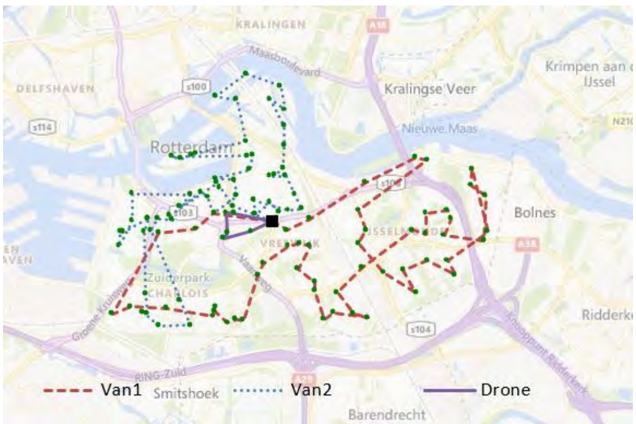

Figure 3. Routing solution future scenario

Figure 2 shows the routing solution for the current situation, in which three vans carry out the daily consignments. In comparison, Figure 3 shows the routing solution for the future scenario, in which one van is eliminated from the fleet composition, to insert one drone. With the elimination of one van and the introduction of one drone, the total available capacity is reduced from 150 products to 107. Consequently, vehicle utilisation is higher in the future scenario: each van visits more customers compared to the previous situation, due to the fact that the drone can only visit a limited amount of customers, mostly due to capacity restrictions. Figure 4 shows a comparison of performance indicators between the two alternative situations. Sensitive data have been omitted, providing just the percentages of variations.

Figure 4. Comparison of Key Performance Indicators

Optimise these two situations provided some interesting results in terms of performance indicators. To evaluate the cost savings brought by the introduction of drones in the vehicle fleet for home delivery of medical products, compare the cost model of the current situation and the future scenario is not sufficient. It is indeed important to consider the different business models and the implications that follow the adoption of drones in the last-mile delivery process. For this reason, two different analysis were made: one compared the costs associated with one day of operation in the current situation with the costs of the same operation in the future scenario. A second analysis considered the business model of adopting the future scenario alternative, characterised by the purchase of one drone and the sale of one van and all the implications that followed, evaluating the monetary benefit in terms of total annual cost. It was estimated that with the adoption of the envisioned future scenario, the pharmacy could potentially save 12.5% of the total annual costs expenses, based on a 5 year depreciation period. Based on their demand distribution, the cost per item is reduced by 5.60% per package delivered. Routes were found to be faster, decreasing the total service time by 12.05%, suggesting that more customers could potentially be served and the geographical area expanded. The introduction of flying vehicles and the consequent reduction of road vehicles brought indisputable improvements under an environment perspective: CO_2 emissions were reduced by 9.00% for a daily operation, and less vehicles were driving in the urban area, decreasing the amount of traffic congestion.

Sensitivity analysis

To evaluate the extent to which changes in model inputs affect the model outputs, thus the performance indicators, a sensitivity analysis was carried out. Several implementations were run, and in each run only one parameter was changed.

Changes in vehicle speed. In the model formulation, time related costs were embedded in distance cost, by transforming the time in the network into distance travelled using the average speed. Therefore, changing the vehicle speed entailed a change in operational cost, given the fact that less or more kilometre can be travelled. Figure 5 shows the trend in cost per item, capacity ratio, service time and fuel consumption related to vehicle speed variations. The performance indicator that was mostly affected by vehicle speed variations was the cost per item, which considerably decreased by increasing vehicle speed. Service times and fuel consumption were slightly affected by vehicle speed variations, showing a small increase in the first one and decrease in the second one. Vehicle capacity ratio remained unaffected by variations of vehicle speed.

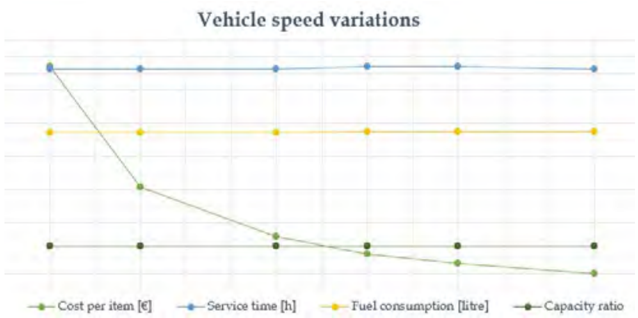

Figure 5. Influence of vehicle speed

Changes in vehicle capacity. Figure 6 shows the trend in cost per item, capacity ratio, service time and fuel consumption related to vehicle capacity variations. All KPIs were somehow affected by these changes: the cost per item decreased after a first increase in vehicle capacity, to remain constant higher values. As expected, capacity ratio values fluctuates depending on the number of vehicle used for deliveries: increase the capacity brought a decrease in vehicle utilisation, to increase again once it is enough to eliminate one vehicle from the fleet.

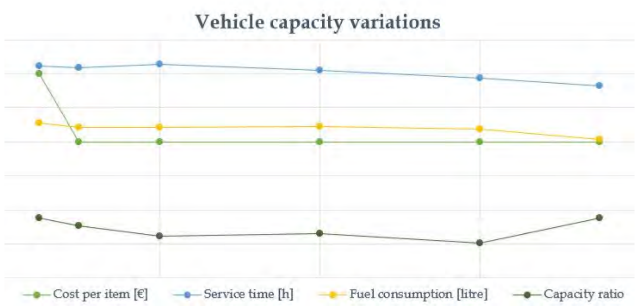

Figure 6. Influence of vehicle capacity

Changes in distance limitation. Variations in distance limits did not cause significant changes performance indicator values. With very restrictive values (from the minimum allowable value of 19 km to 25 km), a small decrease in cost per item, fuel consumption and service time was noticed, to settle to a constant value for bigger distances. Vehicle capacity ratio remained constant for all the distance limitations considered.

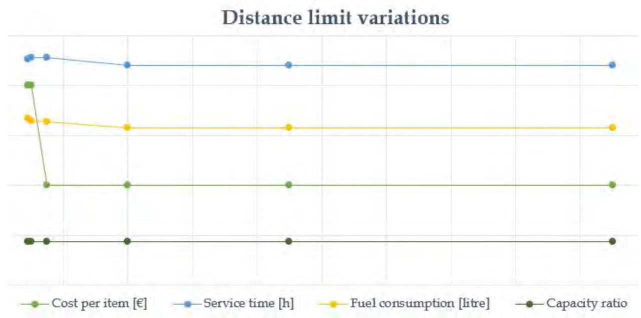

Figure 7. Influence of distance limitation

Changes in time limitation. Variations in working time limits did not cause any change in cost per item, service time fuel consumption and vehicle capacity ratio. The reason behind these results is that the time limit constraint for the van fleet was not as restrictive as other constraints, for example the capacity constraint. Therefore, provided that a minimum distance range is guaranteed, increasing this parameter did not bring any changes in the performance indicators.

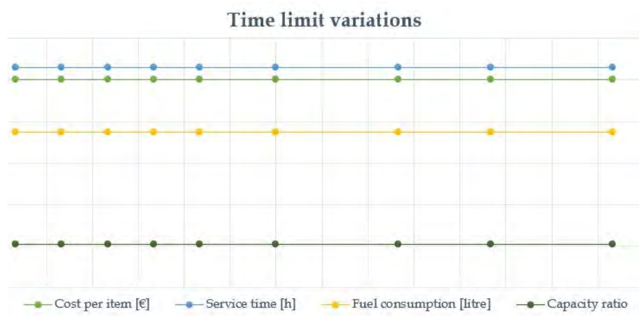

Figure 8. Influence of time limitation

To conclude the sensitivity analysis, other potential future situations were assessed and compared with the future scenario envisioned in this research. One situation referred to a fleet entirely composed by electric vehicles (EVs), i.e. electric vans and drones. One other situation concerned a fleet composed by only drones. In this way, the influence of the power supply mode and the vehicle fleet composition on Key Performance Indicators was assessed. Lastly, based on some ideas shared with the owner of the pharmacy BENU 't Slag on future logistic development, a scenario with multiple depots was briefly analysed, to assess the influence of depot location.

Test scenario with only EVs. In this test scenario, only EVs were considered for the delivery fleet, composed by 2 e-vans and 1 drone. A new cost model was developed, considering the cost related to the e-van fleet, which results showed an increase of 13.9% in annual costs. Figure 9 shows a comparison of Key Performance Indicators for the envisioned future scenario with 2 vans and 1 drone and the testing scenario with 2 e-vans and 1 drone in the vehicle fleet. Vehicle capacity of e-vans was assumed to remain the same as non electric ones, hence the vehicle capacity ratio did not change between the two compared scenarios. For the energy consumption it was assumed that the consumption of e-vans is equal to 0.11 kW/h (Energy Guide 2019). The total energy consumed for a day of operation was almost 30 times higher than the scenario with non EVs. With a fleet entirely composed by EVs, CO_2 emissions and fuel consumption were reduced to a null value, since no gasoline was needed to operate vehicles. Therefore, the total cost of power supply referred only to the energy cost, and it was dropped by 98.72% per day of operation. Cost per item changed substantially, with an increase of 53.6%. Lastly, service time changes marginally, being only 2.35% higher in the test scenario with EVs only.

Figure 9. Test scenario EVs

Test scenario with only drones. The aim of this test was to define how many vehicles would be needed in case of a fleet composed entirely by drones. For this purpose, the model was implemented with an unlimited amount of drones available. Demand was kept equal to the initial values and fixed and variable costs referred to the one found in the cost model for the future scenario. After having found the total number of drones needed, a new cost model was developed, in order to properly evaluate the KPIs for this testing scenario. After performing a first LNS iteration, the model found a non-feasible solution due to range limitation: with a maximum range of 4 km, some customers could not be reached and had to be excluded from the home delivery service. To avoid this loss, the drone range was increased up to 32 km at the expenses of payload capacity (UAV System International 2019). With a range of 32 km and a drone capacity of 3 products, a new implementation was run. Time constraint remained unchanged. Results of this implementation showed that the minimum number of drones needed to complete a daily operation was 35. With these information, a new cost model was developed, which results showed that annual costs increase of 243.8%.

Figure 10. Test scenario drones

Referring to the comparison with the original future scenario of Figure 10, indicators showed an overall improvement. Vehicle capacity improved by 10 percentage points. Environmentally speaking, the test scenario brought considerable benefits, dropping to 0 the CO_2 emissions and the fuel consumption. Cost of power supply dropped by 98.42%, due to the fact that the energy cost is lower that the fuel cost and the consumption rate is less in electric vehicles. Service time also improved, with a reduction of 27.4%. As expected, the energy consumption largely increased, due to the introduction of a big number of electric vehicles. The delivery cost per item also experienced a steep increase, which was related to the higher annual cost associated with this test scenario.

Test scenario with 5 depots. According to the owner of the pharmacy, additional depot locations are likely to be included in the near future. For this reason, it was decided to provide a brief analysis of the influence of depot location. Two alternatives were assessed, both having a vehicle fleet composed by only drones (with the optimal amount of 35 drones). The difference was that in the first test scenario, vehicles started and ended their trip just at the pharmacy BENU 't Slag, while in the second test scenario starting and ending locations were increased up to 5 depot locations (including the pharmacy). The cost model was considered to be the same as the one for the test scenario with drones only, hence with an increase in annual costs of 243.8%. Vehicle characteristics were also kept unchanged from that test scenario. Analysing the KPI comparison of Figure 11, it can be seen that some indicators did not change when the number of depots was incremented. Vehicle capacity ratio remained the same, due to the fact that the same demand and the same vehicle capacity was considered for the two scenarios. Same line of reasoning for the CO_2 emission and fuel consumption: characterised by a fully electric drones fleet, both alternatives had zero emissions and zero fuel consumption. When multiple depots were introduced, vehicles could carry out their deliveries in a faster way, travelling a shorter distance. Therefore, a decrease in service time and cost of operations was noticed: adding four more depots reduced the service time by 11.8% and the cost of power supply by 33.3%.

Figure 11. Test scenario multiple depots

Conclusion

Throughout the research, several problems of the current last-mile transportation means have been addressed. The main challenges that were defined consisted in cost reduction and congestion and pollution diminution. Two design alternatives were elaborated and tested to understand the extent to which the pharmaceutical sector can benefit from the adoption of a heterogeneous fleet composed by vans and drones.

Cost benefits. To evaluate the cost savings brought by the introduction of drones in the vehicle fleet for home delivery of medical products, comparing the cost model of the current situation and the future configuration was not sufficient. For this reason, two different analysis were made. A first analysis considered the business model of adopting the future scenario alternative, characterised by the purchase of one drone and the sale of one van and all the implications that follow, evaluating the monetary benefit in terms of total annual cost. Results showed that with the adoption of the future fleet configuration, the pharmacy could save 12.5% of the total annual expenses. The second analysis compared the costs associated with one day of operation in the current situation with the costs of the same operation in the future configuration. Performance indicators showed that with the introduction of drones in the vehicle fleet, delivery cost per item is reduced by 5.60%.

Environmental benefits. Environmental benefits were compared evaluating the CO2 emission, the fuel consumption and the energy consumption in each network configuration. With the removal of one van from the vehicle fleet and the introduction of one electric vehicle, the total distance travelled by road vehicles decreases, leading to a consequent decrease in CO2 emission and fuel consumption, but an increase in energy consumption. As expected, CO2 emissions decreased on average by 9% per day of operation and fuel consumption was reduced by 8.6% a day.

Service time. Service time is defined as the time that each vehicle spends to complete its tour, summed over all vehicles. It indicates the total time spent in the system, to conclude the daily deliveries. Drones are faster than vans, and most importantly are not bounded by the physical infrastructure. As expected, the adoption of the future scenario alternative reduced the total service time by 12&.

Payload utilisation. Payload utilisation was calculated as the ratio between the used capacity and the available capacity. Total demand was kept unchanged between the two network alternatives. For what concerns the total vehicle capacity, van capacity was assumed to be 50 units whereas drone capacity only 7 units, meaning that scenario 1 had a maximum available capacity of 150 products while scenario 2 only 107 products. As expected then, payload utilisation increased drastically in the future scenario, with an improved capacity ratio of 25.75 percentage points.

Further recommendations

Once results showed that the introduction of drones would bring substantial improvements in the logistic operations of last-mile delivery for the pharmacy BENU 't Slag, several scenarios alternatives were hypothesised, to check the extent to which different network configurations would provide different performance indicators. A fully-drone configuration, a combination of EVs and drones configuration and a multiple depot configuration were suggested. First results showed that a homogeneous fleet of only drones brought a considerable increase in cost per item. Environmental benefits were undoubtedly interesting, with a drop of CO2 emission and fuel consumption down to zero. Same environmental results were obtained with a fully electric heterogeneous fleet composition, with 2 e-vans and 1 drone. Moreover, with 2 e-vans and 1 drone, cost per item was considerably reduced, as well as the cost of power supply. Lastly, the test scenario with multiple depot showed that, in comparison with the situation where only one depot is arranged, service time could be reduced by 12% and cost of power supply by 33%. Therefore, the main recommendation for further research is the implementation of the scenario with a fully electric heterogeneous fleet, composed by e-vans and drones, with multiple depot locations. The choice of avoiding a fleet composed only by drones and keeping road based vehicles with drivers carrying out deliveries is also justified by the delivery agreements of BENU 't Slag. Twice a week, drivers consign several packages that are meant to fit in the mail box, without the customer having to collect them in person. If BENU wants to maintain this service, it is believed that a homogeneous fleet of drones is not feasible.

For what concerns the implementation method, further research can be extended including solution approaches that account for multiple distance computations and average vehicle speed in the same implementation setup. Examples are the Simulated Annealing or the Genetic Algorithm implemented using Matlab or Python. Compare the results obtained with the one of this research might provide a better insight on the feasibility assessment of drones for last-mile logistics. Moreover, it is recommended to undertake some practical test as soon as regulations will allow drones to fly.

Under a technical perspective, it might be interesting to further investigate on some technical characteristics of the vehicle fleet. As an example, fuel consumption was assumed to be static, fixed at 5 litres/100km. In reality, this value changes dynamically based on vehicle speed and traffic congestion (i.e. if the vehicle needs to stop and re start the engine several times). Another characteristic that might be worth investigating, is the effect of weather condition on drone flight performances, e.g. how wind or rain might affect the possibility of drones to reach customers locations.

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