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Reject or Embrace Electric Cargo Bikes?

An investigation of the Sustainability Effects of a Transition from Electric Vans to Electric Cargo Bikes in Last-Mile Delivery

Ola Edvin Heggedal and Øivind Wøien Stø

Supervisors: Stein Wallace,

Cosku Can Orhan and Jaikishan Soman

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Abstract

In the recent period, there has been a massive increase in e-commerce. This has vastly changed Norwegian customers' shopping behavior and provided an increase in last-mile delivery. Simultaneously, the focus on sustainability has become more significant, and the Bergen Municipality is looking for ways to reduce traffic in the city center.

This thesis investigates how a transition from e-vans to e-cargo bikes will affect sustainability in a city center. Both the Vehicle Routing Problem (VRP) and the Traveling Salesman Problem have been used to solve the route optimization problem, where it is assumed that all deliveries are made with either e-vans or e-cargo bikes. A mathematical model was developed from the beginning, but due to the large number of addresses, each address was assigned to a cluster. Then, Google OR-Tools was used to solve the VRP. The mathematical model and the Google OR-Tools model proved to perform equally well when compared using a small number of addresses.

The main findings show that sustainability in a city center will be positively affected by a transition from e-vans to e-cargo bikes in last-mile delivery. This is because the social, environmental, and economic sustainability pillar will be positively affected due to lower noise levels, lower environmentally harmful emissions, and the potential for lower costs. The sensitivity analysis shows, however, that the number of meters traveled with e-cargo bikes increases faster than for e-vans when the demand for parcels increases. We believe that our findings will apply to cities with the same characteristics as Bergen, such as population and the size of the city center.

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1. Introduction

1.1 Motivation and purpose

In recent decades, e-commerce has vastly changed Norwegian customers' shopping behavior. As a result, the parcel delivery system has changed, as we see a massive increase in last-mile delivery (Haugen, 2020). The share of chain stores offering e-commerce was 77 percent in 2022, whereas the same share was 56 percent back in 2015 (Bach, 2022). In March 2020, the Norwegian authorities introduced strict actions to prevent the spread of the coronavirus. This forced physical stores to close for a short period, followed by restrictions on the number of customers allowed in the stores simultaneously. The inconvenient situation for the customers led to an immense increase in e-commerce.

In Norway, e-commerce increased by 37,8 percent from 2019 to 2020 (DNB, 2021). The expansion in e-commerce continued throughout 2021, and according to SSB (2022), the Norwegian e-commerce market increased by 26 percent that year. Furthermore, the escalation in e-commerce has led to a change in last-mile delivery. The company Helthjem reported in November 2020 an increase in last-mile delivery by 148 percent and an increase in customer-to-customer deliveries (C2C) by 277 percent in the same year (Haugen, 2020). Moreover, PostNord reports that the preference for last-mile delivery doubled from Q1 2021 until Q1 2022 (PostNord, 2022, p. 31) and that this development happens at the expense of delivering at delivery locations. Additionally, the new trend of last-mile delivery and urbanization leads to a greater demand for parcels and more vehicles in the city (Fossheim, 2021). As a result, the number of heavy vehicles in the city center will increase.

Simultaneously with a greater demand for infrastructure, Bergen Municipality are working on multiple logistics plans for the city center. The goal is to facilitate a more sustainable city by establishing Bybane through Bryggen (Bergen kommune, 2022b), zero-emission zones (Bergen kommune, 2022a), and a traffic plan for the city center (Bergen kommune, 2022c). The traffic plan for the city center is a scheme to reduce car traffic, where the goal is to create better conditions for walkers, bikers, delivery, and public transport. There has been a suggestion to close Torget, inside the orange circle in Figure 1.1, for private cars and only allow goods delivery and public transportation.

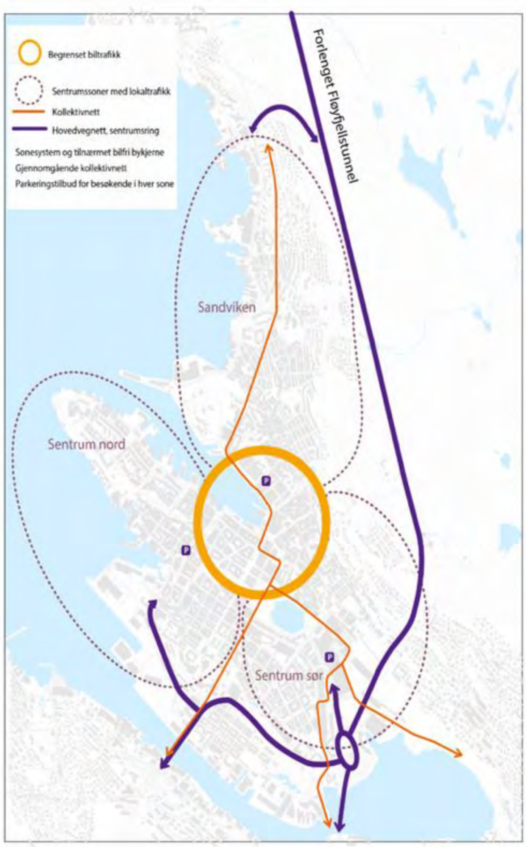

Figure 1.1: Traffic plan for Bergen city center (Bergen kommune, 2022c).

A central issue for municipalities is how they face the consequences regarding growth in last-mile delivery. The most significant consequence is the increased traffic due to its considerable adverse environmental and social effects. However, a sustainable city not only requires less traffic, but a balance between economic, environmental, and social sustainability pillars. Jernbanedirektoratet has the following goal for city logistics: "A secure transport system promotes economic growth and contributes to the transition to the zero-growth target."(Jernbanedirektoratet, 2018, p. 12). Therefore, there is a need to look at new methods to accommodate the demand for last-mile delivery. One method that has increased in popularity in recent years is cargo bikes, which have shown the potential to be a more sustainable alternative to the traditional van.

Figure 1.2 shows the average noise level from traffic throughout the day in Bergen city center. According to the EU´s noise directive, noise in larger urban areas must be surveyed. This applies to areas with noise levels above 55 dB during the day and above 50 dB at night (Miljødirektoratet, 2022). Unfortunately, as the figure shows, large areas exceed these limits, which has negative consequences for human health, general community well-being, and quality of life at a neighborhood level.

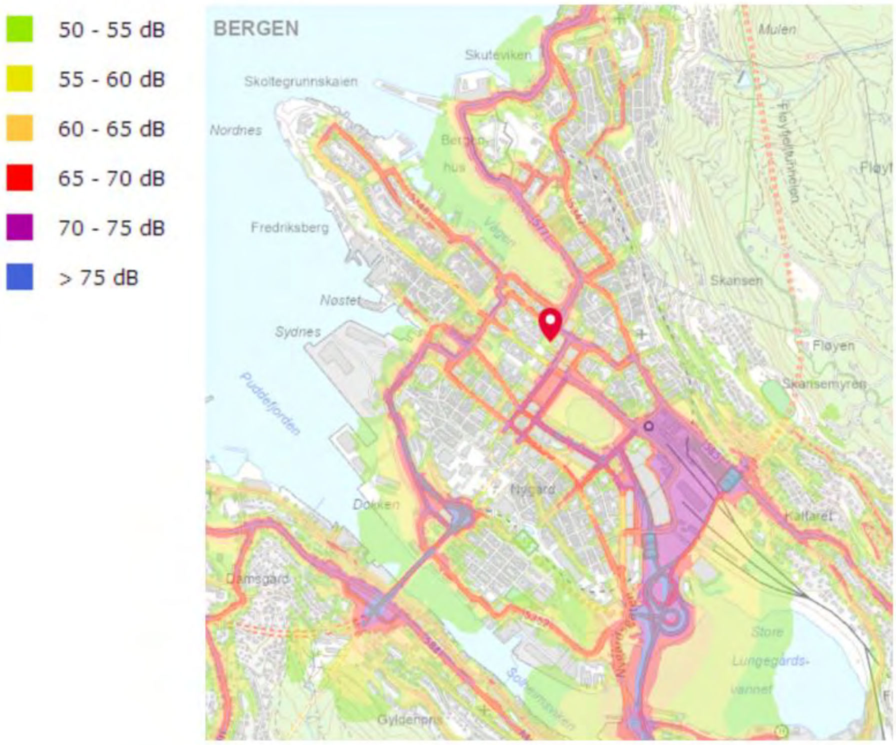

Figure 1.2: Average noise pollution from road traffic in Bergen in 2016 (Miljødirektoratet, 2022).

Moreover, in September 2006, the Environment Protection Agency (EPA) revised the 24-hour particulate matter (PM) standards from 1997 down to 35 µg/m3 for PM2.5 and 150 µg/m3 for PM10 (EPA, 2022). OECD (2001) defines air quality standards as follows: "Air quality standards refers to levels of air pollutants prescribed by regulations that may not be exceeded during a specified time in a defined area."

Figure 1.3 shows the calculated air pollution in Bergen done by Miljødirektoratet (Miljødirektoratet, 2022). The figure shows the air pollution from PM10 on the left-hand side and PM2.5 on the right-hand side at 8 a.m. on the 19th of November in Bergen city center. Miljødirektoratet defines the green parts as low to non-risk for human health, the yellow part as moderate risk, and the red areas as high risk. This clearly shows that taking PM10 pollution seriously is vital in Bergen. However, on the right-hand side of the figure, there is a faint yellow color in Bergen. This states that there are pollution levels above the level where it affects human health and will have an impact on global warming, but that there are smaller areas that exceed the limits for PM2.5 than PM10.

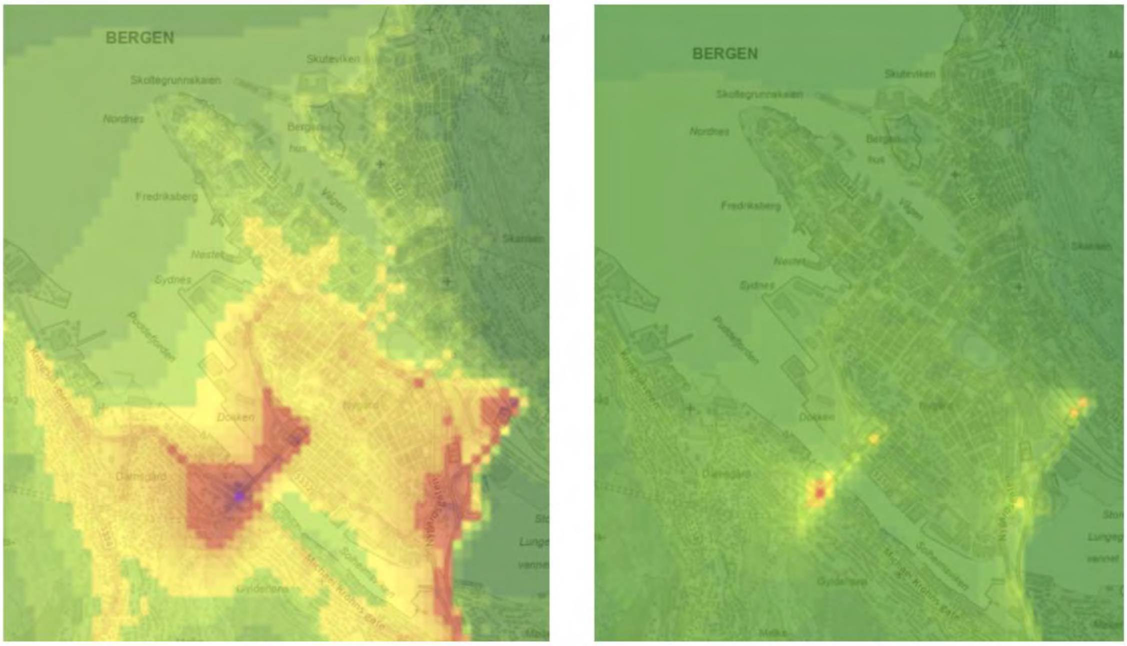

Figure 1.3: PM10 (left-hand side) and PM2.5 (right-hand side) concentration in Bergen city center (Miljødirektoratet, 2022).

Bergen Municipality requires Bergen to be a sustainable city. E-commerce is growing, and it is essential to find a way to accommodate the demands of last-mile delivery. However, this must happen simultaneously as taking the environmental, social and economic effects seriously since this affects the population of Bergen. Therefore, there is a need to investigate new methods to handle the rapid development of last-mile delivery. This thesis will analyze the sustainable effects of using electric cargo bikes instead of electric vans in last-mile delivery in Bergen.

1.2 Research question

We use demand, distance, and time data to analyze the effect a change from electric vans to electric cargo bikes in last-mile delivery will have on different sustainability parameters. The demand data is estimated parcel deliveries in Bergen municipality, while distance and time data are retrieved using Google API. Furthermore, we utilize the programming language Python to solve a Capacitated Vehicle Routing Problem (CVRP) and apply our knowledge within business analytics to investigate how a change from e-vans to e-cargo bikes affects different sustainability parameters.

In this thesis, we seek to answer the following research question:

How are the pillars of sustainability affected by a transition from electric vans to electric cargo bikes in last-mile delivery in Bergen city center?

To answer this question, we will establish which sustainability factors are affected by last-mile delivery. Further, to examine the difference between e-vans and e-cargo bikes, we need to determine how these delivery methods affect these factors. To do this, we have drawn up the following two sub-questions:

i) Which factors affect the sustainability of city centers?

ii) How are these factors affected by whether the packages are delivered by electric vans or electric cargo bikes?

Sub-question i) will determine which factors affect a city center´s sustainability and will be answered using empirical studies of the topic. Further, sub-question ii) will give us insight into how a transition from e-vans to e-cargo bikes may affect these factors.

1.3 Thesis overview

In the following section, we will present both relevant literature and theory (Section 2). Further, we will give an overview of the underlying data used in the investigation (Section 3). Next, we will present and describe the methods used and the models we will analyze (Section 4) before presenting the results (Section 5). Section 5 is twofold; the first part presents the results from the different models, while the second contains a sensitivity analysis. In Section 6, we will discuss the limitations and external validity of the thesis, while our conclusion will be presented in Section 7.

2. Literature review

This part will present the relevant theory and literature that will be important in understanding the following sections of the thesis. We have chosen first to present the theory of interest since this forms the basis for understanding the literature section to a larger degree.

2.1 Theory

In this part, we will present the phenomenon of sustainability. Sustainability is defined in various ways, but most definitions are based on meeting today's needs without compromising future generations' ability to meet theirs. This is about companies and authorities finding alternative ways to use the limited resources and implementing ways to solve problems with severe consequences. Sustainable development, which, if successful, will contribute to better sustainability, was first introduced and gained major prominence in the report Our Common Future. This is known as the Brundtland Report, and the definition of the term is widely used today (Brundtland, 1987):

> "Sustainable development is a development that meets the needs of the present without compromising the ability of future generations to meet their own needs.
>
> It contains within it two key concepts: the concept of ´needs´, in particular the essential needs of the world's poor, to which overriding priority should be given; and the idea of limitations imposed by the state of technology and social organization on the environment´s ability to meet present and future needs [...]. (p. 37)."

This definition implies that sustainable development has three main components: environmental, social, and economical. These pillars are often referred to as people, planet, and profits. How these dimensions work together is decisive for whether the development is sustainable (Hestvik, 2020). In the following, we will present the three pillars.

The social pillar is generally about how public health, happiness, education, human rights, and other important factors for community well-being are taken care of. This pillar ensures that everyone's basic needs and rights are met. For public authorities, social sustainability means protecting the population against hunger, poverty, disease, and other social failings (brightest, n.d.). This pillar is broadly about well-being, social capital, and quality of life at a neighborhood level (Woodcraft et al., 2012).

The environmental pillar is about taking care of the nature and as a renewable resource for people. People's livelihood is utterly dependent on nature, and how we use this today has significant consequences for both nature and people in the future. The greenhouse gas emissions warm the sea and air, destroy entire ecosystems and contribute to species extinction. Moreover, it can make us more vulnerable to natural disasters, threaten our livelihood, and provide fertile ground for conflicts in the fight for natural resources (Rudi, 2021).

The economic pillar is generally about economic development, fair compensation, job creation, and sustainable economic circularity. This pillar allows society to solve problems, innovate, and improve standards of living. Nevertheless, it is crucial to not only focus on this pillar, but to develop it in harmony with the social and environmental goals. A challenge in modern society is raising standards of living and increasing general welfare without increasing emissions and overconsumption of natural resources (brightest, n.d.).

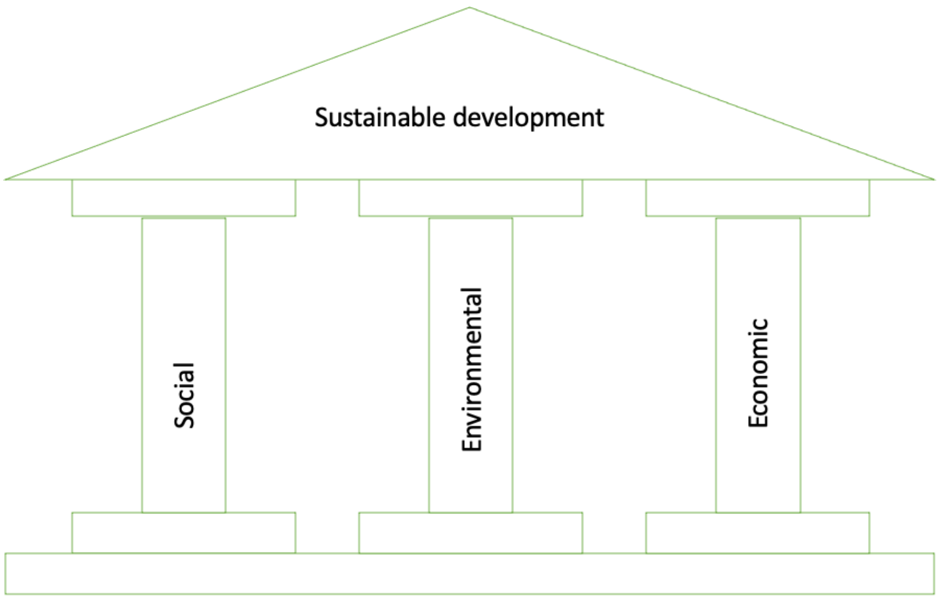

Figure 2.1: The three pillars of sustainable development

As we have seen, the three pillars must act together harmoniously. This is because sustainability does not support itself without all three pillars being "up and standing", as seen in Figure 2.1. However, individually they show important sustainable elements in society. In conclusion, the three pillars of sustainability are important individually, but there must be harmony between them for sustainability to be achieved.

2.2 Literature review

In this part of the thesis, we will first present literature investigating which sustainability factors affect a city center's sustainability. Further, we will look at how a transition from e-vans to e-cargo bikes affects these factors.

2.2.1 Which factors affect the sustainability of a city?

Social factors

Social sustainability is mainly about satisfying various stakeholders (including internal employees, external stakeholders, and locals). Therefore, a company or authority must identify how they positively and negatively influence people. Further, they affect employees, customers, and the local population directly and indirectly, and it is essential to proactively manage the social impact (United Nations Global Compact, n.d.). Abdel-Raheem & Ramsbottom has done a study on social factors affecting social sustainability. Some of the factors mentioned are respecting and caring for communities, improving the quality of living, minimizing the usage of non-renewable resources during project construction, as well as changing attitudes and practices (Abdel-Raheem & Ramsbottom, 2016, p. 550). Further, Quak (2007) mentions factors such as injuries and deaths resulting from traffic accidents, noise disturbance, and vibration from freight transport vehicles.

Environmental factors

A report by the Institute of Occupational Medicine in 2006 claims that removing air pollution could have a more significant impact on life expectancy than removing either passive smoking or traffic accidents. Furthermore, a DEFRA report states that the average life expectancy in the UK is reduced by six months due to just one of the human-made components of air pollution. In addition, it is said that transport-related emissions are responsible for a greater cause of pollutants in urban areas than before. These pollution emissions include oxides of nitrogen (NOx), carbon monoxide (CO), carbon dioxide (CO2), and fine particulate matter (PM), such as PM10 and PM2.5. The particulate matter emissions come primarily from brake wear, tire wear, road wear, and engine emissions. Furthermore, nitrogen dioxide emissions are caused by diesel and petrol combustion (Davoudi, 2012).

Economic factors

The economic part of sustainability is about the ability to create jobs, contribute to economic growth, and the infrastructure´s long-term financial viability (Milani et al., 2021). Quak (2007) presents several factors that affect economic sustainability, such as inefficiency and waste of resources and decreasing city accessibility because of congestion. Further, he mentions the importance of delivery punctuality and journey reliability and that reducing this will result in less service to consumers.

2.2.2 How are these factors affected by whether the packages are delivered by e-vans or e-cargo bikes?

PostNord states in its Annual and Sustainability Report 2021 that their vehicle fleet will become fully fossil-free by no later than 2030 (PostNord, 2021). Posten, another large freight company operating in Norway, has also started its transition towards fossil-free delivery options and recently purchased 177 electric vans (Nesheim, 2022). These are in addition to the 378 electric vans they ordered in 2021. Like PostNord, Posten has a goal of emission-free distribution by 2030 (Posten, 2021). The transition from fossil fuel-powered vans to electric vans and other more environmentally friendly vehicles is happening quickly. Therefore, we have chosen to compare the e-cargo bikes with Posten´s new electric vans called Maxus e-Deliver 3 (Wardrum, 2021). The e-cargo bike we will use in the comparison is Yokler U, which is well-suited for last-mile delivery. This type of cargo bike combines the best of a regular bike with the carrying potential of a small truck. Further, the three-wheeler can reach a speed of 25 km/t, which will be advantageous when delivering over longer distances (Yokler, n.d.). The Yokler U can operate legally in Norway due to its battery capacity of 0.25 kW and that the engine power ceases at 25 km/h (Kjøretøyforskriften, 1994, § 2-5).

Social factors

McDonald et al. (2019) estimated annual rates of fatal and nonfatal injuries related to urban freight from 2005 through 2015. The findings are that the number of urban freight-involved crashes increased rapidly through the years and that freight-involved injuries and fatality rates increased faster than overall road traffic-related rates.

Noise has been a concern of several regional governments. Long-term environmental noise can be painful for those affected and causes 12 000 premature deaths and contributes to 48 000 new cases of ischemic heart disease each year in Europe (Garus, 2022). Noise disturbance can therefore be said to be a problem, and it will be positive for the social bottom line to reduce this form of emission. The World Health Organization (WHO) recommends that the noise pollution level not exceed 45 dB at night and 55 dB during the daytime in the European Union since higher noise levels may affect human health (World Health Organization, 1999). A study from 2012 concluded that noise pollution from road traffic is putting human health in danger, which is the primary source of pollution (EEA, 2016). According to Koning & Conway (2016) and Llorca & Moeckel (2021), e-cargo bikes do not produce any noise, so they can be considered silent.

Environmental factors

A vehicle's emissions depend on many factors, such as weight, age, fuel type, temperature and humidity, terrain traveled, and the driving pattern (Alwakiel, 2011). Furthermore, EVs are often said to have zero emissions. That is, however, not true in a regional or global sense because of the upstream emissions that electricity generation can produce (Winkler, 2018). The approach of zero emissions is based on evidence that the tailpipe emissions are zero when driving an EV, and it is therefore postulated that an EV achieves zero emissions (Fernández, 2018). Even though EVs have indirect emissions of, among other things, CO2, we have chosen to disregard this as we only want to focus on direct emissions. This also includes the omission of NOx, as this is not emitted from EVS, unlike what is the fact of conventional internal combustion engine vehicles (ICEVs) (Hawkins, 2013).

Non-exhaust airborne particles are generated from brake wear, tire wear, and road surface wear, and all of these sources are closely related to vehicle weight. The higher the weight, the higher the emissions (Liu, 2021). The particulate matter affects human health, visibility, and climate change and is considered a climate forcer with a high global warming potential (Zazouli et al., 2021; Prasad & Bella, 2010). These are non-exhaust emissions, including brake wear, tire wear, and road wear. Furthermore, electric vehicles have regenerative braking as a feature (Liu, 2021). This could lower brake wear emissions; for instance, Ligterink et al. (2014) state that regenerative braking may reduce 95% of these emissions. Furthermore, Van Zeebroeck and De Ceuster (2013) pointed out that there is a linear relationship between regenerative braking and reduction in brake wear emissions. Regenerative braking slows down the vehicle's speed by converting kinetic energy into a form that can be stored till needed or used immediately. As a result, when regenerative braking is used, no brake wear emission is emitted (Liu, 2021).

When we found figures showing the emission of PM2.5 and PM10 (particulate matter smaller than 10μm and 2.5μm respectively), we made use of the study by Liu et al. (2021). This investigated the emission of, among other things, particulate matter from EVs where they divide the vehicles into weight classes. The weight class we have looked at has an average weight of 2276 kg, which is about 200 kg lower than the Maxus e-Deliver 9's weight. There will therefore be a minor margin of error, but this will be very small. Furthermore, since the particulate matter is closely related to the vehicle's weight, we will downscale the PM emissions from EVs with regard to weight. This is to find a reasonable estimate of PM emissions from Yokler U. Since Yokler U weighs 18 times less than Maxus e-Deliver 9, we will assume that the E-cargo bike emits 18 times less particulate matter than the van. A summary of the environmental emissions is shown in Table 2.1.

Table 2.1: Environmental emissions from the two vehicles

Environmental	Unit measure	E-van	E-cargo bike
CO_2	g/km	-	-
NO_x	mg/km	-	-
PM10 (Brake wear)	mg/km	17	0.9
PM10 (Tire wear)	mg/km	11.5	0.6
PM10 (Road surface)	mg/km	8.5	0.47
PM2.5 (Brake wear)	mg/km	6	0.33
PM2.5 (Road wear)	mg/km	8	0.5
PM2.5 (Road surface)	mg/km	4.5	0.25

Economic factors

Conway et al. (2017) studied local operators in New York City. This study shows that cargo bikes can be a competitive last-mile delivery option compared to motorized vehicles in congested neighborhoods. In addition, cargo bikes prove to be able to drive (legally or illegally) on off-street paths and to cycle in the opposite direction of motor vehicle traffic. This reduces the travel distance since the freight vehicles must operate on limited networks where directionality restrictions exist. Therefore, they may reach the demand point more quickly than a car.

The same Conway et al. (2017) study shows that cargo cycles have a lower ratio between stop time and travel time than trucks. This means that cargo bikes can have shorter stop times than vehicles. It also states that cargo bikes can be more reliable than motorized vehicles in congested areas because of their size, weight, and opportunity to ride in places where cars are not allowed. According to the same study, their independence from parking regulations is also essential to cargo bikes′ better delivery punctuality. Further, Rajesh & Rajan (2020) investigated the sustainable performance of using cargo bikes in last-mile delivery compared to a petrol-powered car. However, we still think several of their findings are directly transferable to our study comparing E-cargo bikes and EVs. In this study, the cargo bikes consumed only 68% of the truck´s delivery time. These were 9.1 min/km and 13.35 min/km, respectively. Both studies show that cargo bikes have the opportunity to score at least as well on delivery punctuality and journey reliability as freight vehicles. It should be noted that these studies have investigated the effects within a certain distance from the depot and that the van may be faster over longer distances.

In the previous paragraph, we presented literature that shows the difference between delivery time and punctuality between a car and a cargo bike. As Conway et al. (2017) state, comparing stop times between different vehicles is challenging due to differences in stop types and load sizes. However, it is clear that cargo bikes can deliver very quickly as a result of, among other things, their ability to drive in places where cars are either not allowed or able to drive, their independence from parking regulations, and their potential to avoid queues during rush hour. This enables them to provide great service to the customer through faster and more punctual delivery.

Lastly, whether the freight actors use EVs or E-cargo bikes in the last-mile delivery will affect the operational costs. The operating expenses related to freight transport may change the costs of goods (Litman, 2007; Hansen, 2014) because 10-20% of a product´s total costs come from transportation costs. This underlines the need to analyze operational expenses and reduce them (Anderson & Van Wincoop, 2004; Rodrigue, 2016). Parts of these costs are direct costs, such as vehicle depreciation. Variable costs include parking, road tolls, fuel, insurance, maintenance, and weight transported expenses. These are variable costs as they depend on the travel conditions, the type of vehicle, and the taxes charged by the market (Litman & Doherty, 2011).

As stated in Section 2.2.1, another economic impact is costs due to congestion delays since congestion leads to decreased city accessibility. A study by Cintra (2014) shows that urban congestion increases transportation costs by 30-40% in Brazil, while Cairns & Sloman (2019) looked at the potential for e-cargo bikes to reduce city congestion. In this study, they concluded that e-cargo bikes have significant potential to replace vehicles and help reduce congestion and pollution in urban areas. This is because they take up less road space, and they may undertake activities more efficiently due to being able to take shorter routes. In addition, the cargo bikes have the potential to be parked more easily, quickly, and closer to the demand points. Furthermore, Conway et al. (2017) have completed several savings scenarios between cargo bikes and vans. Their minimum saving scenario shows that cargo bikes may only take up around 35% of the space required by a van. In the best-case scenario, a cargo bike only takes up 15% of the space a van takes up.

Summary of the sustainability pillars

We have now presented the pillars of sustainability and discussed how empirical evidence shows that they are affected by whether the parcels are delivered by e-van or e-cargo bikes. The studies by Conway et al. (2017) and Rajesh & Rajan (2020) show, as mentioned, that cargo bikes can deliver goods faster than vans in congested urban areas. As we have seen, environmental factors are directly affected by the distance traveled. This is because particulate matter is released when the vehicle is in motion, and the longer the distance covered, the more PM is released. Furthermore, both social and economic factors are affected by the distance, as well as the time used. Since the time used usually increases simultaneously with the distance, we can state that time and distance depend on each other to a large degree. Because of the focus on global warming and major discussion on how to reduce air pollution worldwide, we find the environmental pillar the most interesting. Further, the environmental pillar is directly affected by travel distance, which affects both the social and economic pillars directly or indirectly. Hence, we cover all the sustainability pillars by focusing on the distance traveled.

2.2.3 Vehicle Routing Problem

A vehicle Routing Problem (VRP) is a problem regarding goods distribution between one or several depots and the final users (Toth, 2000). VRP is a combinatorial optimization problem that calls for determining the optimal set of routes for a certain number of vehicles to serve a given number of customers that starts and ends at its given depot. The classic VRP aims to find the optimal delivery routes for vehicles with the same characteristics. One of the decision rules is that each vehicle only travels one route and that there is only one depot where the vehicle leaves and arrives (Braekers, 2016). Further, the goal is to optimize the objective function, which can be the minimization of transportation cost, traveling time, traveling distance, or the number of vehicles or workers. The constraints could be that each vehicle starts and ends at the depot, each customer is visited once and the vehicle capacity is not exceeded (Zirour, 2008). The optimal solution must fulfill all the customer's requirements, and all operational constraints must be satisfied (Toth, 2000).

In VRP, the nature of customer demand is an important issue. Each pickup (depot) or demand point is considered separately, and in the road network, it is identified with a specific location. The VRP is, in this case, called a node routing problem. There are several other categories of problems in the literature, but in this thesis, we will focus on the node routing problem. In the literature, most of these problems are based on the key assumption that the best origin-destination path can be pre-defined for each pair of points of interest (e.g., customers, depots). After the path is defined, the road network is described through a graph where one node represents each point of interest, and one arc represents the optimal path between its endpoints. Then, the different arcs' attributes are computed in accordance with this path (Ben Ticha, 2018).

Furthermore, VRP includes several constraints that must be satisfied. One type of constraint is the operational constraint. This refers to infrastructure restrictions such as one-way streets, pedestrian zones, and public transport fields. Another element to consider is the requirements of the customer. This is associated with the customer's location, demand, and whether it requires delivery, collection of goods, or both. The customer's requirements define the size and composition of vehicles used to transport goods. Lastly, VRP can consider one or several objectives for a solution. The objectives can be minimizing transportation costs, traveling time or distance, or minimizing the number of vehicles or workers used (Liong, 2008).

Moreover, there exist different variants of the classical VRP, such as Capacitated VRP (CVRP). In this variant, the vehicles have a maximum capacity. This restriction may concern the number of units, size or weight of the parcels. An extension of the CVRP, is the VRP with Time Windows (VRPTW). In the VRPTW, each customer must be serviced within a specific time window, while the vehicle must remain with the customer during service. In this thesis, we will use the CVRP due to the vehicles´ maximum capacity and no time windows.

As mentioned, CVRP operates with restrictions for vehicles. These restrictions are related to the vehicle's maximum carrying capacity, such as maximum weight, volume, and the number of parcels. In addition, the range of the vehicle is determined. Lastly, VRP can consider one or several objectives for a solution, such as minimizing transportation costs, traveling time or distance, or minimizing the number of vehicles or workers used (Liong, 2008).

2.2.4 Traveling Salesman Problem

Several studies have been carried out on routing problems, and the traveling salesman problem (TSP) has undoubtedly received the most attention (Rahman, 2019). The TSP can be stated as: what is the least costly route a traveling salesman can take if he or she is supposed to visit each place exactly once of a list of *m* places while returning to the origin place (where the traveling cost from place *i* to place *j* is cij) (Hoffman, 2013)? According to Gutin & Punnen (2016), understanding the TSP formulations does not require much mathematical sophistication. However, the problem is seen as a typical "hard" optimization problem, where solving large instances is demanding and impossible if the instances are too many (Gutin, 2006). Furthermore, there exist both symmetric and asymmetric forms of TSP.

In a symmetric TSP, the distance from place *i* to place *j* is the same as from place *j* to place *i*, i.e., that $d(i, j) = d(j, i)$. Unlike in symmetric TSP, the distance function in an asymmetric TSP is not necessarily symmetric. Asymmetric distances mean that the distance from place *i* to place *j* is not the same as from place *j* to place *i*. That is, $d(i, j) \neq d(j, i)$ (Gilbert, 2015).

Figure 2.2 below illustrates both the TSP and the VRP and clearly shows the difference between these routing optimization methods (Liu et al., 2014). The round points, called *customers*, in the VRP are what we refer to as the main points later in the thesis. Each main point is associated with a cluster that contains up to several addresses in the Bergen city center. When solving our model, we will use TSP to optimize the route within each cluster.

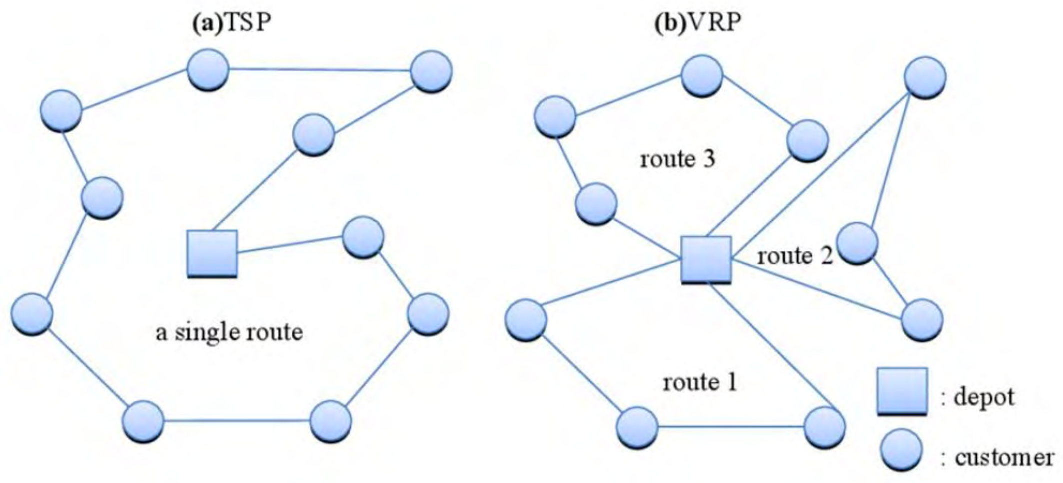

Figure 2.2: Illustration of the Traveling Salesman Problem and the Vehicle Routing Problem

The research articles we have reviewed have been a great source of inspiration and given us increased insight into the sustainable effects of e-vans and e-cargo bikes in last-mile delivery. Further in this thesis, we want to contribute with a study of Bergen city center. Here, collected data will be used to analyze the sustainable differences between e-vans and e-cargo bikes in last-mile delivery.

3. Data

Our underlying data is proceeded by Cosku Can Orhan, a PhD student at NHH. This provides insight into 887 addresses (demand points) and their parcel demand, spread over 53 postal codes that constitute the Bergen metropolitan area. In addition, the data contains a matrix for both driving and walking, showing the distance between each demand point. Each distance matrix holds the alleged depot point, placed at Lundegårdskaien 30, from where the parcels are sent. Since our research is limited to the Bergen city center, the number of postal codes is reduced to 21 inside the city center. As a result, the number of demand points is down to 452 in addition to the depot. Figure 3.1 shows the geographical area the 21 postal codes constitute.

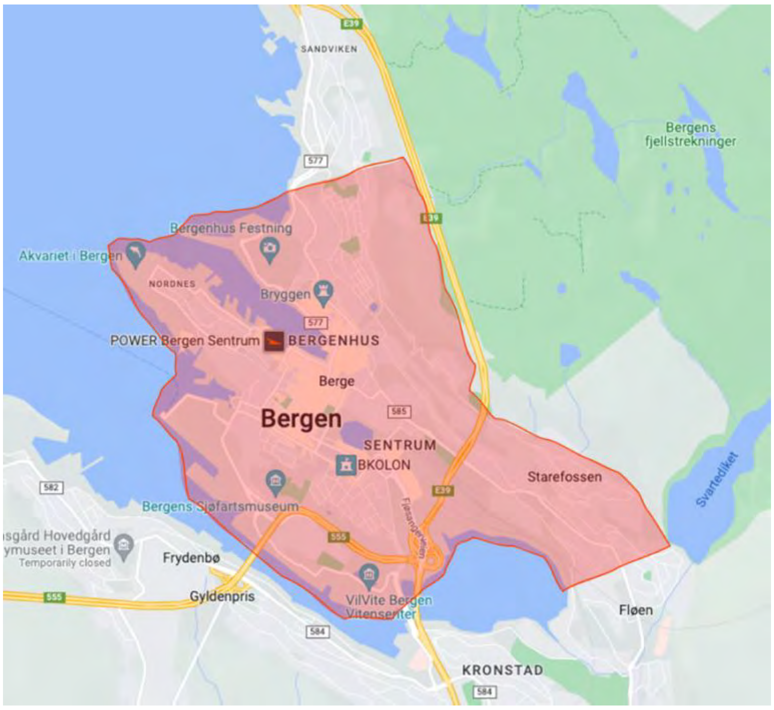

Figure 3.1: Illustration of the geographical area of interest

3.1 Data Cleaning

3.1.1 Clustering

The data contains 453 demand points in the Bergen city center, and the matrices hold 205 209 distances between these points. The consequence is that it is too costly to retrieve time and distance data for biking and driving using google API. This API returns information about the recommended routes between two points, and one may request distance and time data for different travel modes (Hwangnyc, 2020). To deal with the cost problem, each demand point is assigned to a cluster using the eclust() function in r. The k-means algorithm separates the dataset into Kpre-defined non-overlapping subgroups where the points only belong to one group (Dabbura,2018).

With the cost challenges in mind, we have set the number of clusters equal to 227, so each cluster, on average, consists of two demand points. The consequence of clustering is the following margin of error that arises: the computed distance will be shorter since we remove half of the points. In last-mile delivery, the delivery takes place directly to the door or the postbox, and the distance should be as precise as possible. Therefore, we must choose a foundation distance matric to compute the clusters that minimizes the margin of error. Foundation means that either the walking or driving matrix is used in the k-means clustering algorithm, which seeks to make the intra-cluster data points as close as possible while keeping the clusters as far as possible apart from each other (Dabbura. 2018). Since the margin of error mainly occurs within clusters, this algorithm is well-suited for minimizing this error. Regardless of which foundation we use, we retrieve the time and distance matrices for biking and driving between the clusters using google API.

Determine the foundation used for k-means clustering

A problem with using the driving matrix as the foundation is that some points may be close to each other geographically but further away from each other in driving distance due to driving restrictions, such as one-way streets and pedestrian zones. If the courier chooses to walk between such points, the driving distance will give an incorrect picture of the actual distance the courier has walked.

If we, on the other hand, use the walking matrix as the foundation for clustering, this error vanishes. However, some other problems arise. For example, if the biking distance is computed from the walking distance matrix, it may be shorter than the actual distance. This is because the walking distance matrix may contain paths a bike cannot commute, like paths with stairs.

We assume that the courier chooses the shortest distance. Therefore, we will use TSP to find the shortest route within each cluster while ensuring the courier visits all the cluster points before returning to the origin point. Further, by allowing the courier to walk within the clusters and then back to the car, we will eliminate some problems regarding stairways and one-way streets. Finally, we eliminate some margin of error by assuming the courier will walk if it is the best option and drive otherwise. Considering the problems regarding the two foundations, we have chosen the walking matrix as our foundation for k-means clustering.

Minimizing the margin of error

Figure 3.2 shows a scenario the courier could take during his route in our model. The courier starts at the depot, and the arrows show the route the courier takes. The green points demonstrate the main point in a cluster, and the black points are the demand points inside a cluster. The number inside the black and the green points equals the demand for the demand point.

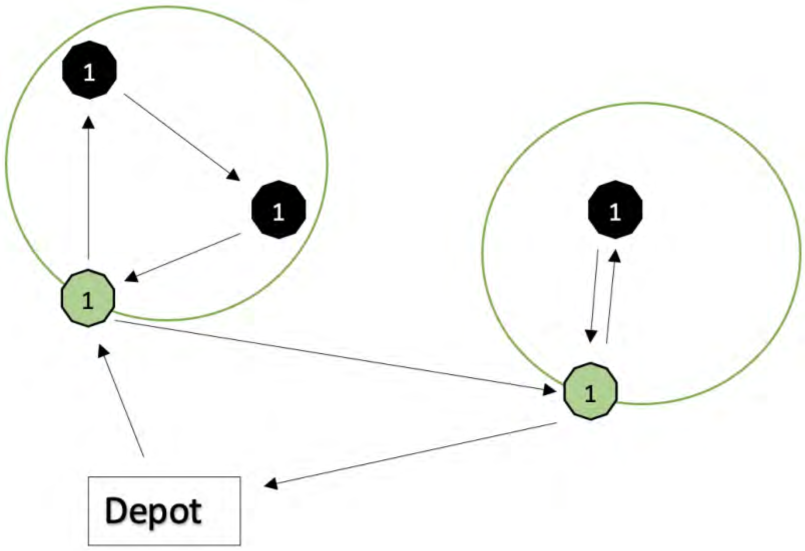

Figure 3.2: Route created by the model. The illustration shows that the courier first must visit the cluster´s main point before visiting the other points in the cluster.

Nevertheless, we must determine each cluster's main points to create a new distance matrix containing the distance between the clusters. To this end, we have chosen the point closest to the depot for driving and cycling, respectively. This makes the clusters for the two delivery methods slightly different, since this point is not necessarily the same. In order to find the most accurate distances for driving and walking inside each cluster, TSP is used. This method assumes that the courier starts and ends his ride at the cluster's main point. This is because our data computed by Google API only contains distances between the main points for each cluster. Therefore, the courier must return to the main point before moving to the next cluster, as shown in Figure 3.2.

Furthermore, the courier may walk to some points in the cluster and drive to another. However, we have yet to find a solution for how we can observe when the courier chooses to drive or walk during the route suggested by TSP. Therefore, we assume that the courier either walks or drives within each cluster. Despite the error that occurs when using TSP, we see it as the best method to find the driving distance closest to the truth since it minimizes the distance from the main point and back by visiting all points within each cluster, which makes it superior to other options.

As mentioned, we assume that the courier may walk within each cluster if the walking distance is advantageous compared to driving. We assume that the courier will choose the fastest option if the distance is between 150 and 400 meters. Further, the courier will choose to walk if the distance is less than 150 and drive if it exceeds 400 meters. Fitspatrick (2016) states that the average walking speed equals just over 4 km/h. Meanwhile, we assume that driving will have an average speed of 15 km/h as it must stop and start, and the speed limit is rarely high in urban areas. If the courier drives within the cluster, we add the driving distance into the cluster matrix.

Further, we use the walking matrix to find distances within the cluster because we assume that the bike route is closer to walking than driving. We assume that the courier will cycle between all points in the route. This assumption causes errors if there are walking routes where the e-cargo bike cannot pass. However, it is the best option since the margin of error will be more significant if using the driving distance matrix due to one-way streets and pedestrian zones where the e-cargo bike can pass. The only time an e-cargo bike cannot take the same route as the suggested one is when stairs are involved. However, stairs do not occur as often as pedestrian zones and one-way streets, which makes the distance for an e-cargo bike look more like walking distance than driving. Therefore, we will add the TSP route for walking into the distance and time bike matrices. Lastly, we assume that if the courier visits a cluster, he visits each point in it.

3.1.2 Producing Time and Distance matrix

With 227 demand points and one depot the matrices will contain 51 984 individual distance and time data points each. As mentioned, Google API is used to retrieve a time matrix for driving and time and distance matrix for biking to get the most accurate distances. The r function mp_directions() retrieves the distance and time data points, which is fetched between

9 a.m. and 15 a.m. on a random Tuesday. Google API provides the route Google Maps suggests from point *i* to *j*; therefore, sometimes, it will give us multiple routes. We have chosen the fastest route suggested, as it is more likely that the courier will choose this route rather than the shortest. The value of time data will differ during the day. At the chosen time of the day, the traffic is moderate and favors driving as the rush hour traffic will affect vehicles more than cargo bikes. Nevertheless, we chose this time interval as it best reflects the daily traffic.

Google API only provides data for conventional bicycles. Therefore, the time data needs to be adjusted. E-bikes have an average speed of 13.3 km/h compared to 10.5 km/h for conventional bicycles (Langford, 2013, p. 54). Since E-bikes use 80 percent of the time that conventional bicycles use, we must change the time matrix API gives us for the bike. This is done by multiplying each time value by 0.8.

3.2 Demand data

Our demand data is weekly estimated demand for each demand point based on empirical data from PostNord. We assume that Postnord has a market share of 30 percent in Bergen, which means that we have divided all demands by 0.3 to get total demand. In order to obtain delivered demand for each cluster, we have summarized the demand data by clusters in r. Furthermore, we separate the weekly demand into daily demand. In addition, we assume that the cluster's demand per day co-occurs, which means the daily demand for each day is available at the depot at any point of that day. Since Posten delivers parcels five days per week (Posten, 2022), we split the weekly demand into five days.

We assume that it is random which day the demand for each cluster occurs. While the weekly demand for a cluster is greater than five, we add one parcel demand to each day and remove five from the weekly demand. If the weekly demand is less or equal to five, we calculate the probability of demand happening on a random day. In other words, if the weekly demand is equal to three, the probability of demand happening on a random day is 0.6. We use this probability to randomly give a day demand or not.

3.3 Cost and capacity data

We want to compare the sustainable effects of using Maxus E-deliver 3 and Yokler U. When comparing the costs of the two vehicles, we have decided to only focus on the variable costs. As a result, the driver's salary and the electric energy costs are included.

Table 3.1 below shows relevant specifications for Maxus E-deliver 3 and Yokler U. We assume a package size of 40cm x 20cm x 20cm, which equals a volume of 24000 cm3. This again equals 0.024m3. Hence, Maxus E-deliver 3 has a capacity of 262 packages, while Yokler U has a capacity of 41 packages.

To find the electricity cost per kilometer driven and cycled, we first found the average electricity price per kWh in Bergen municipality from 2017 to September 2022. The average price for this period is 0.7441 NOK/kWh (Fjordkraft, n.d.). This price is then multiplied by the electricity consumption of each vehicle, which is, as shown in Table 3.1, 0.211 and 0.004 kWh/km for the Maxus E-deliver 3 and the Yokler U, respectively. Hence, the electricity cost per kilometer driven and cycled is 0.157 NOK and 0.003 NOK.

In addition to the electricity price, the driver's salary must be considered. We have found this cost by dividing the average annual salary for a courier by 1950 hours, since 1950 hours (including vacation) is considered one year's work in Norway (SSB, n.d.). The average annual salary is 450 000 NOK, which gives an hourly salary of 230 NOK (Nick, 2021). The cost per minute driven or cycled is found by dividing the hourly driver's salary by 60, which gives a cost per minute equal to 3.83 NOK per minute. Since the hourly salary of 230 NOK does not include the employer's tax and vacation pay of 14.1% and 12% of the salary the company must pay, we round this price up to 5 NOK per minute. This equals to a cost of 0.083 NOK per second.

Table 3.1: Specifications and properties for the two vehicle types

item	unit measure	E-van	E-cargo bike
market price	NOK	369 900 [1]	71 000 [2]
weight	Kg	1700 kg [3]	125 [2]
size capacity	M^3	6.3 [3]	1 [5]
number of packages	-	262 [4]	41 [5]
weight capacity	Kg	905 [3]	150 [2]
battery capacity	kWh	50.23 [3]	0.25 [2]
range	Km	238 [3]	60 [2]
consumption	kWh/km	0.211[6]	0.004 [7]
driver´s salary	NOK/h	230	230
cost per km	NOK/km	0.157	0.003
cost per second	NOK/s	0.083	0.083

[1] Maxus. (2022). *Kundeprisliste nye e-Deliver3 06.05.2022*.
[2] Yokler. (n.d). *The professional cargo bike for local stores and craftsmen*.
[3] Wonder. (2019). *Research Outline*.
[4] $6.3m^3 / 0.024m^3 = 262.5$
[5] $1m^3 / 0.024m^3 = 41,67$
[6] 50.23 kWh / 238 km = 0.211 kWh/km
[7] 0.25 kWh / 60 km = 0.004 kWh/km

4. Model

As mentioned, this thesis aims to compare the use of electric vans and electric cargo bikes in last-mile delivery in Bergen city center. We formulated a mathematical model for our problem inspired by the VRP model of Toth and Vigo (2002), and implemented this model in a Python script. Furthermore, we used the linear solver of GUROBI to solve our model in PyCharm. Due to our analysis's great number of addresses, we need to use heuristic packages of Google OR Tools to solve the problem. In order to validate the heuristic approach, we will compare the heuristic results with the results from the mathematical model for some smaller instances of the problem. The problem is modeled so that all packages is delivered by either e-vans or e-cargo bikes. The model is solved for the two delivery methods by changing the vehicle parameters accordingly.

Section 4.1 will introduce the sets and parameters for our mathematical formulation, while section 4.2 presents the decision variables and objective function. Moreover, section 4.3 will go through the constraints. Section 4.4 includes an overview and explanation of the Google OR Tools model. Lastly, in section 4.5, we validate the two models using 10 and 20 addresses to see if the mathematical model corresponds with the google OR Tools model.

4.1 Sets and parameters

The model contains one set, presented in Table 4.1. The set is called *P*, which consists of the depot and all the demand points. The demand points are the same as the main points (see section 3.1.1). This set will change depending on whether e-vans or e-cargo bikes are used since the main points differ for the two vehicle types (see Section 3.1.1).

Table 4.1: Model sets

Set	**Description**	**Value**
P	Demand points	See Appendix A1

Table 4.2 below presents the parameters considered. The parameter called *veh_cap* shows the maximum capacity for each vehicle type. It will be different for the two vehicle types due to the difference in capacity between e-vans and e-cargo bikes. The maximum number of vehicles available, called *veh_num*, will also change because we need more tours when using

e-cargo bikes than e-vans due to the different vehicle capacities. The number of vehicles available is found by dividing the total demand by the vehicle capacity, and add five vehicles. By adding five vehicles we ensure that the model will be feasible. Furthermore, the distance, D_{ij}, and the time, T_{ij}, between the different demand points i and j will be different for the two vehicle types (see Section 3.1.2).

Table 4.2: Model parameters

Parameter	Description	Value e-van	Value e-cargo bike
veh_cap	Maximum number of parcels in one vehicle	262	41
veh_num	Maximum number of vehicles available	demand / veh_cap + 5	demand / veh_cap + 5
D_{ij}	Distance between demand point i and j	Large matrix retrieved from Google API	Large matrix retrieved from Google API
T_{ij}	Time between demand point i and j	Large matrix retrieved from Google API	Large matrix retrieved from Google API
$Demand_i$	Demand in place i	See Appendix A1	See Appendix A1
max_time	Maximum time for one vehicle to deliver parcels	28 800	28 800

4.2 Decision variables and objective function

Table 4.3 shows the model decision variables, which can be binary and continuous. Variable x_{ij} is a binary variable that gets value 1 if and only if demand point j is visited immediately after demand point i, and 0 otherwise. Furthermore, variable s_i is the arrival time at demand point i. In addition, variable u_i keeps track of the cumulative demand in demand point i. Both variables s_i and u_i are continuous.

Table 4.3: Model decision variables

Variable	Description	Type
x_{ij}	A binary variable that determines whether demand point *j* is visited immediately after demand point *i*	$\begin{cases} 1: j \text{ is visited immediately after } i \\ 0: \text{otherwise} \end{cases}$
s_i	Time of arrival at demand point *i*	Continuous
u_i	Cumulative demand in the vehicle at demand point *i*	Continuous

The objective function

As mentioned in the literature section, cargo bikes have on average shorter travel distances than vans, leading to shorter travel time. Furthermore, we have discussed the impact of traveled distance on a city center´s sustainability. Hence, the objective function minimizes the total distance traveled. Therefore, it consists of the distance matrix D_{ij}, and the binary variable x_{ij}. As mentioned, the distance matrix reflects the distance from demand point *i* to *j*, where the courier has chosen the fastest route. Therefore, the time between demand points *i* and *j* are minimized. The value of the objective function depends on whether the distance D_{ij} has been traveled. If a vehicle has traveled between demand points *i* and *j*, the distance will be multiplied by 1, and 0 otherwise. Hence, the objective function is as follows:

$$\min \sum_{i}^{P} \sum_{j}^{P} x_{ij} * D_{ij}$$

4.3 Constraints

The constraints are made to create a realistic model that follows the rules for vehicle routing problem. Firstly, the model must ensure that each demand point is visited (4.1) and left (4.2) exactly once. Therefore, we have that:

$$\sum_{i \epsilon P} x_{ij} = 1 \ , \ \forall j \in P\backslash\{0\} \tag{4.1}$$

and

$$\sum_{i \epsilon P} x_{ij} = 1 \ , \ \forall j \in P\backslash\{0\} \tag{4.2}$$

In addition, the number of vehicles leaving the depot must be less than or equal to the number of available vehicles (4.3). Hence, we have that

$$\sum_{i \epsilon P} x_{i0} <= veh\_num \tag{4.3}$$

Furthermore, we must ensure that the demand in demand point i is less than or equal to the cumulative demand in the vehicle at demand point i. Also, the number of parcels in the vehicle must be less than or equal to the vehicle capacity, which computes

$$Demand_i \leq \mathrm{u}_i \leq veh\_cap \tag{4.5}$$

We must also ensure that sub-tours are eliminated, which means that a vehicle cannot travel back to a demand point it has already visited. In addition, the demand in each demand point must be fulfilled (4.6), and the maximum time cannot be exceeded (4.7). Hence, we include the following constraints:

$$u_i + Demand_j - veh\_cap * \left(1 - x_{ij}\right) \leq u_j \ , \qquad \forall i,j \in P\backslash\{0\} \tag{4.6}$$

and

$$s_i + t_j - max\_time * \left(1 - x_{ij}\right) \leq s_j, \qquad \forall i,j \in P\backslash\{0\} \tag{4.7}$$

The expression (4.8) defines x_{ij}.

$$x_{ij} \in \{0,1\}, \ i,j \in P \tag{4.8}$$

Google OR-Tools

In section 4.3, we presented the benchmark model. As mentioned, we use Google OR-Tools to solve the VRP optimization problem because of the number of addresses that must be visited. This tool is an open-source software that is well-suited for optimization and tuned for handling challenging problems in, for instance, vehicle routing (OR-Tools v9.4). This section will briefly explain how this solves our problem and which functions we have included in the model. Before continuing, we would like to inform the reader that this section is not essential for understanding the rest of the thesis, but is included to evaluate the validity of the Google OR Tools model.

Firstly, the model input needs to be created. The input includes the distance matrix, time matrix, demand for each cluster, vehicle capacity, and the number of vehicles available. This has been done in R Studio and inserted into the model in Python. Furthermore, the objective is still to minimize total distance since the sustainable parameters depend on the total meters traveled.

In our case study, the vans and cargo bikes have a capacity of 262 and 41 parcels, respectively. Therefore, a capacity constraint is included in our VRP model. Hence, it becomes a capacitated vehicle routing problem (CVRP), a VRP where vehicles with a limited capacity must deliver parcels at various locations. The capacity constraint ensures that the vehicles fulfill the demand in each cluster without exceeding the capacity of each vehicle.

Furthermore, we must add a distance callback function. This function returns the distance between any pair of locations, the distance callback. Finally, we include the distance callback in the solver as transid_callback_index using the RegisterTransitCallback function. Then, the function SetArcCostEvaluatorOfAllVehicles gives the solver the cost of traveling between two demand points. In our case, traveling costs equal the distance between the two points.

In addition, the solver requires a demand callback. The demand callback returns the demand for each demand point and a dimension for capacity constraint, which states that the capacity limit of each vehicle may not be exceeded. This dimension uses the function AddDimensionWithVehicleCapacity and keeps track of the cumulative sum of parcels carried for a vehicle along the route.

A time callback is included to compute the time each vehicle uses at its route, and returns the time the vehicle uses between any pair of locations. A time dimension is also included to keep track of the accumulated travel time of the vehicle. For this, we use the function routing.AddDimension. Here, the allowed waiting time is set to 0, and the maximum travel time per vehicle is set to 28 800 seconds since this is the regular daily working hours in Norway.

4.4 Comparison of the mathematical model and the Google OR Tools model

To control for reliability, the Google OR model has been run several times for a different number of seconds, from 1 to 600. However, after just a few seconds, the number of meters traveled stopped decreasing, so we chose to run it for 300 seconds, which proved to be enough for the model to find the optimal solution. When running the two different models for 10 and 20 addresses, the results in Table 4.4 are obtained.

Table 4.4: Comparison of the two models

Variable	Number of addresses	Mathematical model	Google OR model
Distance	10	6 825 m	6 825 m
	20	22 254 m	22 254 m
Number of tours	10	2	2
	20	5	5

The table shows that when 10 and 20 addresses are included, the two models are equal for distance and number of tours. This implies that the Google OR model will perform well for more addresses, making it fair to go further with this model.

5. Results and analyses

In this chapter, we will run our model several times using the estimated daily demand for the two transportation methods, as well as including a sensitivity analysis for the factors we find the most interesting and influential. Section 5.1 contains an overview of the results obtained from running the model for driving and biking as transportation methods while we at the same time will present and discuss their influence on the three sustainable pillars. Furthermore, section 5.2 includes a sensitivity analysis where we change the value of some variables to see how the results are affected.

5.1 Results

Table 5.1 shows the average results from running the model for driving and biking each weekday separately. The results for each weekday are found in Appendix A1. In Table 5.1, only figures showing the number of meters traveled, time used, and the number of tours driven or cycled for each delivery method is included. In addition, a column showing the percentage change by using e-cargo bike instead of e-van is included. The later sections will present and discuss results related to each sustainability pillar.

Table 5.1: Results from running the model for e-van and e-cargo bike

	Unit measure	**E-van**	**E-cargo bike**	**Change in %**
Meters traveled	m	66 073	100 257	+ 51,7
Time used	s	27 853	27 405	- 1,6
Number of tours	Z	3	19	

Next, we will present the results associated with each of the three pillars of sustainability.

Social impact

Social sustainability is about how one can satisfy various stakeholders and how companies and authorities influence people. We have chosen to analyze this pillar from a qualitative point of view since it is challenging to calculate how, for instance, the number of traffic accidents will be affected by a transition from E-vans to E-cargo bikes.

The number of accidents and the severity of these entails a high socioeconomic cost and a strain on the people involved. Therefore, getting this number down as much as possible will be beneficial. On the one hand, e-cargo bikes can cycle in pedestrian zones and pavements, where many people walk and stay. This means that accidents will often involve pedestrians, which can have fatal consequences. In addition, the more elements one has to deal with at any given time, the greater the likelihood of an accident occurring. On the other hand, e-cargo bikes have a relatively low speed, and the driver can perceive dangers fast. Hence, the number of accidents using e-cargo bikes can be lower than e-vans. Furthermore, the potential for damage may be high when e-vans are involved in an accident due to their high maximum speed and heavy weight. Moreover, the damage potential when e-cargo bikes are involved is also significant since they can cycle in areas where people are poorly protected and unaware of the potential danger of an e-cargo bike coming around the corner.

Another aspect that should be discussed around the social effect is the noise pollution of the two vehicles. The noise emissions from electric vehicles mainly come from the interaction between the vehicle´s tires and the road and are higher for heavier vehicles. According to Maffei (2014), noise pollution will be more significant the higher speed. Since an e-van is both heavier and can hold a higher speed than an e-cargo bike, the noise pollution will be higher when using e-vans. However, Figure 1.2 in section 1.1 clearly shows that noise pollution mainly occurs near the main roads. Therefore, noise pollution will be reduced by switching from e-vans to e-cargo bikes. Further, the places where noise pollution exceeds the healthy limit will be even more reduced as e-cargo bikes do not necessarily travel on the main road. Conversely, noise pollution may increase in areas where the e-cargo bike can travel and not cars, such as pedestrian zones.

The last social aspect we will examine is the visibility of the two vehicle types in the cityscape. On the one hand, Table 5.1 shows that more kilometers will be travelled when using e-cargo bikes. This implies that the e-cargo bike will be a greater part of the cityscape than the e-van. On the other hand, one e-cargo bike takes up less place than one e-van. Hence, the total space used by the two vehicle types may be the same. As we see it, the most remarkable difference lies in which area they will use space, as the e-cargo bike is allowed to travel in pedestrian zones where the e-van is not permitted. Furthermore, the E-van will affect traffic to a more significant extent due to the following reasons. E-vans may not park on the pavements as e-cargo bikes can and has to park illegally, thus blocking the road. E-vans have to always use the road. Meanwhile, e-cargo bikes can use the bike lane, pavements and pedestrian zones.

This will lead to a better traffic flow. However, e-cargo bikes will to a larger extent, affect pedestrian citizens. Switching from e-vans to e-cargo bikes will lead to more bikes in zones where pedestrians stay.

Environmental impact

Table 5.2: Environmental results

	Unit measure	E-van	E-cargo bike	Change in %
PM10 (Brake wear)	mg	1 123 241	90 231,3	- 92,0
PM10 (Tire wear)	mg	759 839,5	60 154,2	- 92,1
PM10 (Road surface)	mg	561 620,5	47 120,8	- 91,6
Total PM10	**mg**	**2 444 701**	**197 506,3**	**- 91,9**
PM2.5 (Brake wear)	mg	396 438	33 084,8	- 91,7
PM2.5 (Tire wear)	mg	528 584	50 128,5	- 90,5
PM2.5 (Road surface)	mg	297 328,5	25 064,25	- 91,6
Total PM2.5	**mg**	**1 222 350,5**	**108 277,6**	**-91,1**

Table 5.2 shows the PM10 and PM2.5 emissions for vans and cargo bikes. We can see that the cargo bikes emit 91,9 and 91,1 percent less for PM10 and PM2.5, respectively. However, to understand to what extent the reduction in air pollution affects the environment, firstly, we need to investigate the impact of e-vans. As mentioned, EPA has 24-hour PM standards of 35 µg/m3 for PM2.5 and 150 µg/m3 for PM10. Because we do not want to exceed the PM standards, we calculate how many cubic meters the PM10 and PM2.5 polluted by e-vans will cover, while not exceeding the standard. The daily e-vans pollution is equivalent to fulfilling the PM standards of 16 298 006,7 m3 for PM10 and 34 924 300 m3 for PM2.5. Figure 5.1 illustrates the cubic meters that equal the fulfillment of PM standards caused by the e-van. To put it more simply, imagine a cube with the blue area as the ground surface and a height equal to 20 meters. PM10 is on the left-hand side, and PM2.5 is on the right-hand side.

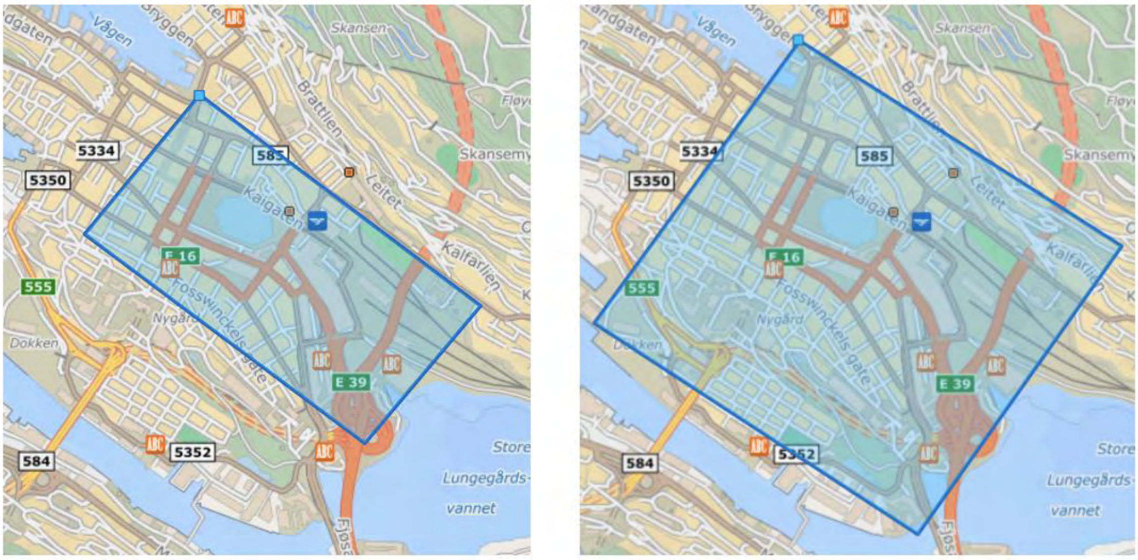

Figure 5.1: Daily fulfillment of the PM standard by using e-vans

Furthermore, we must examine how e-cargo bikes affect the environment. The blue area in Figure 5.2 illustrates the daily fulfilment of cubic meters of the PM standards caused by the e-cargo bikes. The blue area is still the ground surface with a height of 20 meters. By comparing Figure 5.1 and Figure 5.2, we can see a tremendous difference. Switching from e-vans to e-cargo bikes will reduce pollution by over 90 percent.

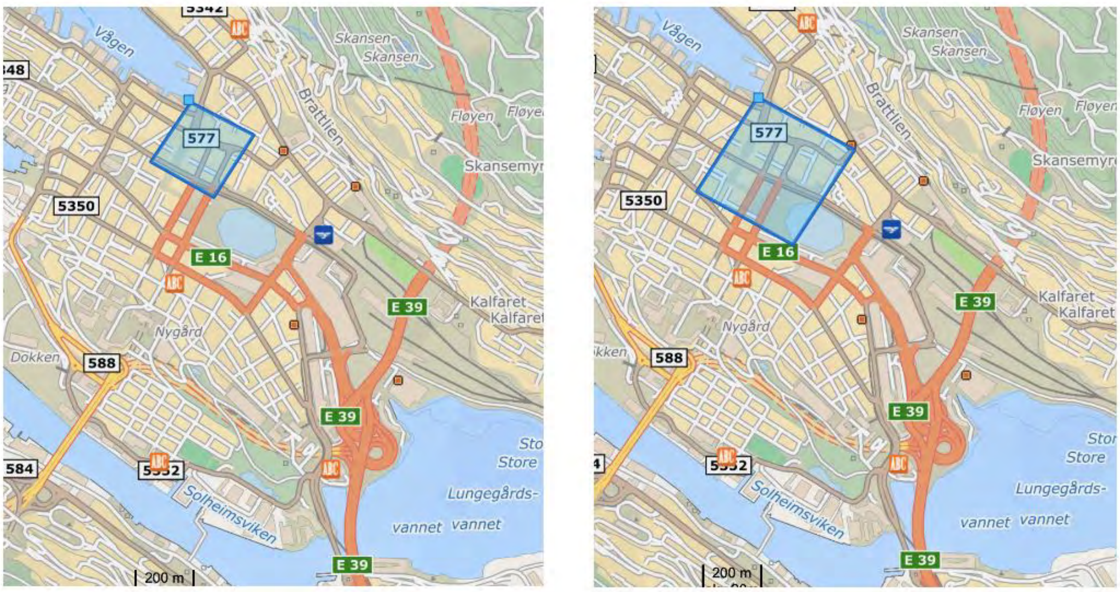

Figure 5.2: Daily fulfillment of the PM standard by using e-cargo bikes

Economic impact

Table 5.3 shows the most substantial variable costs when delivering packages with Maxus E-deliver 3 and Yokler U. We have chosen to not include the initial cost as a result of the vehicles´ ability to have an alternative utilization at times they are not used to deliver goods. Listing the entire fixed cost of an acquisition if the vehicles are used for more than just delivering parcels would be incorrect. Since we are not sure to what extent and in which way the vehicles have an alternative area of use, we have chosen to omit this cost. Furthermore, the salary cost is found by multiplying the time used for the two vehicles with 0.083 (see Table 3.1). The distance cost is found by multiplying the distance traveled for the e-vans and e-cargo bikes with 0.157 and 0.003, respectively.

Table 5.3: Cost results

	E-van	**E-cargo bike**	**Change in %**
Salary cost	2 312	2 275	- 1,6
Distance cost	10 373	82	- 99,2
Total cost	12 685	2 357	- 81,4 %

From Table 5.3, we see that the effect on salary cost is small, and the savings when using the e-cargo bike is only 1.6%. The difference, on the other hand, is far greater when it comes to distance cost. This cost is based on the number of kilometers driven. Here, the decrease in cost is 99.2%, due to the cargo bike´s low electricity consumption. Overall, we see that the variable costs we have chosen to include will decrease by 81.4% if the packages are delivered with an e-cargo bike instead of an e-van.

Another point that should be included in the discussion of the economic results is the assumption we have made that says all packages can leave the depot at the same time. This means that in our model, one can use the capacity of the E-vans to a larger degree. However, with the customers´ increased expectations and needs in mind, this is not necessarily the case in reality, as we know that many parcels are so-called express packages that must be delivered within a particular time. The low capacity of e-cargo bikes may therefore be more positive than what the model states, as there may be cases with several short trips during an actual day. The e-cargo bike´s agility and size are well-suited in these cases.

In conclusion, the results show that e-cargo bikes outperform e-vans in total costs. In addition, e-cargo bikes may be a better option for express packages, as they leave the depot more often than the e-van. Thus, customer satisfaction will increase, and the economic pillar is positively affected.

5.2 Sensitivity analysis

This section includes a sensitivity analysis of how the distance traveled and time used is affected by a change if the demand. As a result of the increase we are experiencing in e-commerce, there is interesting to investigate the effect an increase in demand has on distance traveled and time used in last mile delivery. Furthermore, the objective is still to minimize the distance traveled, and the model has been run for 600 seconds since this is where the optimal solution was found. Even though the model minimizes the distance traveled, a graph showing the time used is included. This is because the time used to deliver the parcels affects most of the variables we have analyzed in this thesis. We have done the analysis by using Monday´s demand and the already existing demand points. An increase in the demand of 10 percent gives 10 percent of the demand points an increased demand of one parcel. The results are shown in Figure 5.3 and Figure 5.4 below.

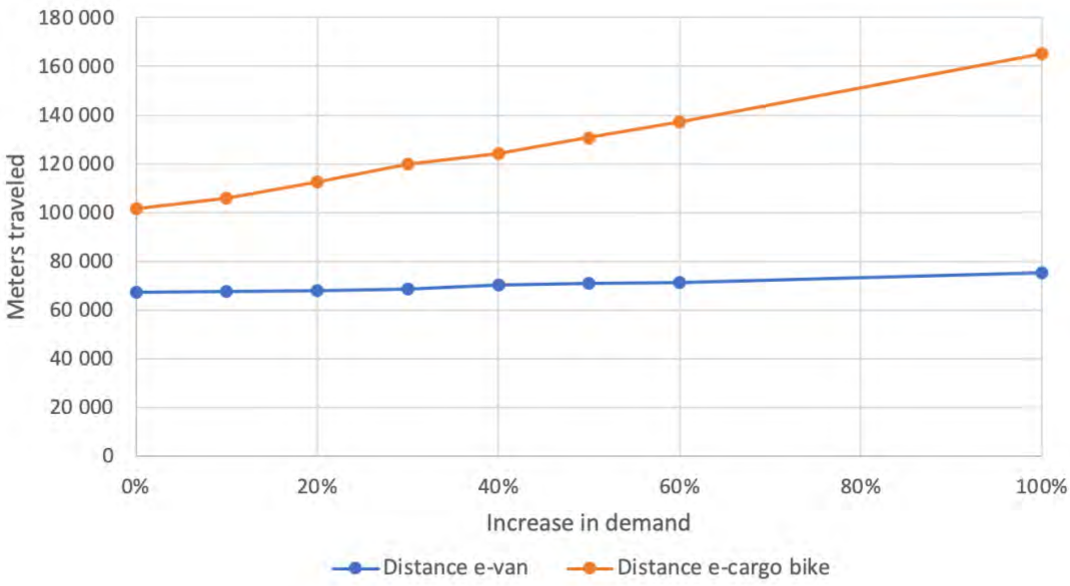

Figure 5.3: Number of kilometers traveled with respect to an increase in demand

In Figure 5.3, the graph of the e-cargo bike stays above the graph of the e-van all the time. Furthermore, we see that the distance traveled by e-van remains relatively constant, while that for e-cargo bikes increases in line with the increase in demand. The difference between the two delivery methods is greater the more packages are delivered. With a 100 percent increase in demand, one must cover 120 percent more meters when using an e-cargo bike.

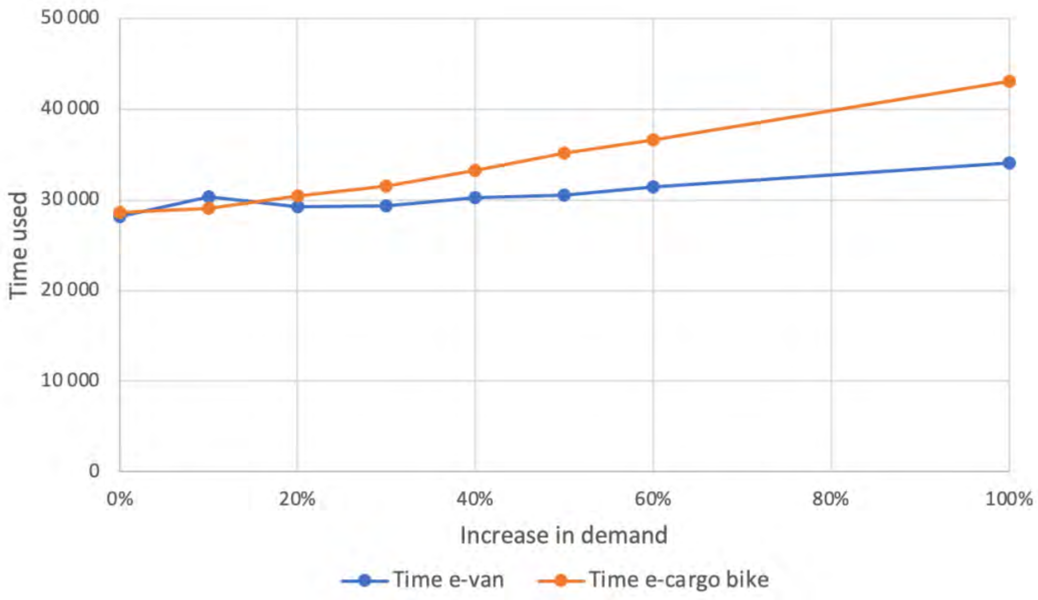

Figure 5.4: Time used with respect to an increase in demand

Figure 5.4 shows the development in time used as the demand increases. The time used is quite similar between the two delivery methods at the start, but the e-van is more efficient than the e-cargo bike as the demand increases. This is primarily connected with the results mentioned above, where the number of kilometers traveled was discussed. The more kilometers that must be covered, the more time must be used. However, since the e-van manages to keep the development in the number of meters traveled relatively stable, we see a different development in time used than we see with the e-cargo bike.

In conclusion, the sensitivity analysis has shown that e-vans are less sensitive to an increase in demand than e-cargo bikes. That the e-van can keep the number of meters traveled low regardless of an increase in demand means that the time they use remains low. On the other hand, the e-cargo bike must increase the number of meters traveled in line with the increase in demand, which means that the time used increases. Therefore, the e-van becomes more advantageous the more packages are delivered.

6. Discussion

In chapter 5, the results were presented and discussed. In this section, we discuss the limitations of the model and data in addition to the method´s external validity. Lastly, we discuss and propose future topics that may be researched to get a deeper insight into this subject.

6.1 Limitations and external validity

As stated, both the data and model used in this thesis are subject to assumptions that affect and might limit the results obtained. These assumptions are discussed below.

Implications of all packages being allowed to leave the depot at the same time

The model used in our thesis allows all the daily demands to depart the depot at any given time of day. In reality, the vehicle can only leave the depot once the package to be delivered to a customer has arrived, which means that the customers' increased needs and expectations in the form of express deliveries and deliveries at a specific time are not considered. In reality, one must deliver packages more sporadically during the day than what the model states. However, the results from Section 5 show that the packages are distributed among three vans during the day. The cargo bike, on the other side, uses nineteen daily trips. These are results that we see as quite realistic.

Implications of the demand not being equal to the real demand

The demand data are of importance for our results. As shown in Figure 5.4 in the sensitivity analysis, an increase in demand will lead to a more significant gap in distance between vans and cargo bikes. The total distance has a steeper degree of ascent for E-cargo bikes than e-vans. Further, the gap in time increases the greater the demand. We will separately analyze the total and daily demand assumptions.

Total demand data:

Our demand data is estimated total demand for a week based on empirical yearly demand. This data excludes December, which is an extraordinary month. This removes some errors due to seasonality. Assuming equal demand throughout the year is a simplification of reality since some months have more demand than others. Further, some addresses will, in reality, not have a demand for each week, as the yearly demand for some points is different from 48. The lowest weekly estimated demand per point is 1. Furthermore, since we assume Postnord has a market share of 30 percent, the underlying data is divided by 0.3 to get as close to the total demand in Bergen as possible.

Weekly demand:
In this thesis, we have split the demand data into different days. Furthermore, we have assumed that which day the demand occurs is random and based on probability. Thus, there may be different demands for e-vans and e-cargo bikes on the same day. By assuming a random distribution of demand during the week, we overlook if there are some days with greater demand, such as Monday, when it has yet to be delivered parcels during the weekend. However, we see random distribution as the preferred method, as this may be the case in a real-life scenario.

Implications of distance matrices

As mentioned, it is costly to retrieve time and distance data using Google API. Therefore, we have used k-means clustering, which minimizes the distances within clusters while maximizing the distances between them (see Section 3.1). As a result, the distance and time will not be exactly as in reality. In return, this applies to both vehicle types, which makes it less of a problem. We find the clustering method the best to get the most accurate distances and times considering our cost problem.

The distance matrix assumes the courier visits each point inside a cluster. Figure 6.1 below shows this with the black arrows. This assumption is correct if each demand point has demand and the courier walks between the points inside the cluster so that the only distance driven is between the main points. Furthermore, the courier may drive within the cluster. In these cases, we calculate our distance matrix with the distances the black arrows show. However, the yellow arrows illustrate the route the courier would choose in a real-life scenario. This assumption gives a higher total distance than in reality, but it applies to both the e-vans and e-cargo bikes. Since e-cargo bikes pollute less and have a lower cost per kilometer, this assumption will benefit e-cargo bikes.

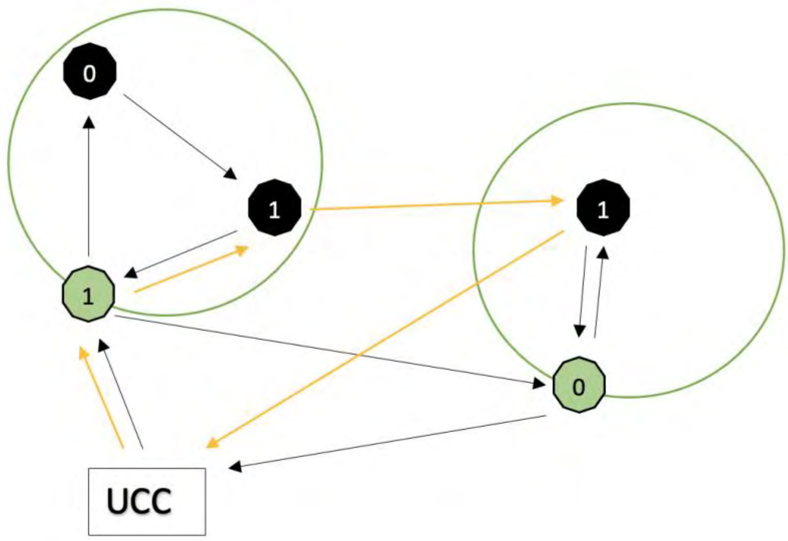

Figure 6.1: Route generated by the model (black arrows) vs optimal route (yellow arrows)

Implications of packages being the same size

In this thesis, we assume all packages to be 40 cm x 20 cm x 20 cm. However, the package size will vary and affect the parcel capacity of the e-vans and e-cargo bikes. Since the model is a CVRP, the capacity constraint will significantly impact the objective function. Our sensitivity analysis shows that an increase in demand affects the e-cargo bikes more than the e-vans. Another way to influence the capacity constraint is changing the number of packages the vehicles can bring per tour. This can be done by changing the size of the packages. Furthermore, the vehicle capacities are calculated so there will be no empty space. In a real-life scenario, the parcels will not fit perfectly and will leave some empty space that will decrease the capacity. Some packages may be too big for the e-cargo bike, which makes them unable to be delivered. However, we see the chosen size as optimal as some parcels are smaller and some are bigger than this, which makes it approximately the average package size.

Implications of the courier always being able to deliver the parcels

This thesis assumes that the courier can consistently deliver the parcels. However, there are situations where the parcels need to be brought back to the depot. For instance, if the parcel is of high value, the customer may not allow the courier to leave it at the doorstep. Then, the courier has to bring the parcel back to the depot to be delivered either on a different route the same day, or on another day. We see these as rare events, since the customer will be home if he expects a parcel of high that cannot be placed at the doorstep to be delivered. As we see it, this implication will not affect the result in a way that will affect the conclusions.

External validity

We have developed a distance and time matrix for demand points in the Bergen city center based on Google API. However, we need to consider some aspects regarding external validity. First and foremost, the time per distance will vary between different sizes of cities, seasons, and times of the day due to traffic, where the time advantages for e-cargo bikes are increasing in line with the level of traffic. Secondly, the sensitivity analysis shows that the greater the demand, the more gap between e-vans and e-cargo bikes in distance and time traveled. Thirdly, the total demand will vary due to the density and wealth of the population. In conclusion, the aforementioned factors affect the extent to which the findings in this thesis are transferable to other places.

6.2 Further work

We will propose some exciting topics within a combination of means of transport, an expansion of the delivery circle, and a potential business model, which we did not include in our thesis.

The results show that the e-vans and e-cargo bikes use approximately the same time to deliver the parcels, but the e-cargo bikes must travel more meters. Furthermore, the results show the importance of time on the social and economic sustainable pillar and distance on the environmental pillar. Therefore, it would be interesting to explore how a combination of the two vehicles, a so-called “mixed fleet”, will affect the results. In such case, it may be possible to find a combination that reduces the total effect on the sustainable pillars to a more significant extent than using either e-vans or e-cargo bikes.

It would also be interesting to look at an extension of the delivery zone. Due to the significant differences in the range between e-vans and e-cargo bikes, the size of the delivery zone will affect the results to a large extent. As the sensitivity analysis shows, time used and kilometers driven will increase at a faster rate for e-cargo bikes than for e-vans.

Furthermore, this thesis does not include a business plan for the logistics providers. However, it would be interesting to investigate how the actors can cooperate in the best possible way and how to ensure that all actors participate in the collaboration. Such a plan should also include an overview of how revenues and costs are distributed.

7. Conclusion

In this thesis, we have sought to analyze to what extent the different pillars of sustainability are affected by whether electric vans or electric cargo bikes are used in last-mile delivery in Bergen city center. Firstly, we have examined which factors that affect sustainability and how they are affected by which delivery method is used. Secondly, the vehicle routing problem is used to determine how these factors are affected by a transition from e-vans to e-cargo bikes. In addition, a sensitivity analysis is included to investigate how an increase in demand affects the distance traveled and time used.

Regarding the social pillar, it is difficult to say how this is being affected. This is because it is hard to say whether the pillar is exclusively positively or negatively affected, since we have found that the two delivery methods affect in different ways. Furthermore, the noise level will not be significantly affected due to both transport methods using an electric motor. This means that noise pollution is very low in the first place. Furthermore, the environmental pillar is the one on which a transition from e-vans to e-cargo bikes will have the most significant effect. Under this pillar, we have investigated how PM10 and PM2.5 will be affected, and the effects are significant with savings of 91.9 and 91.1 percent for PM10 and PM2.5, respectively. When we have looked at the economic pillar, we have examined financial costs of using the two transport methods. The results show that the e-cargo bike´s low distance cost means that is better from a financial point of view.

In conclusion, our findings are that the e-cargo bike is slightly faster but needs to cover more meters than the e-van with today´s demand. Of course, this affects the sustainability pillars in different ways, but overall we would say that they are positively affected by a transition from e-vans to e-cargo bikes. However, the sensitivity analysis shows that the greater the demand, the better it is to use e-vans due to their large capacity.

Hence, a transition from e-vans to e-cargo bikes in last-mile delivery may affect the sustainability pillars in a positive way as long as the demand does not become too great.

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Appendix

A1 Tables

Table A1.1: Clusters, demand points and main points

Cluster	Demand	Main Point E-van	Main point E-cargo bike
1	3	16255	14123
2	1	7930	7930
3	2	642	10168
4	1	12299	12299
5	2	16471	16469
6	25	14250	14250
7	1	7404	7404
8	2	14240	14240
9	7	12206	12206
10	8	12637	12634
11	2	17443	17443
12	3	3129	3129
13	3	15479	15479
14	1	2253	2253
15	1	6172	6172
16	1	12879	12879
17	11	11472	11481
18	2	16674	16674
19	40	15659	15659
20	1	9095	9095
21	1	15754	15754
22	10	1054	1054
23	10	1352	1352
24	6	237	3494
25	2	17039	17039
26	1	16611	16611
27	4	12837	7119
28	1	11686	11686
29	1	11464	11464
30	1	5369	5369
31	7	5521	5527
32	1	1817	1817
33	17	15771	15771
34	3	15788	15788
35	2	15624	15624
36	19	9195	9195
37	7	1413	1413
38	2	15705	15705
39	2	13875	13815
40	16	15969	15966
41	1	15623	15623
42	7	14190	14190
43	4	15521	15521
44	1	9079	9079
45	31	16217	16219
46	4	12196	12196
47	2	4775	4775
48	2	11857	11857
49	5	14208	14206
50	1	9546	9546
51	2	4765	4765
52	2	6808	6808
53	1	9163	9163
54	5	9196	9196
55	1	11651	11651
56	5	15706	15706
57	2	15655	15655
58	3	16682	16693
59	4	14212	14211
60	2	14155	14155
61	1	1784	1784
62	1	3120	3120
63	3	14585	14585
64	5	14828	12188
65	1	755	755
66	2	16275	16275
67	2	6361	6361
68	2	6444	6444
69	2	12221	12221
70	16	11485	11485
71	8	15650	15651
72	2	1747	1747
73	1	7883	7883
74	2	12631	12631
75	1	11650	11650
76	2	16684	16684
77	4	16997	16997
78	1	6179	6179
79	3	208	210
80	2	445	445
81	26	15977	15974
82	2	12639	12639
83	3	232	232
84	1	14159	14159
85	7	5912	5909
86	4	1351	1351
87	5	14216	14216
88	2	14203	14203
89	1	15880	15880
90	4	15978	15978
91	1	7162	7162
92	5	10431	10436
93	4	4127	4125
94	2	11491	11491
95	2	4702	4702
96	4	16913	16913
97	2	15633	15631
98	1	5534	5534
99	1	10493	10493
100	2	9089	9083
101	1	3233	3233
102	3	14221	14221
103	2	11099	11102
104	8	12298	12298
105	2	6416	6416
106	2	16240	16240
107	2	17053	17053
108	5	7943	7943
109	1	11694	11694
110	3	10934	10934
111	33	14149	14146
112	2	14245	14245
113	1	14405	14405
114	4	12209	12209

115	1	7243	7243
116	3	15759	15757
117	1	14172	14172
118	2	7186	7186
119	2	7098	7098
120	2	1411	1411
121	5	10427	10429
122	2	10180	10180
123	2	12878	12878
124	2	10456	10456
125	2	10419	10419
126	4	4667	220
127	1	11439	11439
128	5	14137	14138
129	4	13896	13896
130	2	14205	14205
131	1	16242	16242
132	3	3263	11117
133	1	12310	12310
134	1	12717	12717
135	2	15931	15931
136	8	15641	15641
137	1	16480	16480
138	2	12201	12201
139	2	3130	3130
140	2	5349	5349
141	4	9075	9075
142	4	1738	1738
143	7	9065	9065
144	4	11469	11470
145	6	4954	13103
146	3	10668	10663
147	1	15775	15775
148	1	15947	15947
149	2	15530	15530
150	1	1119	1119
151	1	7610	7610
152	13	10492	10492
153	5	9193	3238
154	2	1249	1250
155	5	11477	11100
156	1	1814	1814
157	2	5524	5528
158	1	651	651
159	2	15772	15772
160	4	16610	16610
161	1	11466	11466
162	11	15626	15626
163	2	14912	14912
164	3	11475	11475
165	3	12649	12649
166	1	11478	11478
167	1	15617	15617
168	6	12643	12643
169	2	15954	15954
170	3	15796	9187
171	3	5859	14842
172	2	302	302
173	1	14204	14204
174	1	8316	8316
175	2	13897	13897
176	1	16244	16244
177	4	4750	11298
178	3	3751	3751
179	2	15443	5302
180	2	10924	10400
181	2	11111	11111
182	1	16496	16496
183	5	15939	15944
184	2	201	201
185	2	9466	9466
186	4	7207	7207
187	2	14180	14180
188	9	14247	14247
189	1	11486	11486
190	9	15781	15781
191	2	14242	14242
192	4	11847	11847
193	7	15794	15794
194	5	4682	4682
195	2	6824	6824
196	1	9084	9084
197	1	16665	16665
198	2	8331	8331
199	1	16430	16430
200	3	11376	11376
201	4	15638	15638
202	1	14148	14148
203	4	16439	16438
204	7	1410	1410
205	3	14136	14134
206	1	1355	1355
207	2	240	240
208	1	16494	16494
209	7	1345	11302
210	2	16369	16369
211	10	15964	15960
212	6	15652	1819
213	4	15787	15787
214	1	14920	14920
215	11	15779	15779
216	4	6366	6366
217	2	16602	16602
218	5	11460	11460
219	4	3236	3236
220	8	13113	13113
221	1	10147	10147
222	2	10491	10491
223	5	15979	15979
224	3	10468	13923
225	3	3254	11115
226	3	15793	15793
227	2	9142	15695

Table A1.2: Results Monday

MONDAY	**Unit measure**	**E-van**	**E-cargo bike**	**Change in %**
Meters traveled	m	67 175	101 722	51,4%
Time used	s	28 211	28 663	1,6%
Number of tours	-	3	19	
Number of stops	-	220	236	

Table A1.3: Results Tuesday

TUESEDAY	**Unit measure**	**E-van**	**E-cargo bike**	**Change in %**
Meters traveled	m	65 436	100 139	53%
Time used	s	26 945	27 206	1%
Number of tours	-	4	19	
Number of stops	-	221	229	

Table A1.4: Results Wednesday

WEDNESDAY	**Unit measure**	**E-van**	**E-cargo bike**	**Change in %**
Meters traveled	m	66 425	99 809	50,3%
Time used	s	29 906	27 178	- 9,1%
Number of tours	-	3	19	
Number of stops	-	219	226	

Table A1.5: Results Thursday

THURSDAY	Unit measure	E-van	E-cargo bike	Change in %
Meters traveled	m	65 768	99 217	50,9%
Time used	s	26 905	26 798	- 0,4%
Number of tours	-	3	19	
Number of stops	-	213	230	

Table A1.6: Results Friday

FRIDAY	Unit measure	E-van	E-cargo bike	Change in %
Meters traveled	m	65 560	100 398	53,1%
Time used	s	27 300	27 179	- 0,4%
Number of tours	-	3	19	
Number of stops	-	212	229	

Table A1.7: Sensitivity analysis

Increase		E-van	E-cargo bike	Change in %
10 %	Meters traveled	67 511	106 023	51 %
	Time used	30 354	28 465	- 4 %
20 %	Meters traveled	67 889	112 682	66 %
	Time used	29 241	30 447	4 %
30 %	Meters traveled	68 553	119 965	75 %
	Time used	29 309	31 526	8 %
40 %	Meters traveled	70 318	124 169	77 %
	Time used	30 267	33 281	10 %
50 %	Meters traveled	71 101	130 709	84 %
	Time used	30 513	35 170	15 %
60 %	Meters traveled	71 384	137 056	92 %
	Time used	31 431	36 597	16 %
100 %	Meters traveled	75 166	164 045	120 %
	Time used	34 080	43 054	26 %