LOAD-DEPENDENT DISCHARGING FOR AN ELECTRIC VEHICLE ROUTING PROBLEM

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ABSTRACT

The increase of using electric vehicles in urban logistics comes with a limited driving range, restricted by a battery's capacity. Often vehicles are restricted by a fixed driving range and is the physical process of battery discharging neglected. No longer can battery discharging influenced by the weight of customer demand be ignored. In this study, the Vehicle Routing Problem is extended by taking a demand weight-based energy function into account. This thesis proposes a model for a multi-compartment vehicle routing problem with load-dependent battery discharging (MCVRPLD), that has a place in the context of perishable food distribution. This is the first study to combine multi-compartments and load-dependent battery discharging. Results show that considering demand weight can create substantial changes in the route planning when emphasizing demand weight in an energy function and that compartment configuration heavily influences the routes, vehicles deployed, and the total kilometers driven and energy used.

Keywords:

load-dependent discharging
multi-compartment
energy consumption
perishable goods
urban logistics

PREFACE

There are several people to whom I would like to give recognition for their support. First, I would like to thank dr. I. Bakir for her guidance and helpful feedback that contributed to this thesis. Secondly, I would like to thank dr. M. Aerts-Veenstra for her critical outlook during our meetings. Next, my gratitude goes to Mr. M. Hol from Bidfood, who provided the data used in this thesis. Also, I want to thank my fellow student Sander Wessel for the useful feedback and discussions about Python and CPLEX. Ultimately, I am very thankful for the mental support and fruitful discussions about difficult topics with my fiancée, Nicole Pirozzi.

1. Introduction

Logistic processes in city centers are increasingly gaining attention. They have become an integral part of today's city centers across the world. Research shows that urban logistics with conventional transportation methods have negative impacts on the city's wellbeing. Fossil fuel-driven vehicles play a key role in these negative impacts by causing hindrance, air pollution, safety issues, congestion, and noise (Dablanc, 2007; Nijkamp & Mobach, 2020; Russo et al., 2021; van Duin et al., 2010). New regulations might forbid access to the inner-city for different classes of vehicles at a certain time or 24/7 (Nolz et al., 2020). The rapid increase of urban freight demand will strengthen the problems in city centers (Charisis et al., 2020).

Green logistics (GL) is the umbrella name used to address environmentally friendly alternatives and is the topic of discussion since conventional transportation may not be maintainable in the long run. Green logistics aims to ensure sustainable and efficient urban logistics. Innovative solutions, such as zero-emission vehicles are required for the continuation of urban logistics sustainably (Charisis et al., 2020; Schneider et al., 2014). An aspect of GL is for instance the use of electric vehicles (EVs) (Schneider et al., 2014). EVs are environmentally friendly but come with battery limitations such as the kilometer range and long charging times (Marshall et al., 2015; Nesterova et al., 2013). The limitations of EVs become more apparent when organizations locate distribution centers outside the periphery of the city, which often occurs (Russo et al., 2021). In such a situation, the EV has to cover more distance to the distribution center, and might result in fewer customers served per vehicle (Kin et al., 2017; Sakai et al., 2015). At the convergence of the action range of an EV and efficiently serving all customers, an interesting research area emerges that will be addressed by this thesis by considering the load-dependent discharging of an EV's battery.

The use of zero-emission vehicles could play a significant role in future urban logistics. One of the most auspicious solutions is the EV, since they do not have any CO2 emissions, yet they still cause traffic congestion in urban areas. A high degree of the goods in urban logistics are perishable goods. In general, distributing perishable goods is a challenging concept. Perishable goods demand different temperatures for different product categories. When transporting perishable goods in an EV, just the movement of the truck is not the only variable that demands energy from the battery. Temperature-controlled transport also demands energy from an EV's battery, which increases the complexity of deploying an EV fleet (Derigs et al., 2011). The study of Nesterova et al. (2013) indicates that further adoption of EV fleets was challenged by barriers such as the limited battery capacity, resulting in a lower travel range. The low performance of the lead-acid, nickel-cadmium battery technologies, high procurement costs, little or no after-sale support, and long waiting time for spare parts, slowed down the adoption of EVs for years, but today's EVs demonstrate better performance parameters such as higher travel range and more capacious batteries (Iwan et al., 2021). The matter of temperature-controlled trucks and the already challenging travel range of EVs provides interesting research directions. Several studies explore the field of load-dependent battery discharging on EVs. For example, results from Reddy & Ramadurai (2020) show that considering load-dependent battery discharge positively affects the optimal solution of routing problems. The work of Lin et al. (2016) is the first extensive study considering load-dependent battery discharging. The results of this study show that future studies cannot ignore the effect of demand weight on battery consumption. Therefore, this study proposes a model with an energy function based on the load the vehicle carries, that aims for higher precision of energy consumption rather than using approximations. The model considers load-dependent discharging of the EV's battery in a setting where perishable goods are transported.

The distribution of perishable goods is rather specific in terms of vehicles. Most industries use vehicles that consist of one compartment, while the food distribution shifts to multi-compartment vehicles to enable transportation of inhomogeneous products simultaneously (Hübner & Ostermeier, 2018). Often challenges arise when customers demand multiple segments of products and the distributor only possesses vehicles with a single compartment. That is where the use of multi-compartment vehicles can be beneficial for companies and customers. Deploying multi-compartment vehicles results in single deliveries that carry multiple segments of products (Derigs et al., 2011). Therefore, considering multi-compartmented vehicles will be included in this study to reflect realistic operational challenges in the food industry.

Optimization models in logistics have been studied extensively throughout the years. The classical vehicle routing problem (VRP) was introduced 62 years ago by Dantzig & Ramser (1959). The study received major attention and increased developments in the fields of exact algorithms and meta-heuristics (Laporte, 2009). The model of Dantzig & Ramser (1959) minimizes the total distance covered by a fleet while satisfying customers' demands. Throughout the years, many extensions have been developed, using the VRP as a foundation. Extensions that are introduced are capacitated problems (C), time windows (TW), and multi-compartment (MC) (Braekers et al., 2015). One extension that is not studied very often yet, is the load-dependent battery discharging (LD). These are valuable extensions for the perishable goods industry. Therefore, this research will introduce a multi-compartment electric vehicle routing problem with time windows, and load-dependent battery discharging. From here on, the problem will be called an MCVRPLD instead of an MCEVRPTWLD, for the sake of readability. To explore the effects of load-dependent discharging, the following research question is addressed:

What are the effects of using a load-dependent battery discharging function on the number of customers served per route, number of routes, number of vehicles deployed, energy used, distance covered, and compartment utilization while minimizing the energy consumption for multi-compartmented vehicles?

To answer the research question, a mathematical model of the MCVRPLD is developed. The model will be a combination of the previously discussed classical model and extensions. The proposed mathematical model will be solved in an exact method for small sets of customers to find an optimal solution while minimizing energy consumption. The data that will be used is provided by an international food wholesaler named Bidfood. The scope of the data is the city of Groningen in the Netherlands. Performance metrics to compare results are the customers served per route, number of routes, number of vehicles deployed, energy used, distance covered, and compartment utilization to quantify the outcomes.

The main contribution of this thesis to the existing literature is that this study takes the effect of load-dependent discharging for electrical vehicles into consideration. In addition, the vehicle yields two compartments for different product categories, which is useful for specific logistics such as perishable foods. To the extent of my knowledge, no previous study has provided insights into the combination of load-dependent discharging and multi-compartmented vehicles. The remainder of this thesis is structured as follows. In Section 2, the theoretical background is presented. Section 3 provides the mathematical model and energy function. Section 4 provides the experimental setup and how the data is prepared and used. Section 5 provides the results and the main discussion. In Section 6 the theoretical and practical implications of the results and discussion are presented, and an outlook to the future is given. Finally, a conclusion is given in Section 7.

2. THEORETICAL BACKGROUND

This section provides a literature review focusing on topics such as food logistics, EVs, and batteries to build an understanding of electric vehicle routing problems in urban logistics. Firstly, the concept of EVs in urban logistics is introduced to provide background information regarding the setting of this research. Secondly, several extensions on the VRP model are elaborated on. Thirdly, the character of the study and meta-heuristics that are used in previous studies are briefly explained. Finally, a comparison between existing literature and this research is presented.

2.1 ELECTRIC VEHICLES IN URBAN LOGISTICS FOR PERISHABLE FOODS

Urban logistics is dealing with influential factors such as congestion and pollution. To manage these factors, logistics companies are forced to find solutions with the lowest negative impact (Savelsbergh & Woensel, 2016). Over the years, EVs, E-bikes, and cargo bikes have earned their place in today's urban logistics. Although EVs earned their place, the development of EVs is one of the most challenging topics for urban logistic systems. The idea of seeking alternatives for fossil fuels has been around since the 1970s (Iwan et al., 2021). Nesterova et al. (2013) indicate that more than 28 years ago, the main challenges of implementing EVs in urban logistics faced by operators were: high procurement costs, limited range of models, and poorly performing lead-acid, nickel-cadmium batteries (Quak et al., 2016). However, today's EVs demonstrate better performance with positive developments of parameters such as travel range, battery capacity, and freight capacity (Iwan et al., 2021). According to Quak et al. (2016), EVs demonstrate to be sufficient for small to medium-sized cities and are contemporarily deployed.

The distribution of perishable goods can already be challenging when using conventional freight vehicles but becomes more complex for GL solutions, particularly for EVs. Perishable goods require specific storage conditions during transportation to ensure the promised quality and shelf life of certain products to customers (Musavi & Bozorgi-amiri, 2017). The distinction between perishable goods can be made by categorizing the type of storage the product requires. Hübner & Ostermeier (2018) found three product categories, precisely: frozen, cooled, and non-cooled. Typically vehicles for perishable goods make use of two compartments with temperature zones, one that is cooled and one that is frozen (Hübner & Ostermeier, 2018). Considering the previous mentioning of logistic activities in cities to restaurants, hotels, and other types of customers, multi-compartmented vehicles may help distributors to manage the route planning activities.

2.2 EXISTING STUDIES AND META-HEURISTICS

This research is built upon the electric vehicle routing problem (EVRP). The electric vehicle routing problem is a combinational optimization model that initially aims for the optimal design of routes for electric fleets to satisfy customers' demands. For electric fleets, one must consider battery restrictions and charging locations. These limitations are also there for fossil fuel-driven vehicles, but they tend to have a larger range of action and fuels are easier to access in the city than recharging stations. Early work of Solomon (1987) and Solomon & Desrosiers (1988) introduce the time window constraint and allow to set a range of time in which the delivery needs to be started. Time windows continued to be an integral component for vehicle routing problems. The development of the extension resulted in CVRPTW. The model itself and some extensions such as capacity and time window constraints have been studied extensively, but an extension on energy use like load-dependent discharging is rather new to the literature.

In urban logistics, many goods are considered perishable. When perishable products are exposed to undesired conditions such as temperature fluctuation, it can cause unwanted ripening and decaying. Considering vehicles that are capable of transporting goods under certain temperatures can solve this problem. Transporting perishable products that need different temperatures becomes a problem for distributors that are using trucks with a single compartment. They can only freeze or cool the compartment, which makes the vehicles less utilizable. An alternative is using compartmented vehicles with a cooled and non-cooled section. The multi-compartment extension was introduced by Brown & Graves (1981), resulting in MCVRP. Most studies on MCVRP consider multi-compartments that have a fixed capacity (Chen & Shi, 2019;

Febriandini et al., 2020; Martins et al., 2019; Mendoza et al., 2010; Wang & Li, 2018). The study of Juan et al. (2014) assumes that the EV's battery capacity is limited to 100 kilometers, while in real-life EVs can potentially cover more distance depending on the weight in the vehicle. The work of Lin et al. (2016) is the first article considering the effect of freight weight on battery consumption.

2.3 Vehicle routing problem and metaheuristics

Considering the problem being a rich extension of the VRP, the MCVRPLD is also an NP-hard optimization problem. This study makes use of an optimization solver, which implies that only a small set of data can be solved within a reasonable time. Previous studies made use of metaheuristics, which are more suitable for real-life problems and have been widely developed throughout the years. The use of metaheuristics enables improving the performance of heuristics methods in solving vehicle routing problems for larger datasets (Tsang & Voudouris, 1997).

Metaheuristics are recognized for their efficient approach to hard problems with bigger datasets (Boussaïd et al., 2013). Local search is considered the base for many metaheuristics. It seeks minimization of the objective function by replacing current solutions (Tsang & Voudouris, 1997). The algorithm ends in local minima, where no further improvement is possible. The solution found is not per se the optimal solution. To escape these local minima, metaheuristics are used. There are two types of metaheuristics. The first is based on local search and the second is based on population search. The often-used local search metaheuristics are, Simulated Annealing (SA), Adaptive Large Neighborhood Search (ALNS), Local Neighborhood Search (LNS), Guided Local Search (GLS), Variable Neighborhood Search (VNS), and Tabu Search (TS) (Elshaer & Awad, 2020). An example of a population-based search is Particle Swarm Optimization (PSO).

Characteristics of relevant previous studies are presented in Table 2.1. The studies Lin et al. (2016, Rastani et al. (2020), and Reddy Kancharla & Ramadurai (2020) consider load-dependent discharging of the electric vehicle routing problem without addressing additional constraints. The studies of Attema (2021), Chen & Shi (2019), and Henke et al. (2015) consider multiple constraints such as multi-compartment, flexibly sizeable compartments, and time windows. Despite the study of Attema (2021) considering most of the extensions considered in this thesis, none of the studies considers the combination of load-dependent discharging and multi-compartments, which is insightful considering the real-life problems with EVs in food distribution. This study aims to explore the effects of load-dependent discharging.

Table 2.1 - Characteristics of existing studies

Research	**Number of compartments**	**Multi-compartment**	**Flexible-compartment**	**Time window**	**Load-dependent battery discharge**	**Approach**
(Reddy Kancharla & Ramadurai, 2020)					✓	ALNS
(Rastani et al., 2020)				✓	✓	LNS
(Lin et al., 2016)				✓	✓	
(Chen & Shi, 2019)	Fixed	✓		✓		PSO, SA
(Henke et al., 2015)	Variable	✓	✓			VNS
(Attema, 2021)	Fixed	✓	✓	✓		GLS
Current study	Fixed	✓		✓	✓	Exact

3. MATHEMATICAL MODEL

This section presents the mathematical model used in this thesis. Mathematical modeling enables solving real-life problems. In this section, the problem description is given with an explanation for parameters and decision variables. Then, the mathematical formulation is given. Finally, the energy function is explained.

3.1 PROBLEM DESCRIPTION

The MCVRPLD can be defined as a directed graph $G = (L, A)$ which consists of a set of locations, $L = \{0, \dots, n\}$, where 0 is the location of the depot and $L_c = L\backslash\{0\}$ the set of customer locations. $A = \{(i,j) \mid \forall i,j \in L, i \neq j\}$ is the total set of arcs between all locations. There are at most v number of EVs available to dispatch and is represented by the set $V = \{1, \dots, v\}$. Each customer should be visited only once by one vehicle. Each product type is assigned to a compartment; therefore, the set of products or compartments is given by $P = \{1, \dots, p\}$. Common for the food industry is to separate fresh and frozen, therefore in this thesis, an individual vehicle yields two compartments, which allows the separation of fresh and frozen products in one vehicle.

The demand in units for product p and customer i is given by d_{ip}. The total weight of the total demand for customer i is given by w_i. The capacity in roll containers of a vehicle is given by Q_v. The total capacity of the compartments of product type p of vehicle v is given by Q_{pv}. The maximum load in kilograms for a vehicle is $Wmax_v$. The battery capacity of a vehicle is given by B_v. The curb vehicle weight is referred to as V_v. The products need to be delivered within a time window $[e_i, l_i]$. For the time windows e_i represent the earliest time servicing can start and l_i the latest time servicing can start. The service time is referred to as u_i, representing the unloading time. The end time of servicing can be at the earliest $e_i + u_i$ and at the latest $l_i + u_i$. Each arc (i,j) is associated with a non-negative travel time t_{ij} and distance a_{ij}. The average travel speed is referred to as S_v. The maximum driving time is referred to as H_v. Parameter M is a large value for calculations purposes.

The model contains several decision variables. The binary decision variable x_{ijv} will be set to 1 if location i is served by vehicle v. The remaining battery charge upon arrival at j will be referred to as z_{iv}. Energy consumption on an arc (i,j) for vehicle v, is given by J_{ijv}. The arrival time at location j is given by b_{iv}. The vehicle load upon arrival of customer j for vehicle v is given by w_{iv}. The load-dependent battery discharge works as follows: when an EV starts the route at the depot (0), the battery is fully charged at the depot; the EV can only recharge at the depot (0) but not during a route. The objective of the model is to create a set of vehicle routes, such that all demand is satisfied without violating constraints, at minimal energy used.

3.2 Model assumptions

For the formulation of the MCVRPLD model, the model must satisfy some reasonable assumptions:

1. Each route starts and ends at the depot;
2. Vehicles can only leave the depot once;
3. Battery charge is 100% at the start;

The first assumption indicates that when vehicles are not driving, they should be located at the depot. The second assumption is made because most customers demand delivery in the morning, meaning that all routes need to be executed simultaneously. The third assumption is that the vehicle can fully recharge when it is located at the depot after the route until the new route.

3.3 MATHEMATICAL FORMULATION

The sets, parameters, and decision variables that are used in the mathematical model are presented in Table 3.1.

Table 3.1 - Mathematical operators

(I) Graph notation	Description
$\boldsymbol{L = \{0, 1, \dots, n\}}$	Set of locations, where 0 is the depot, and 1, …, n are customers
$\boldsymbol{L_c = L \backslash \{0\}}$	Set of customers
$\boldsymbol{A = \{(i, j) \mid \forall i, j \in L, i \neq j\}}$	Set of arcs
$\boldsymbol{V = \{1, \dots, v\}}$	Set of vehicles
$\boldsymbol{P = \{1, \dots, p\}}$	Set of product temperature classes
(II) Parameters	
$\boldsymbol{d_{ip}}$	Demand volume (number of roll container) of customer i for product p
$\boldsymbol{w_i}$	Weight (kg) of demand of customer i
$\boldsymbol{e_i}$	Earliest delivery time of location i
$\boldsymbol{l_i}$	Latest delivery time of location i
$\boldsymbol{u_i}$	Service time (minutes) at location i
$\boldsymbol{t_{ij}}$	Travel time (minutes) on arc (i, j)
$\boldsymbol{a_{ij}}$	Travel distance (kilometers) on arc (i, j)
$\boldsymbol{Q_{pv}}$	Capacity (number of roll container) of product type p of vehicle v
$\boldsymbol{B_v}$	Battery capacity (kWh)
$\boldsymbol{V_v}$	Vehicle weight (kg)
$\boldsymbol{S_v}$	Average travel speed (km/h)
$\boldsymbol{Wmax_v}$	Maximum load weight (kg)
$\boldsymbol{H_v}$	Daily work time limit (minutes)
$\boldsymbol{M}$	Sufficiently large number
(III) Decision variables	
$\boldsymbol{x_{ijv}} = \begin{cases} \mathbf{1}, \\ \mathbf{0}, \end{cases}$	If location i is served by vehicle v and visited right before location j otherwise
$\boldsymbol{z_{iv}}$	Remaining battery charge (kWh) of vehicle v on arrival at j
$\boldsymbol{J_{ijv}}$	Energy consumption (kWh) on arc (i, j) for vehicle v
$\boldsymbol{b_{iv}}$	Arrival time at location j
$\boldsymbol{W_{iv}}$	Vehicle load (kg) on arrival at j for vehicle v

$$MinZ = \sum_{v \in V} \sum_{i \in L} \sum_{j \in L} x_{ijv} J_{ijv} \tag{1}$$

Subject to:

Basic constraints:

Ensures that each customer is visited by exactly one vehicle:

$$\sum_{v \in V} \sum_{j \in L} x_{ijv} = 1, \quad \forall\, i \in L_c \tag{2}$$

Ensures that each vehicle starts at the depot and can only depart once:

$$\sum_{j \in Lc} x_{0jv} \leq 1, \quad \forall\, v \in V \tag{3}$$

Ensures that each vehicle ends at the depot:

$$\sum_{i \in Lc} x_{i0v} \leq 1, \quad \forall\, v \in V \tag{4}$$

Route continuity: ensure that if a vehicle arrives at location i, it also leaves that location:

$$\sum_{j \in L} x_{ijv} = \sum_{j \in L} x_{jiv}, \quad \forall\, i \in L_c, \; v \in V \tag{5}$$

Capacity constraints:

Ensures that the assigned products do not exceed compartment capacity:

$$\sum_{i \in Lc} x_{ijv} d_{ip} \leq Q_{pv}, \quad \forall\, p \in P, \; v \in V \tag{6}$$

Weight constraints:

Ensures that total assigned weight to vehicle v cannot exceed the maximum load of the vehicle:

$$\sum_{i \in Lc} x_{ijv} w_i \leq Wmax_v, \quad \forall\, v \in V \tag{7}$$

For tracking the vehicle load:

$$W_{jv} \leq W_{iv} - w_i + M\left(1 - x_{ijv}\right), \; \forall\, i,j \in L_c, \; \forall\, v \in V \tag{8}$$

Energy constraints:

For tracking the vehicle battery charge: ensures that the remaining battery charge upon arrival of location i, considers energy consumption on arc i, j and battery charge at the previous location:

$$z_{jv} \leq z_{iv} - J_{ijv} + M\left(1 - x_{ijv}\right), \; \forall\, i,j \in L, \; \forall\, v \in V, \; j \neq 0 \tag{9}$$

Energy use function:

$$J_{ijv} = f\left(W_{jv}, a_{ij}\right), \; \forall\, i,j \in L, \; \forall\, v \in V \tag{10}$$

Time constraints:

Ensures that daily work hours do not exceed limit:

$$\sum_{i \in L} \sum_{j \in L} x_{ijv} t_{ij} + u_i \leq H_v, \ \forall v \in V \tag{11}$$

Ensures that arrival time at location j considers arrival time b_i + unloading time u_i of the previous location + travel time t_{ij} between the locations:

$$b_{iv} + u_i + t_{ij} - M(1 - x_{ijv}) \leq b_{jv}, \ \forall i, j \in L, \ \forall v \in V \tag{12}$$

Variable domains:

$$x_{ijv} = \{0, 1\}, \qquad \forall i, j \in L, \ v \in V \tag{13}$$

$$0 \leq z_{iv} \leq B_v, \qquad \forall i, j \in L, \ v \in V \tag{14}$$

$$0 \leq J_{ijv} \leq z_{iv}, \qquad \forall i, j \in L, \ v \in V \tag{15}$$

$$0 \leq Q_{pv}, \qquad \forall p \in P, \ v \in V \tag{16}$$

$$e_i \leq b_{iv} \leq l_i, \qquad \forall i \in L_c, \ v \in V \tag{17}$$

Formulations of different studies about the vehicle routing problem have been studied and used as inspiration for the proposed model. From existing models, constraints (2), (3), (4), (5), and (6) are obtained from Lin, Zhou, and Wolfson (2016) and Derigs et al. (2011). Constraints (12) and (14) are from Chen and Shi (2019).

The objective function (1) of the model is to minimize the energy consumption of the EV during a route. It must be noted that the objective function is non-linear, but modern solvers as used in this thesis can handle these simple non-linearities. Constraint (2) ensures that each location is visited exactly once. Constraint (3) ensures that each vehicle starts at the depot and constraint (4) ensures that each vehicle ends at the depot. Constraint (5) is for route continuity, ensuring that if vehicle v arrives at location i, it also leaves that location. Constraint (6) ensures that the demand for location i of product p does not exceed the compartment size of product p. Constraint (7) ensures that the assigned demand weight does not exceed the maximum load of vehicle v. Constraint (8) is to track the vehicle weight throughout the route and forces the vehicle weight at leaving location i for j to be the weight at location i minus the demand weight of location i, and is used for further energy calculations over arc $[i, j]$. Constraint (9) is to track the battery charge throughout the route and forces the vehicle's battery at leaving location i for j to be the battery charge at location i minus the energy consumed over the arc $[i, j]$ for vehicle v. Constraint (10) is the function of calculating energy over $[i, j]$ for a potential route of vehicle v, using W_{jv} and a_{ij}. Further explanation about the energy function is given in section 3.4. Constraint (11) is limiting the total time the vehicle is operating. Constraint (12) ensures that the arrival time at location j considers the arrival time b_{iv} plus the unloading time u_i of the previous location i in plus the travel time t_{ij} between these locations. Constraints (13), (14), (15), (16), and (17) define the variable domains, of whom (17) ensure that servicing at location i starts within the delivery time window.

3.4 Energy consumption function

Adopted from Barth et al. (2005), Barth & Boriboonsomsin, (2009), Bektas & Laporte (2011), Eshtehadi et al. (2019), Lin et al. (2016), and Rastani et al. (2020), a simplified form of energy usage function is shown, which is a linear function of vehicle weight and a quadratic form of vehicle speed in. The total amount of energy consumed on an arc for a vehicle can be calculated by: $J_{ijv} \approx \frac{((\alpha_{ij}(W_v + W_{jv})a_{ij} + \beta(v^2)a_{ij})/e_f)}{40}$, where $\alpha_{ij} = a + gsin\theta_{ij} + gC_r cos\theta_{ij}$ is an arc-specific constant, and $\beta = 0.5C_d A\rho$ is a vehicle-specific constant. The numerator is divided by 40 instead of 1000, to artificially increase the energy consumption. This is done to ease the detection of differences in numbers at first glance. If the original value of 1000 was used, J_{ijv} would provide small numbers that are very close to each other. By increasing J_{ijv} for all calculations, the model will function similarly. The rest of the notations are as follows:

C_d	:	Unitless coefficient of rolling drag
e_f	:	Engine efficiency for an EV
A	:	Frontal surface area of a vehicle (m^2)
a	:	Acceleration (m/s^2)
θ_{ij}	:	Road angle degree
ρ	:	Air density (kg/m^3)
C_r	:	Unitless rolling resistance
g	:	Gravitational constant (m/s^2)
v	:	Travel speed in (m/s)
W_v	:	Vehicle curb weight in kg

4. NUMERICAL EXPERIMENTS

In this section, the characteristics and preparation steps of the used real-life data are presented. Next, the experimental setup and base case parameters are explained. Lastly, the conducted experiments are explained.

4.1 DATA

The focus of this thesis is to investigate the effects of considering vehicle load in the energy consumption of an electric truck for food distribution in the city center of Groningen. First, a base case of this model is presented. Then, seven experiments are conducted. This research focuses on the inner city of Groningen. The city of Groningen will introduce environmental zones where only EVs are allowed in the inner city. The definition of the inner city in this thesis is all urban areas in between the canals. With the environmental restrictions only allowing EVs in the area between the canals, Bidfood aims for a shift in their fleet to more EVs. The real data used in this thesis is provided by Bidfood. Bidfood is one of the largest food wholesalers in the Netherlands and focuses on business-to-business, serving institutions, hotels, restaurants, canteens, and cafés (Bidfood, 2022).

Data from week 30 in the year 2021 about Bidfood's operations are used for this research. Specifically, week 30 is chosen because it falls exactly in the period where the middle and northern part of the Netherlands had summer vacation, and that week was not affected by a COVID-19 lockdown, meaning the data reflects a more accurate image. Bidfood provided data containing the number of fresh and frozen products, the weight of the products, delivery time window per customer, and service time for the delivery. The delivery time window is a range between the earliest time and the latest time the unloading is allowed to start. The service time is defined as the amount of time it takes to unload the truck after arrival at the customer. From the data in this period, a selection was made based on the geographical character of the customers. Customers located in areas with zip codes 9711 and 9712 were included in the first selection. Some parts of zip code 9712 are outside the canals. These are removed from the dataset. Then the data was filtered on the maximum capacity for the eCanter electric truck that Bidfood possesses. The truck can carry a total of 12 roll containers and is currently divided into 9 roll containers of fresh food and 3 roll containers of frozen food. Customers that did not exceed these constraints made it through the selection. Customers in this final dataset received deliveries 1-5 times per week.

Since the number of deliveries per customer for week 30 varies between 1 and 5, the sum for fresh and frozen products, service time, and demand weight are divided by the sum of the number of deliveries for that specific customer in week 30 to calculate the averages for week 30 for that customer. For the experiments, the number of roll containers is continuous, meaning that multiple customers can fit in one roll container (e.g., five times 1/5). In a real-life situation filling roll containers with continuous numbers results in higher service times, but for this study that is not considered. Details on the deliveries per week per customer are depicted in Figure 1.

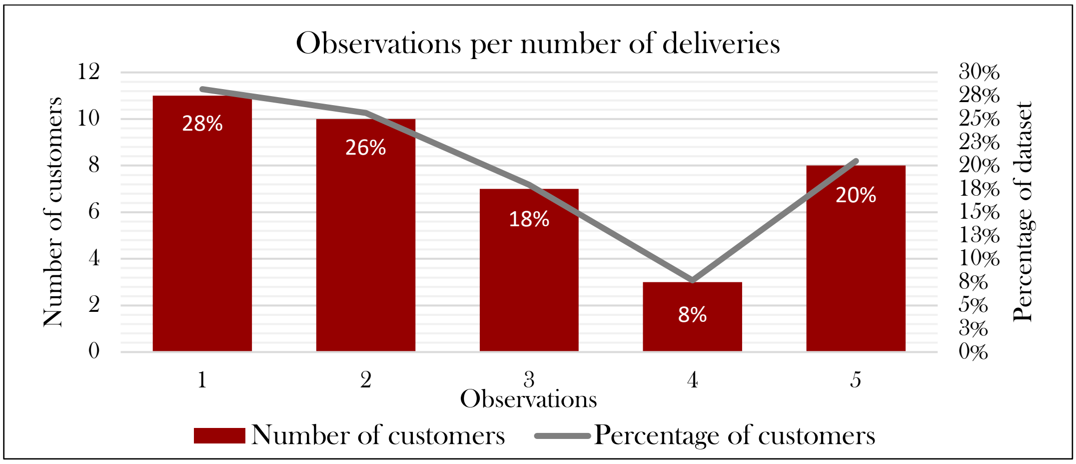


Figure 1 - Observations per number of deliveries

In Figure 2, the actual locations of the 39 customers are depicted as dots. The dataset of 39 customers is randomly divided into three datasets of 13 customers to achieve reasonable computation times. As the legend shows, the blue dots represent dataset 1, the green dots represent dataset 2, the red dots represent dataset 3 and on the South-East corner of the figure, the actual location of Bidfood's depot is depicted with a white truck in a green circle.

Figure 2 - Actual locations of the 39 customers and the depot[1]

The distribution of demand of the final datasets is shown in Figure 3. The data shows a concentration of demand around 1.00-1.50 fresh roll containers and 0.20-1.75 units of frozen roll containers. The figure shows that one outlier in the data has a demand of 8.00 fresh roll containers. This customer is not removed from the dataset.

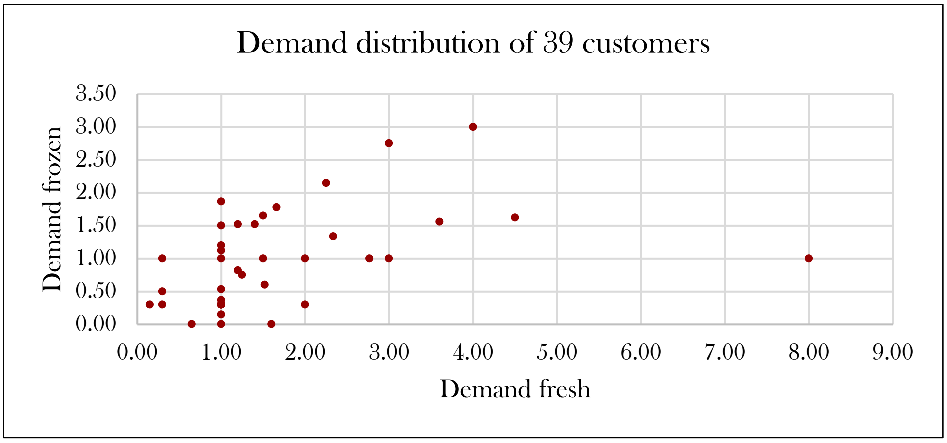


Figure 3 - Demand distribution of 39 customers

Table 4.1 shows the minimum and maximum demand of fresh and frozen, the average demand volume, and the average demand weight over all 39 customers. The minimum amount of fresh roll containers in the complete dataset is 0.15 and the maximum is 8, thus the range is 0.15-8.00 fresh roll containers. The minimum amount of frozen roll containers is 0.00 and the

[1] This figure has been removed from this public version for reasons of confidentiality

maximum is 3, meaning the range is 0.00-3.00 frozen roll containers. The average demand volume for fresh is 1.69 roll containers and the average demand volume for frozen is 0.97 roll containers. The average demand weight is 40.07 kilograms for fresh demand and 37.8 kilograms for frozen demand.

Table 4.1 – Overall statistics datasets

	Fresh	**Frozen**
Minimum	0.15	0.00
Maximum	8.00	3.00
Avg. demand volume	1.69	0.97
Avg. demand weight	40.07	37.80

Looking more in-depth into the characteristics of the individual datasets, the data in Table 4.2 shows that the average total demand weight for dataset 1 is 99.14 kilograms, with a standard deviation of 65.29 kilograms. Dataset 2 shows 71.61 kilograms, with a standard deviation of 67.30 kilograms, and dataset 3 shows an average weight of 62.84 kilograms, with a standard deviation of 51.35 kilograms.

Table 4.2 - Statistics per dataset

	Dataset 1	**Dataset 2**	**Dataset 3**
Avg. demand weight	99.14	71.61	71.72
Std. dev demand weight	65.29	64.66	44.87

4.2 Experimental setup

The mathematical model proposed in this thesis is modeled using CPLEX and Python in IDE Atom. All experiments ran on a personal computer with 3.40GHz AMD Ryzen 5 2600 processor with 6 cores and 12 threads, 16GB DDR4 RAM, and Microsoft Windows 10 Pro x64. To define different experimental settings, some values for the model parameters are established in the following section.

4.2.1 Fixed parameters

For all locations, Euclidean distance matrices were calculated using the real latitude and longitude information of customers. The latitude and longitude information were obtained by using a tool provided by Bing Maps. An alteration in the formula was made by multiplying the outcome by 150, to obtain an approximately real-life distance in kilometers. The formula used is as follows:

$$a_{ij} = \sqrt{(coord\_x_i - coord\_x_j)^2 + (coord\_y_i - coord\_y_j)^2} * 150, \quad \forall\, i,j \in L$$

The average speed used to calculate travel times in minutes is 15km/h (Grooten & Kuik, 2010). Travel time between locations is calculated using the distance between these locations and the average vehicle speed of 15km/h using the following formula:

$$t_{ij} = \frac{a_{ij}}{S_v} * 60, \quad \forall\, i,j \in L$$

Driving time for a route was capped at 8 hours, meaning that the routes cannot exceed this. The number of vehicles available for all experiments was 8 and is labeled from A-H. The number is chosen based on having sufficient capacity to serve all customers. All vehicles have the same compartment configuration consisting of a total roll container capacity of 12. Divided into 9 roll containers of fresh products and 3 roll containers of frozen products. All vehicles can carry the same maximum load of 4250kg, with a curb weight of 3240kg this results in a total maximum weight of 7490kg. All vehicles have a sufficiently large battery capacity of 150kWh to generate realistic routes. Fixed parameters for the vehicles are shown in Table 4.3.

Table 4.3 - Fixed vehicle parameters

Fixed vehicle parameters for eCanter truck					
$\boldsymbol{H_v}$ **(minutes)**	**S**	$\boldsymbol{Wmax_v}$ **(kg)**	**Fresh capacity**	**Frozen capacity**	$\boldsymbol{B_v}$ **(kWh)**
480	15	4250	9	3	150

For the energy function in the proposed model, multiple parameters are used. The corresponding values are shown in Table 4.4.

Table 4.4 - Energy function parameters

Parameter	Description	Values	Source
C_d	Unitless coefficient of rolling drag	0.7	Akçelik & Besley (2007)
e_f	Engine efficiency for an EV	80%	Davis & Figliozzi (2013)
A	Frontal surface area of a vehicle (m^2)	5	Akçelik & Besley (2007)
a	Acceleration (m/s^2)	0	Lin et al. (2016)
θ_{ij}	Road angle degree	0^o	Lin et al. (2016)
ρ	Air density (kg/m^3)	1.2041	Lin et al. (2016)
C_r	Unitless rolling resistance	0.01	Lin et al. (2016)
g	Gravitational constant (m/s^2)	9.81	Lin et al. (2016)
v	Travel speed in (m/s)	4.17	Grooten & Kuik (2010)
B_v	Battery capacity (kWh)	150	Specsheet in relation to the denominator
W_v	Vehicle curb weight kg	3240	E-Canter specsheet (2020)
Q_v	Vehicle load capacity in kg	4250	E-Canter specsheet (2020)

4.2.2 Experiments

Based on the described data and fixed parameters a total of seven experiments are executed. Experiment 1 aims to set a base-case of the delivery route to which other experiments can be compared on basis of the proposed model with load-dependent discharging. Experiment 2 aims to explore the differences between having a model using a fixed-range for the vehicle's battery and having a load-dependent discharging function. Experiment 3 aims to understand to influence of the demand weight of a customer for the load-dependent discharging model, by increasing the weight of three customers. Experiment 4 is built upon experiment 3 and aims to provide a deeper insight into the influence of the demand weight of a customer on the optimal route. Experiment 5 investigates different compartment configurations for fresh and frozen products to determine the best vehicle configuration by comparing energy, distance and trucks deployed. Experiment 6 investigates the influence of tightening the delivery time windows for customers. Experiment 7 aims to understand the differences between having the objective of the shortest route and the lowest energy use.

5. RESULTS

This section presents the results obtained from the experiments as presented in section 4.2.2. First, optimal routes are computed with the base parameters to set a base case. After that, the differences between having a truck with a fixed-range in kilometers for battery capacity compared to having a truck with a battery depending on load-dependent discharging are explored. Then the behavior of demand weight is introduced in two separate experiments. After that, having different compartment configurations is explored. Then, the effects of tightening delivery time windows are explored. Lastly, the differences between having the objective of lowest total distance versus lowest total energy usage are explored. Different performance metrics are used to benchmark and compare the results. For experiment 2, the performance metrics are the total distance covered and compartment utilization. For experiments 3 and 4, the performance metric is the customer position in the delivery sequence. For experiment 5, the performance metrics are the total distance covered, the total energy used, and the number of vehicles deployed compared to the base case. For experiment 6, the performance metrics are the percentual change in energy used and the number of routes. For experiment 7, the performance metrics are the total distance covered and total energy used.

5.1 BASE CASE

This section discusses experiment 1, considered the base case. The first experiment seeks optimal routes with the proposed model considering standard parameters. In Table 5.1, the weight for all customers is presented and sorted from largest to smallest per dataset. All constraints were satisfied, meaning no infeasibility was detected for the chosen parameters.

Table 5.1 – Customer weight for dataset 1, 2, and 3 sorted high to low

Dataset 1		Dataset 2		Dataset 3	
Customer	Demand weight (kg)	Customer	Demand weight (kg)	Customer	Demand weight (kg)
1	228.69	4	213.08	1	189.82
2	227.43	1	211.52	2	127.88
13	134.16	2	101.67	4	91.63
4	133.01	13	83.20	12	80.40

5	103.14	6	57.57	10	76.00
9	92.00	7	54.21	3	69.40
12	86.47	8	51.54	5	68.02
8	81.88	10	38.63	13	66.19
7	71.05	11	35.82	6	51.13
11	57.68	5	27.64	7	45.14
10	26.85	12	27.20	11	27.60
6	26.00	3	14.95	8	22.70
3	20.50	9	13.87	9	16.50
Total	**1288.85**	**Total**	**930.89**	**Total**	**932.41**

Noticeable about the data is the fact that all of them are rather low for the capacity of the vehicle in terms of weight. The data depicted are sorted from heavy to light for the ease of finding the customer with the highest demand weight first. The results in Figure 4 show the customer locations, what route they are assigned to and the sequence they are served in.

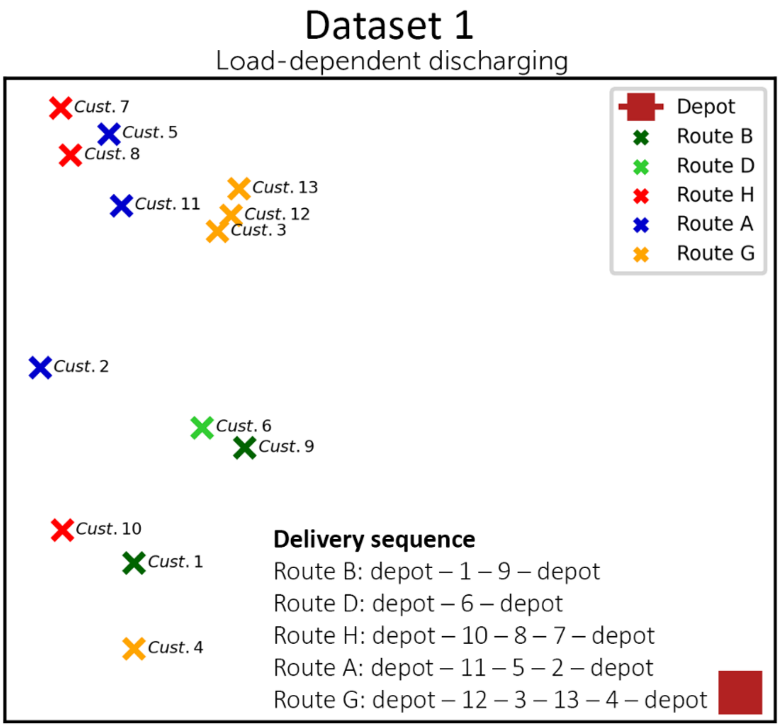


Figure 4 - Customer locations and delivery sequence dataset 1 base case

The results for dataset 1 in Table 5.2 show that the total energy used is 595.24kWh and the total distance covered is 51.87km. The total weight per route is relatively similar, considering that route H has one less customer. Route D is significantly lower than the others. This can be explained by the time window, starting relatively late compared to the other customers. For all other customers, time windows do not seem to affect the route. The differences in energy between A and G arise because of the geographical difference while having almost similar weights. Noticeable is that the trucks with a heavy load do not specifically serve shorter routes, which logically results in more energy used. The kWh/kg for route D is significantly higher compared to the other routes. This is mainly due to the high energy usage from the depot to the first customer and back, considering that D is only serving one customer, implying that the model relies heavily on distances. The customer's weight seems dominant in determining the optimal route in the base case, considering that some customers that are farther away are served first.

Table 5.2 - Results base case dataset 1

Dataset 1: Weight, distance, and energy per route for the base case						
	B	**D**	**H**	**A**	**G**	**Total**
Weight per route (kg)	320.69	26.00	179.78	388.25	374.14	1288.85
Distance (km)	9.69	8.62	11.68	11.45	10.43	51.87
Energy per route (kWh)	112.33	95.82	132.68	133.41	121.00	595.24
kWh/kg	0.35	3.69	0.74	0.34	0.32	-
kWh/km	11.59	11.12	11.36	11.65	11.60	-

Results show that the customer (1) with the highest demand weight is served first in route B. The same route served customer (9) with an average demand, directly after. Route D is dedicated to only one customer (6), which has one of the lowest demand weights of the dataset. Route H starts with customer (10), then serves (8) and (7), all three have no significant high demand weight. Route A starts with customer (11), continues to (5), and finishes at (2). Customer (2) has the highest demand but is served last, even though the customer is the closest to the depot. The last route G, starts with customer (12), then (3) which are relatively low-weight customers, and then serves two heavy weights as last (13) and (4), which is an interesting occurrence.

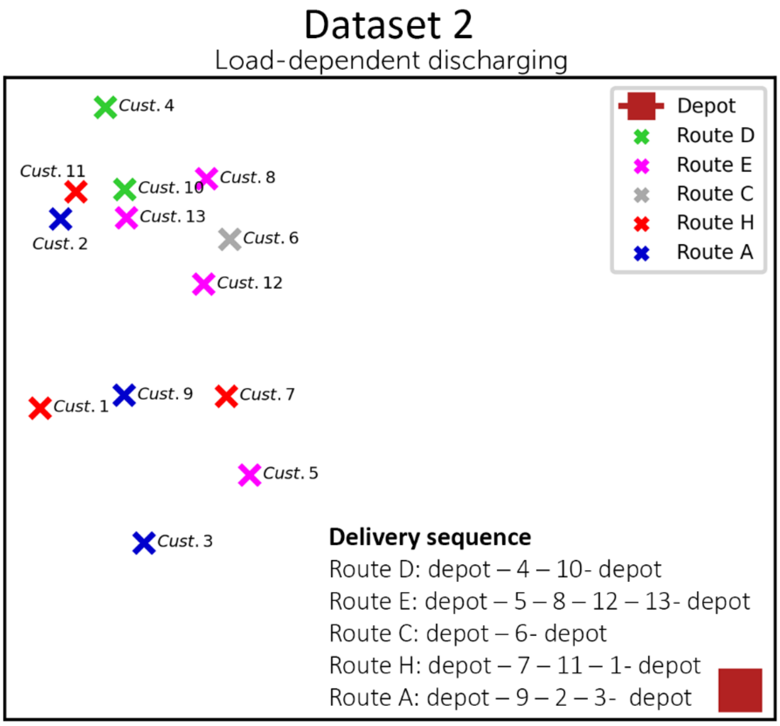


Figure 5 - Customer locations and delivery sequence dataset 2 base case

The results for dataset 2 in Table 5.3 and Figure 5 show that the total energy used is 590.47kWh and the total distance is 51.96km. The total weight per route is less balanced compared to dataset 1. The results are not affected by the time windows, considering that the customers with the smallest time windows are not served first. The weight per customer seems dominant for dataset 2 as well. Some customers that are geographically farther away, are served earlier. However, the results show more focus on distance than the model intended. The high kWh/kg for route C holds the same reason as for dataset 1, serving one customer.

Table 5.3 - Results base case dataset 2

Dataset 2: Weight, distance, and energy per route for the base case						
	D	**E**	**C**	**H**	**A**	**Total**
Weight per route (kg)	251.71	189.58	57.57	301.54	130.49	930.89
Distance (km)	10.42	10.42	8.34	11.53	11.25	51.96
Energy per route (kWh)	119.44	118.26	93.11	132.82	126.85	590.47
kWh/kg	0.47	0.62	1.62	0.44	0.97	-
kWh/km	11.46	11.35	11.16	11.52	11.28	-

Results show that for the first Route D, customer (4) is served first, which has the highest demand weight of dataset 2, and then served customer (10) which is in the lower half in terms of weight. Route E starts with customer (5), then moves to (8), (12), and (13), which is remarkable, since customer (13) has the highest demand weight of the route. Route C is dedicated to customer 6. Then, route H has the sequence of (7), (11), (1), which is remarkable, since customer (1) is second in the list with the highest demand weight. Route A serves customers (9), (2), and (3).

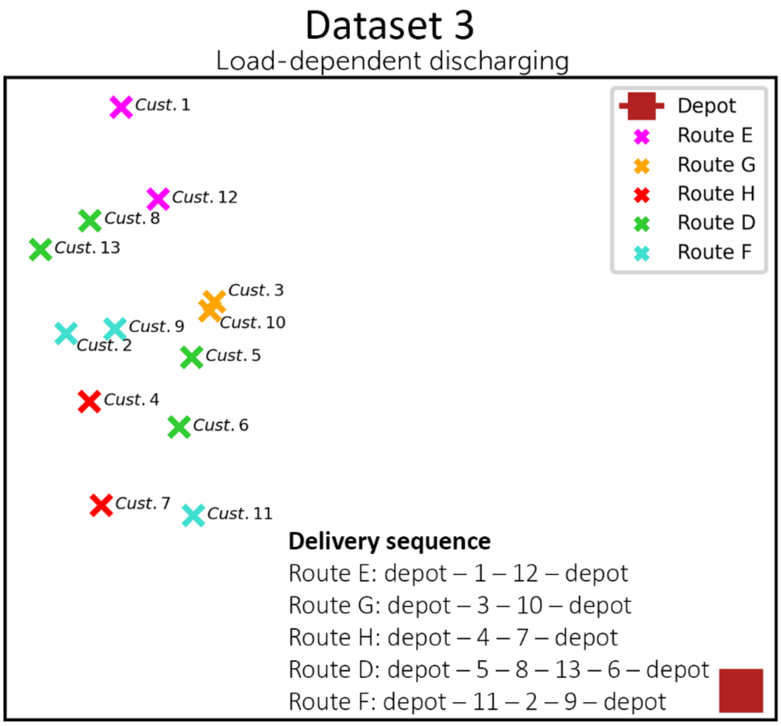


Figure 6 - Customer locations and delivery sequence dataset 3 base case

The results for dataset 3 in Table 5.4 and Figure 6 show that the total energy used is 563.04kWh and the total distance traveled is 48.48km. The total weight per route is better balanced for dataset 3 compared to datasets 1 and 2. Comparing route G and H, both serving two customers show a similar weight, but different total distance, resulting in significantly higher energy use for route H. This implies that also for dataset 3, the distance component in energy use weighs heavily and results in different results than expected. The time windows in dataset 3 are not affecting the optimal routes, since the customer with the tightest time window is customer 13, and is near the end of route D.

Table 5.4 - Results base case dataset 3

Dataset 3: Weight, distance, and energy per route for the base case						
	E	**G**	**H**	**D**	**F**	**Total**
Weight per route (kg)	270.22	145.40	136.77	208.04	171.98	932.41
Distance (km)	9.81	8.28	10.15	9.79	10.45	48.48
Energy per route (kWh)	112.68	93.43	114.45	123.99	118.49	563.04
kWh/kg	0.42	0.64	0.84	0.60	0.69	-
kWh/km	11.49	11.28	11.28	12.66	11.34	-

Again, for the first route, route E, the customer (1) with the highest demand weight is served first, then customer (12) is served, which is at the higher end of demand weight for the dataset. Route G serves customers (3) and (10) which are at the higher end of the set. Route H starts with customer (4), which has the third position in terms of weight and serves (7) next. Route D serves three slightly below average customers (5), (8), (13), and (6). The last route F, serves (11), (2), and (9). Where (2) is the second-highest demand weight customer.

Concluding on experiment 1, time windows do not affect the optimal routes for most outcomes in the base case, only customer 6 in dataset 1 affects the outcome. The number of routes is for all three datasets 5. This is due to the capacity volume restrictions. Also, the distance component in the calculation of energy consumption takes an unintended dominant role in the model. All routes had excessive battery capacity and could have potentially fit more customers in the route. Since uncertainty in demand is not considered, Bidfood might need to deploy more or fewer trucks.

5.2 FIXED-RANGE V. LOAD-DEPENDENT DISCHARGING

This section discusses experiment 2. In this experiment, two different objectives and parameters are used. The objective is based on the dominant experimental parameter. For fixed-range (FR), the model minimizes the total distance covered by all deployed vehicles and for the load-dependent (LD) discharging the model minimizes total energy used for all deployed vehicles. To ensure the validity of the test, the values for the parameter maximum driving range and the parameter of maximum battery capacity are carefully considered and the rationale for the values is explained next.

For the fixed-range test, the maximum driving range per vehicle is chosen as follows: for all datasets, the maximum distance between depot-to-customer (D-P) and customer-to-customer (C-C) is selected from the distance matrix and results in the maximum driving range with the following equation $MaxRange = 2 * MaxCuSDepot + MaxCusCus$. These maximum values are found suitable for the experiment since the minimum values can be much lower than the maximum, as depicted in Table 5.5. For instance, the lowest C-C value for dataset 1 implies that all 13 customers would potentially fit in one route. The values used for the FR parameter are presented in Table 5.5, column "*FR km*".

For the load-dependent test, the battery capacity is based upon the average energy consumption in kWh/km for datasets 1, 2, and 3 as found in the base case, experiment 1. Then, that value is multiplied by the chosen parameter value for the FR test, resulting in the values as presented in Table 5.5, column "*LD kWh*". Linking the values to each other increases the validity of the relational outcome.

Table 5.5 – Statistics and settings experiment 2

Statistics and settings for experiment 2							
Dataset	**Average kWh/km**	**Min. C-D**	**Max. C-D**	**Min. C-C**	**Max. C-C**	**FR km**	**LD kWh**
1	11.48	3.96	5.60	0.08	1.48	12.68	145.51
2	11.36	3.94	5.62	0.29	1.34	12.59	143.08
3	11.62	4.10	5.43	0.17	1.13	11.99	139.25

The results in Figure 7 for dataset 1 (red v. gray) show that the total distance covered is lower for the objective of distance minimization, as expected. However, the results for dataset 2 (blue v. yellow) and dataset 4 (green v. orange), show a lower total distance for the load-dependent model. It must be noticed that for dataset 1, the difference is relatively large and can be explained by the fact that the characteristics of dataset 1, concerning the chosen parameter values for FR and LD, are affecting the route outcome more towards the expectation than for datasets 2 and 3, which implies that the set parameters are less suitable for dataset 2 and 3. The result of higher distances for datasets 2 and 3 in the FD test means the upper bound of the range was reached.

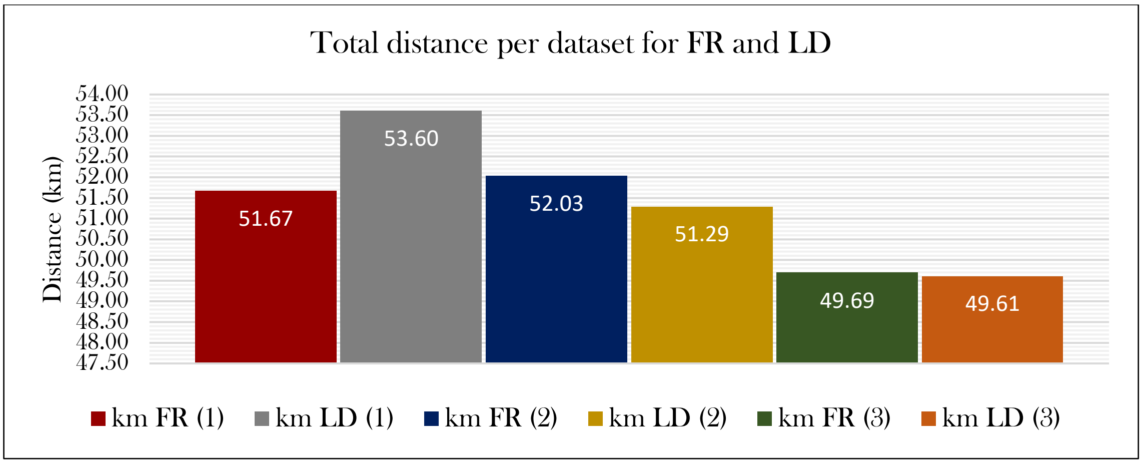


Figure 7 - Total distance for FR and LD

Another result of the fixed-range and load-dependent discharging experiment is compartment utilization. Figure 8 presents the percentual utilization per route for all three datasets and both tests. Only the results of dataset 2, LD shows a more balanced compartment utilization compared to FD, which can be considered as randomness. The results for datasets 1 and 3 show similar results in terms of compartment utilization for both FR and LD. This means that neither of the models yields an advantage in terms of compartment utilization optimization.

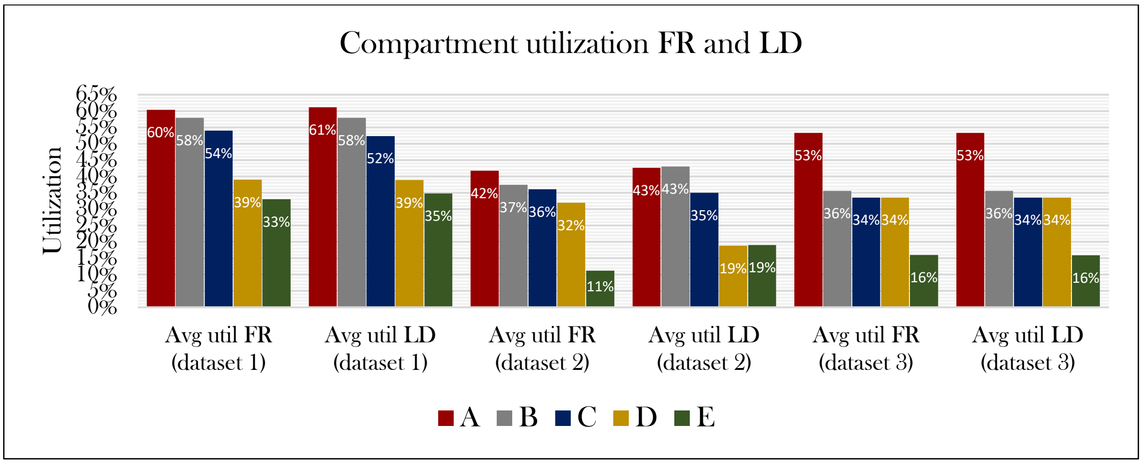
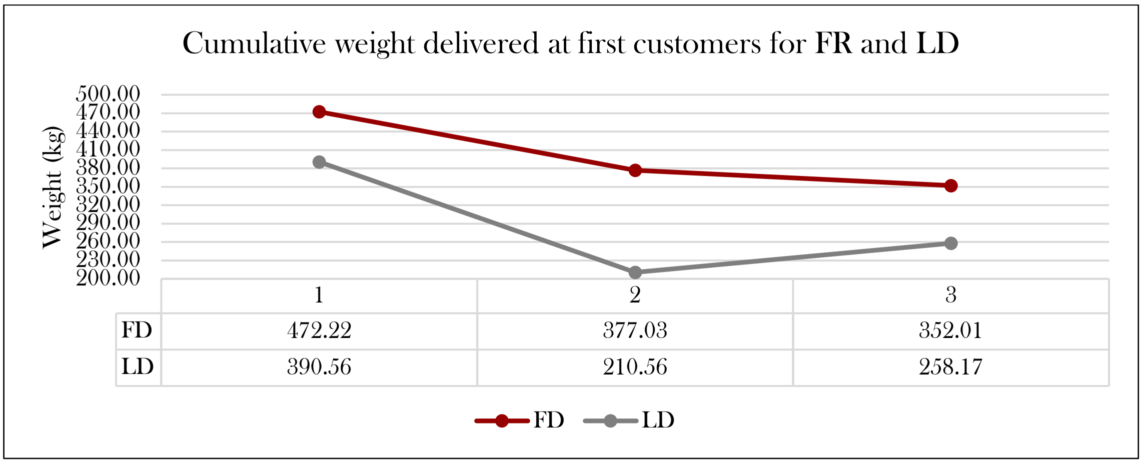


Figure 8 - Compartment utilization FR and LD

In Figure 9 the cumulative weight of the first customer in every route is shown for all three datasets and both **FR** and **LD**. An interesting observation is that for all three datasets, the **LD** drops off a lower cumulative weight compared to the shortest route model. It must be noted that for all three datasets, three routes showed similar starting customers, except for two routes per dataset. The differences per route are as follows: for dataset 1, in the **FR** solution customer 1 and 10 are served first, in the **LD** solution customers 8 and 9 are in that place. Then the difference in weight is due to customer 1, which yields the highest weight of the whole dataset and is geographically close to the depot. Customer 10 is located behind 1 and is also close to the depot. For the **LD**, customer 8 is geographically located far from the depot, which implies that this was more energy efficient. For dataset 2 in **FR**, customers 4 and 8 are served first and are almost in a straight line behind each other, whereas for **LD** customers 3 and 13 are served first. For dataset 3 **FR**, customers 2 and 11 are served first, whereas for **LD** customers 7 and 9 are served first. Customer 11 lies before customer 7, which shows the shortest route objective in **FR**. The results reflect a geographically less logical solution for the **LD** test, which shows that the model bases its decision on different characteristics than the **FR** test, while demand weight in relation to energy use was a dominant factor because the model did not prioritize these customers over customers with lower demand weight.



	1	2	3
FD	472.22	377.03	352.01
LD	390.56	210.56	258.17

Figure 9 - Cumulative weight delivered at first customers for FR and LD

5.3 STANDARD DEVIATION SENSITIVITY TEST

This section discusses experiment 3. This experiment aims to understand to influence of the demand weight of a customer for the load-dependent discharging model by increasing the initial demand weight of three customers, by one standard deviation at a time. The expectations are that by increasing the weight of specific customers, these customers will gain priority in the order sequence.

In this experiment, the initial demand weight of customers 4, 8, and 12 is increased by the $mean + \sigma * x$. The standard deviations are calculated over the whole dataset. Outcomes of the experiment represent a cumulative score of customers 4, 8, and 12's position. A lower cumulative score means the customers are served earlier on average. This experiment is designed to explore the effect of demand weight delivery sequence priority. The initial demand weight of the customers per dataset can be found in Table 5.6.

Table 5.6 - Initial demand weights of customers 4, 8 and 12

Initial weight for customers 4, 8, and 12 in datasets 1, 2 and 3			
Dataset	**Customer 4**	**Customer 8**	**Customer 12**
1	228.69	227.43	134.16
2	213.08	211.52	101.67
3	189.82	127.88	91.63

In Table 5.7, the values that are used in the experiment per dataset are presented. The values represent the $mean + \sigma * x$ and are added to the initial demand weight of customers 4, 8, and 12.

Table 5.7 – Mean plus standard deviation matrix

Standard deviation matrix dataset 1-3									
Dataset	**Mean (M)**	**SD (σ)**	**M + σ1**	**M + σ2**	**M + σ 3**	**M + σ 4**	**M + σ 5**	**M + σ 6**	**M + σ 7**
1	99.14	65.29	164.43	229.71	295.00	360.28	425.57	490.85	556.14
2	71.61	64.66	136.26	200.92	265.58	330.23	394.89	459.55	524.21
3	71.72	44.87	90.63	124.14	157.65	191.16	224.67	258.18	291.69

The results for dataset 1 can be found in Table 5.8. The results show that for 2 and 3 standard deviations, the total score is similar, namely 5. For standard deviations 4 and 5, the total score increases to 6, implying that increasing the weight did not have the expected result. However, standard deviation 6 shows a decrease to a total score of 5 again and standard deviation 7 shows a total score of 4, implying that the model reacts to the weight increase. However, for standard deviation 8, the model increases the total score to 6. The results seem to be inconsistent and do not meet the expectations.

Table 5.8 - Customer position dataset 1

Position of customers in dataset 1							
Customer	**σ1**	**σ2**	**σ 3**	**σ 4**	**σ 5**	**σ 6**	**σ 7**
4	1	2	2	2	1	1	3
8	2	2	1	2	2	2	2
12	2	1	3	2	2	1	1
Total	**5**	**5**	**6**	**6**	**5**	**4**	**6**

The results from the second dataset are shown in Table 5.9. The results for standard deviation 2, 3, and 4 show a total score for customer position of 4. However, for all three standard deviations, two customers are in the first place Noticeable is, when a standard deviation of 5 is applied, the total score increases to 7. This is against expectations and a shift between customer positions could be a logical result, but moving all customers back in the sequence is not expected. However, for standard deviation 6, the total score decreases back to 5 and for standard deviation 7 and 8, the total score achieves the lowest possible value of 3, meaning the effect of increasing weight gives the expected result of serving those customers first.

Table 5.9 - Customer position dataset 2

Position of customers in dataset 2							
Customer	**σ1**	**σ2**	**σ 3**	**σ 4**	**σ 5**	**σ 6**	**σ 7**
4	2	1	2	2	3	1	1
8	1	1	1	2	1	1	1
12	1	2	1	3	1	1	1
Total	**4**	**4**	**4**	**7**	**5**	**3**	**3**

The results from the third dataset are shown in Table 5.10. Standard deviation 2 shows a total score of 6. Standard deviations 3, 4, and 5 show a total score of 7, which is relatively high. For standard deviations 6 and 7, the total score lowers to 5 and for standard deviation 8, the total score decreases to 4, which is within the expectational value.

Table 5.10 - Customer position dataset 3

Position of customers in dataset 3							
Customer	**σ1**	**σ2**	**σ 3**	**σ 4**	**σ 5**	**σ 6**	**σ 7**
4	1	2	1	2	2	1	1
8	4	2	4	4	2	3	2
12	1	3	2	1	1	1	1
Total	**6**	**7**	**7**	**7**	**5**	**5**	**4**

All results from experiment 3 are depicted in Figure 10. The behavior of dataset 1 seems rather random, but dataset 3 shows some sensitivity to the experiment, and dataset 2 shows a more intense reaction.

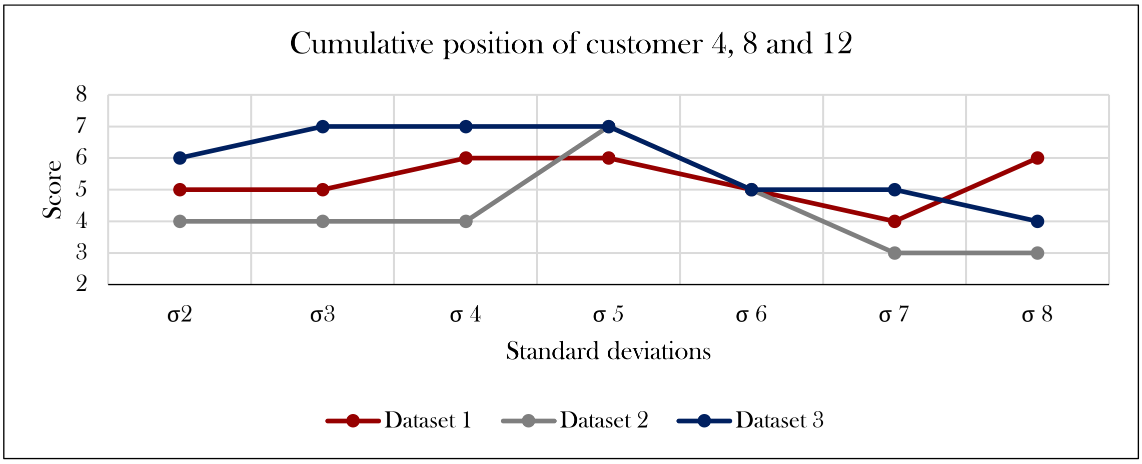


Figure 10 - Cumulative position customer

The average over all datasets is shown in Figure 11. Customers 12 and 8 show the most significant decrease. Customer 4 is rather inconsistent in its behavior. Overall, the results do not show the expected sensitivity to this test and might imply that the model does not emphasize the value for weight as intended.

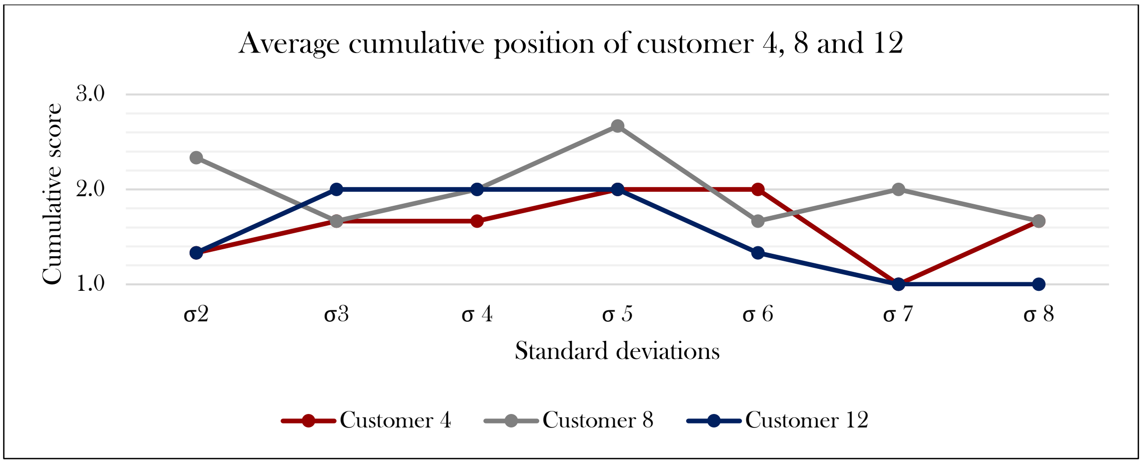


Figure 11 - Average cumulative position over three datasets

5.4 Energy factor sensitivity test

This section discusses experiment 4. For all datasets, the data has been manipulated to equal values for customers and to ease the exposure of any effects due to the energy consumption with the added weight factor. First, time windows are set from the earliest starting time 06:00 AM to the latest starting time for servicing, 05:00 PM. All service times are set to 15 minutes per customer. All demand weight is set to 500kg, while demand volume in unit roll containers remains original. The chosen customers per dataset to manipulate, are selected based on two criteria 1) their demand volume must be close to the average of the dataset, and 2) they were served last in the routes calculated with factor 1. This test increases the factor by steps of 5. That factor is added to a specific part of the energy function. The altered energy formula is as follows:

$$J_{ijv} \approx \frac{((\alpha_{ij}(W_v + W_{jv} * \boldsymbol{Factor_j})a_{ij} + \beta(v^2)a_{ij})/e_f)}{500}$$

The bold part shows the placement of the factor and affects only the weight that the vehicle is carrying to node j. The denominator is increased from 40 to 500, otherwise, the battery capacity would be the limiting factor in this experiment. All other parameters remain equal to the model as presented in section 3.4. Since the goal of this experiment is to investigate the effect of adding a factor to the energy consumption function, a scoring system is designed. The scoring system works as follows: if the selected customer is at the end of a route, it will have a score of 3.

If a customer is not at the end or the beginning it will have a score of 2. If a customer is served first in a route, it will have a score of 1.

For dataset 1, customers 5, 7, and 9 are selected. Figure 12 shows that with a factor of 5, all customers remain last in the sequence of serving. With factor 10, customer 7 moves to the middle of a route, while customers 5 and 9 remain in the last position. This continues for factor 15. For factor 20, positions are swapped. Customer 5 is in the middle of a route, while customer 7 is lowered in priority. This is probably because the optimal solution can only have one customer in the middle for factor 20, so customer 7 is lowered in priority. However, with factor 25, also customer 9 gained priority, and for factor 30 customers 5 and 9 are served first, and customer 7 gained priority again. This implies that an emphasis on weight in the energy function can result in a higher priority in the delivery sequence.

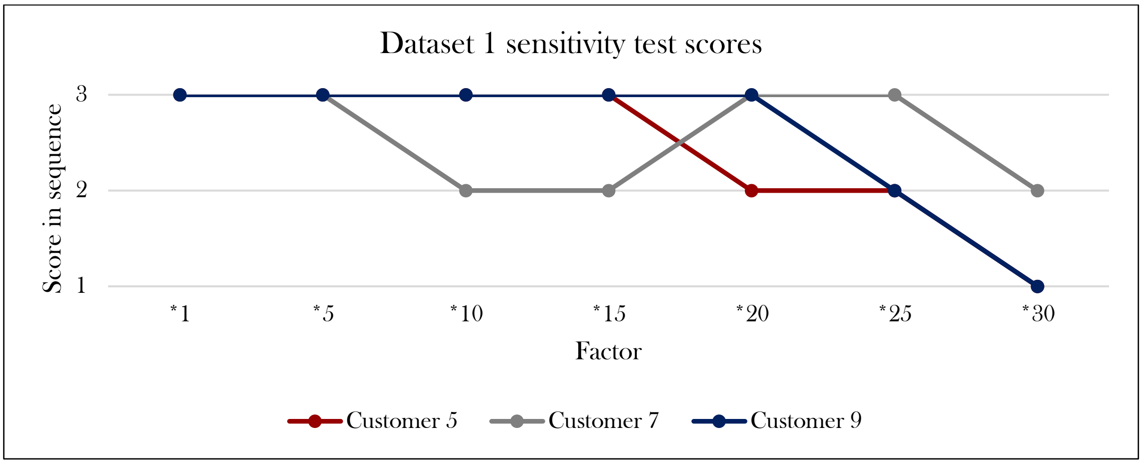


Figure 12 - Sensitivity scores dataset 1

For dataset 2, customers 6, 10, and 11 are selected. Figure 13 presents the behavior for dataset 2. At first, factor 5 and 10 does not affect the positions of the customers. While with factor 15, customer 6 jumps from last in route to first in route and occupies that position for factor 20 as well, whereas customer 10 also gained priority. An interesting observation is that for factor 25, both customers 6 and 10 are respectively served in the middle and the end of a route, whereas customer 11 gained priority. For factor 30, customers 6 and 10 are served first, whereas customer 11 is lowered in priority. This behavior of the model strengthens the presumption that the model seeks an optimal solution where only either one or two of the selected customers can have a high-priority position, rather than all selected customers gaining priority over all others.

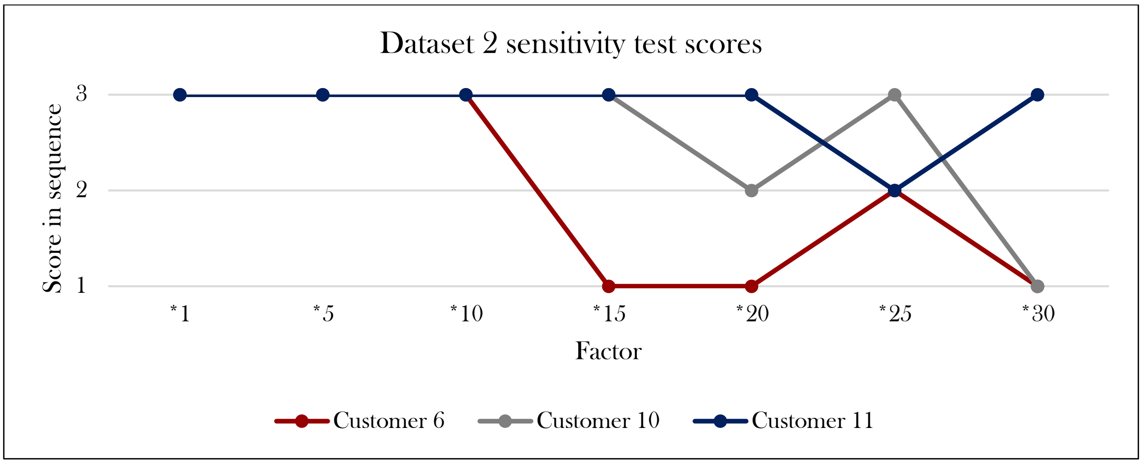


Figure 13 - Sensitivity scores dataset 2

For dataset 3, customers 3, 9, and 13 are selected. Figure 14 shows the behavior of dataset 3. First, the customers remain in a similar position for factor 5. However, at factor 10 customer 3 gains priority. For factor 15 it switches position with customer 9, which might be due to an earlier explanation, that for the optimal solution only one of the customers can be in the middle of a route – for now. For factor 20, customers 9 and 13 are served in the middle of a route, whereas customer 3 remains at the end. For factor 25, customer 3 jumps two places and is served first, whereas customer 9 is lowered in priority, customer 13 stays put. For factor 30, customer 9 jumps from last to first, whereas both customers 3 and 13 are set back a position the respectively middle and end in a route.

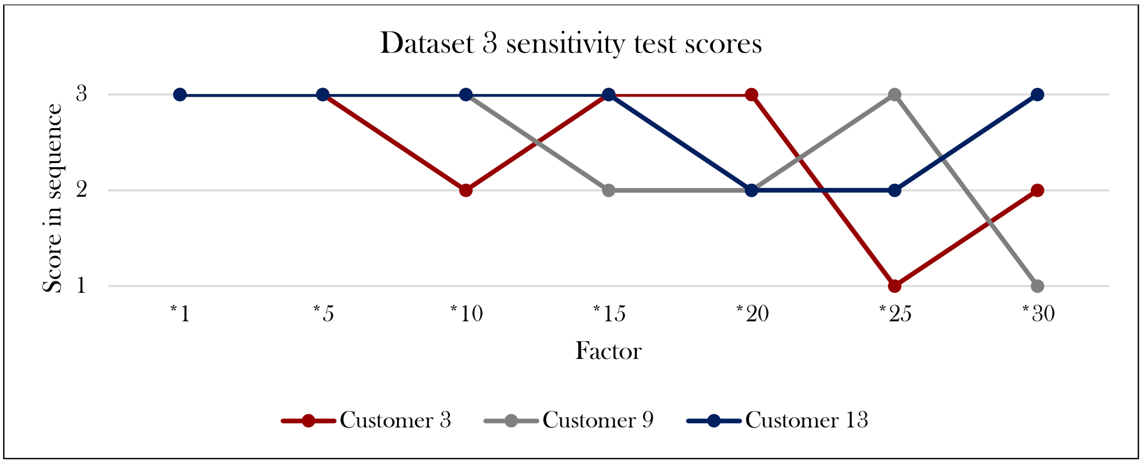


Figure 14 - Sensitivity scores dataset 3

The behavior of the model in this test seems to switch positions between customers, which implies that the optimal routes only have space for either one of the customers being served first, resulting in the selected customers are being swapped continuously.

5.5 Compartment configuration test

This section presents the results of experiment 5. This experiment seeks the best compartment configuration and explores the effects based on the three datasets. In total eleven different compartment configurations were tested for all three datasets. The configurations tested ranged from [11, 1] to [1, 11] for fresh and frozen roll containers. The total energy consumed per test is shown in Table 5.11. For compartment configuration [11, 1] and [10, 2] all three datasets returned infeasible, which is according to expectations since there is almost no capacity for frozen products. For the configuration [9, 3] (standard from the eCanter truck specification sheet), the values of the total energy used are from the base case. An unexpected result in performance shows when using an [8, 4] compartment configuration. All three datasets show lower total energy used which is due to the fewer trucks deployed for this configuration and can have serious implications for operational efficiency and cost. Important to note is that configuration [7, 5] for dataset 1 is infeasible due to the fresh demand of customer 1, which is 8.

Table 5.11 - Total energy used per compartment configuration

[Fresh, Frozen]	Dataset 1	Dataset 2	Dataset 3
[11, 1]	Infeasible	Infeasible	Infeasible
[10, 2]	Infeasible	Infeasible	Infeasible
[9, 3]	595.24	590.47	561.91
[8, 4]	572.09	474.84	458.98
[7, 5]	Infeasible	364.19	363.86
[6, 6]	Infeasible	377.59	454.07
[5, 7]	Infeasible	468.96	459.17
[4, 8]	Infeasible	586.95	564.00
[3, 9]	Infeasible	707.32	766.12
[2, 10]	Infeasible	Infeasible	Infeasible
[1, 11]	Infeasible	Infeasible	Infeasible

The results are depicted in Figure 15 show a steep decrease in energy consumed for datasets 2 and 3 and a minor decrease for dataset 1. The results show that for datasets 2 and 3, a compartment configuration of [7, 5] is resulting in a decrease of 38.32% for dataset 2 and a decrease of 35.2% for dataset 3, which is significant

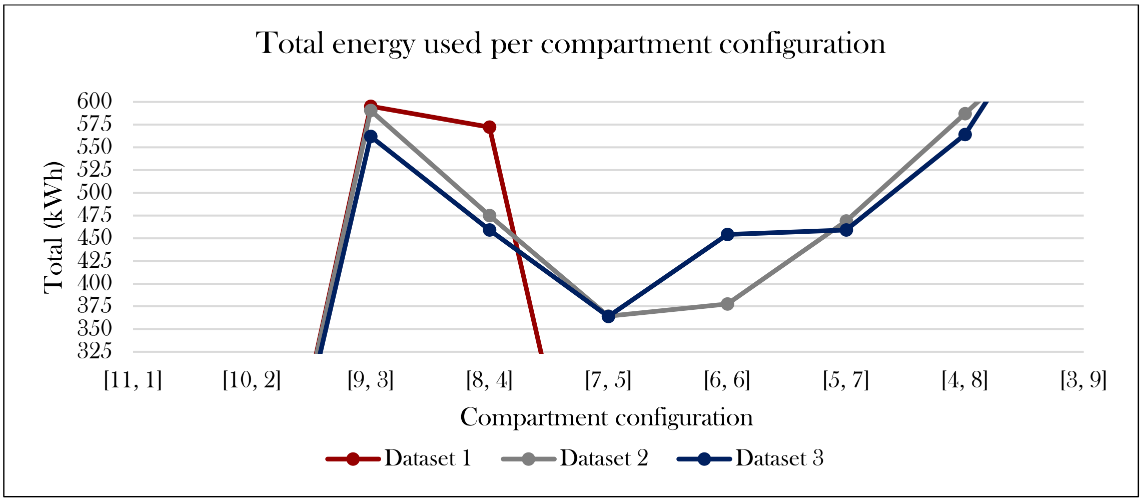


Figure 15 - Total energy used per compartment configuration

However, choosing the compartment configuration that fits all three datasets will result in a configuration of [8, 4]. This will give a decrease in energy use of 3.89% for dataset 1, a decrease in energy use of 19.58% for dataset 2, and a decrease in energy use of 18.48% for dataset 3 as presented in Table 5.12.

Table 5.12 - Decrease in distance covered and energy used

	Dataset 1		Dataset 2		Dataset 3	
	km	**kWh**	**km**	**kWh**	**km**	**kWh**
[9, 3]	51.87	595.24	51.96	590.47	48.48	563.04
[8, 4]	45.71	572.09	41.49	474.84	40.26	458.98
Difference	-11.88%	-3.89%	-20.15%	-19.58%	-16.96%	-18.48%

The differences for compartment configuration [8, 4] compared to the base case [9, 3] are significant for both distance and energy. Figure 16 shows the difference in kilometers covered for both settings per dataset. Dataset 1 shows a distance decrease of 11.88%, dataset 2 shows 20.15% and dataset 3 shows 16.96%. The results show that considering different compartment configurations may have a serious impact on Bidfood's operational efficiency and can lower capital-intensive investments.

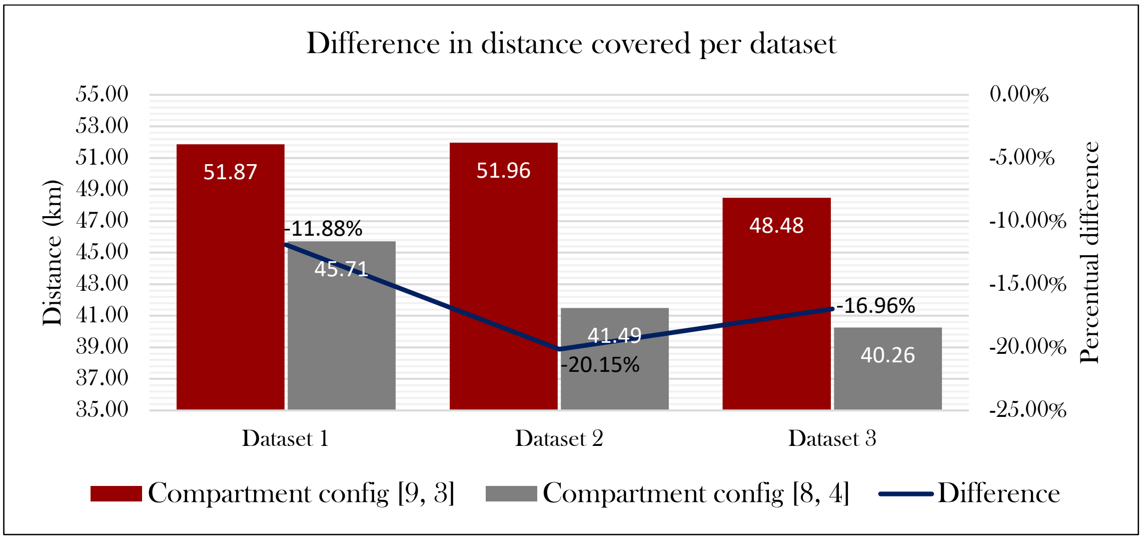


Figure 16 - Difference in distance covered per dataset

Considering Figure 17, the results show that the number of trucks deployed per dataset decreased. With the base case compartment configuration of [9, 3], five trucks per dataset were deployed, resulting in a total of 15. The total trucks deployed when using the compartment configuration [8, 4] were respectively 5, 4, and 4. Resulting in a total of 13 trucks deployed. The decrease of 2 trucks is -13.3% and can potentially be operational cost-saving.

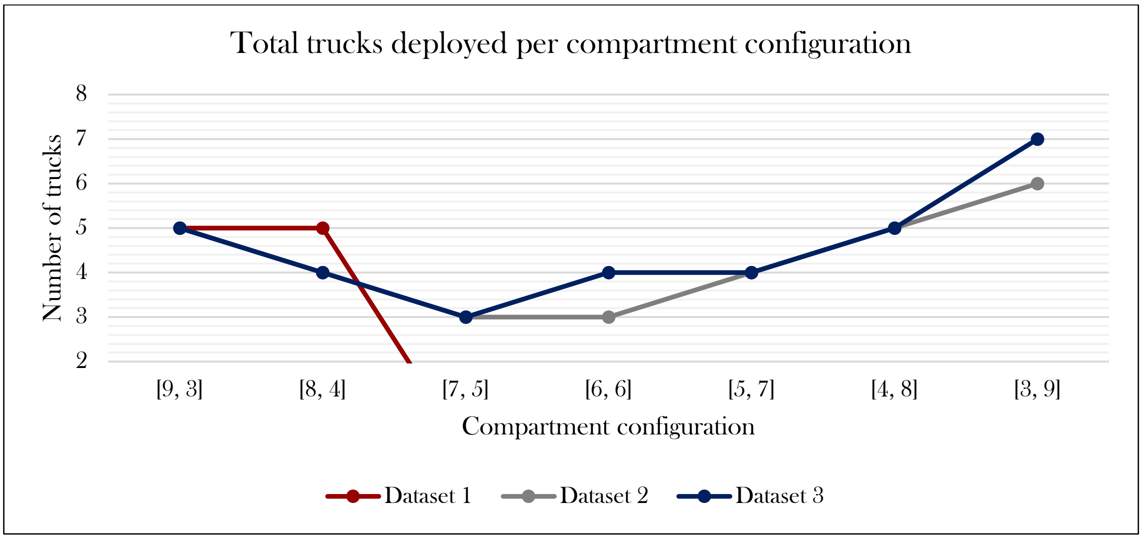


Figure 17 - Number of trucks deployed per compartment configuration

5.6 Tightening delivery time windows

This section presents the results of experiment 6 and explores the effect of tightening the latest time unloading at a customer can start. For this experiment, the original customer data is used. Tightening the time window is done one-sided, which means that the time window decrease is achieved by altering the parameter l_i, meaning e_i is unaffected. In this experiment, the parameter is decreased by increments of 2.5%, starting with a minimum of 0% and a maximum of 10%.

In Figure 18 the results for all three datasets are depicted. Dataset 1 and 2 show somewhat similar behavior over the whole experiment. It decreases in total energy used when delivery time windows are tightened by 2.5%. Then a slight increase occurs and dataset 1 continues increasing. Dataset 2 stays on a similar level of energy used and increases for the last increment, whereas dataset 1 decreases. Dataset 3 is overall stable in energy use. This implies that for datasets 1 and 2, a tightening of windows by 2.5% leads to less energy used, whereas dataset 3 is not affected by these changes. This can be explained by the large delivery time windows in dataset 3.

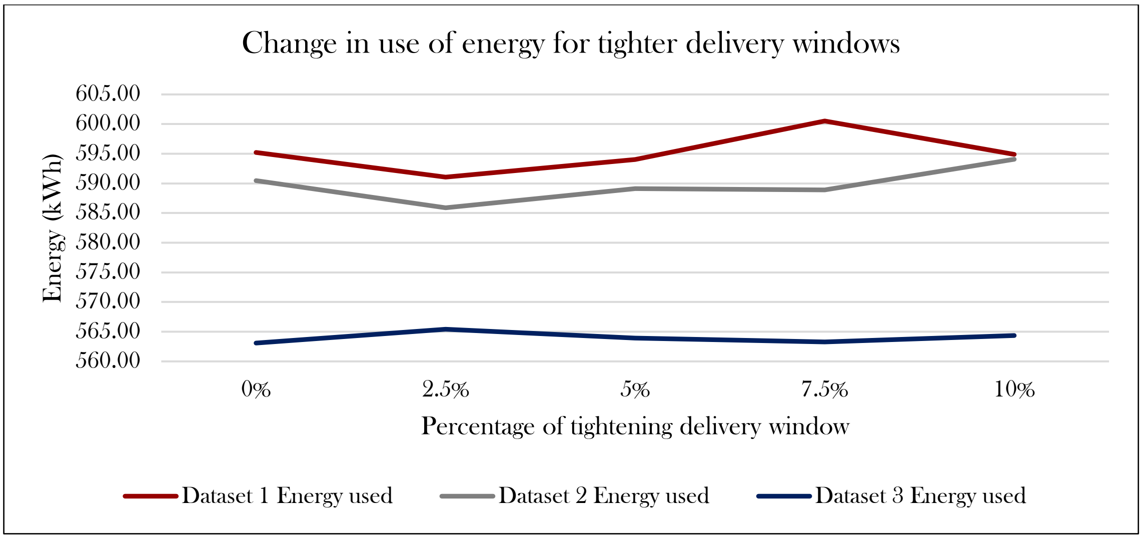


Figure 18 - Change in energy use for tighter delivery windows

5.7 Objective comparison: energy v. distance minimization

This section presents the results of experiment 7 and explores the differences between having the objective of minimizing energy (E) versus distance (D). The expectation for this experiment is to find that minimizing energy outperforms minimizing distance in energy used. In Table 5.13 the total distance covered and the corresponding total energy used for both objective functions are presented.

Table 5.13 - Total distance and energy used for shortest route v. base case

Total distance and energy used base case v. shortest route						
	Minimize energy use (E)		**Minimize distance (D)**		**E v. D**	**E v. V**
	Total km	*Energy in kWh*	*Total km*	*Energy in kWh*	*Difference in km*	*Difference in kWh*
Dataset 1	51.87	595.24	51.48	597.95	-0.8%	0.5%
Dataset 2	51.96	590.47	51.57	599.16	-0.8%	1.5%
Dataset 3	48.47	563.09	49.55	563.60	2.2%	0.1%

As stated in Table 5.13 and supported by Figure 19, for datasets 1 and 2, the total kilometers for the objective function of energy minimization are higher than the objective function of distance minimization, which is obviously as expected. It must be noted that for dataset 3, the energy minimization results in less distance traveled, which is remarkable since that is not the objective. The differences in kWh used as presented in Table 5.13 and Figure 20 are neglectable.

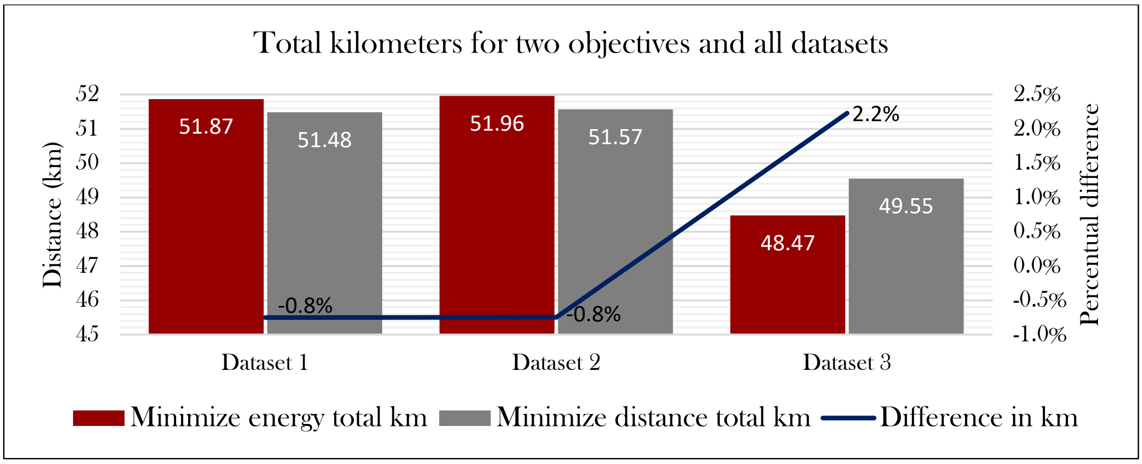


Figure 19 - Total kilometers and percentual difference in km

The total number of trucks deployed for all datasets was 5, which results in an average higher use of energy per truck of 2kWh for the distance minimization objective. Even though the results are nearly similar, the energy difference is remarkable. Looking at the energy usage results, this implies that one extra customer can be served with the energy minimization model, considering the 2kWh difference.

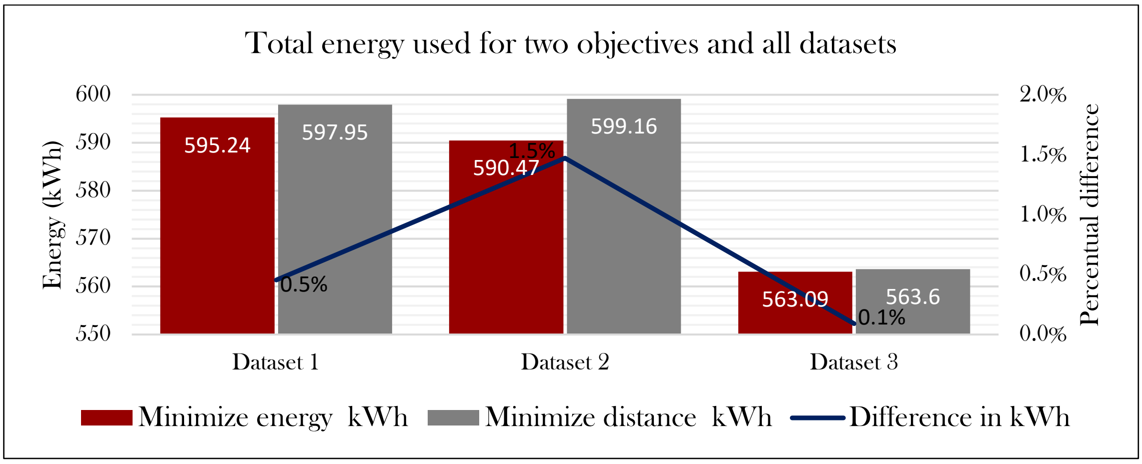


Figure 20 - Energy and percentual difference in energy

6. DISCUSSION

By studying the real data from one food retailer Bidfood in the inner city of Groningen, this thesis aimed to answer the research question: "*What are the effects of using a load-dependent battery discharging function on the number of customers served per route, number of routes, number of vehicles deployed, energy used, distance covered and compartment utilization while minimizing the energy consumption for multi-compartmented vehicles*". This section further discusses the implications of these results and gives an outlook on the future.

6.1 THEORETICAL IMPLICATIONS

This thesis proposed a mathematical formulation of the multi-compartment vehicle routing problem with load-dependent discharging and time windows. Thereby it elaborates on existing models of Lin, Zhou, and Wolfson (2016), Derigs et al. (2011), and Chen and Shi (2019) by making unique combinations of two-folded capacity constraints, time windows, and the novel element of load-dependent discharging of electrical vehicles. The results in this study are supporting Reddy Kancharla & Ramadurai (2020) in their finding that adding the load-dependent discharge function resulted in similar computing times, in contradiction to Lin et al. (2016) finding, that resulted in higher computation times. The results do not support the finding of 15% to 80% more accuracy as presented by Reddy Kancharla & Ramadurai (2020). However, the experiments in this research show that different compartment configurations can be beneficial for food retailers. This thesis found that different compartment configurations decrease the use of energy by almost 20% and vehicles deployed by 20%, which is significant since vehicles are capital intensive and potentially decrease operational costs.

6.2 PRACTICAL IMPLICATIONS

The first practical implication is concerned with the proposed mathematical model in this thesis. For the model to show a change in behavior in the experiments, the intended energy function was changed by adding a factor for demand weight. Therefore, the mathematical model is not yet usable for logistic planners or any other individual with interest. However, further research might improve the model in such a way, that it then can be used in the industry. The second implication is that this thesis demonstrates quantitative insights that can be used in determining the ideal battery capacity and compartment sizes for future trucks of a food retailers' fleet. The third implication is that customer-to-customer distances in the city center are rather small. Meaning that it can be advantageous for food retailers to experiment with different hub locations or strategies of serving the customers in the future, such as using a fossil fuel-driven vehicle that will park outside the environmental zone and using smaller electric vehicles to serve customers from there. Several locations for these hubs were found to be promising in the research of Attema (2021, p.37)

6.3 FUTURE OUTLOOK AND LIMITATIONS

A proposed first direction for future research is to build upon the model and alter the energy use function with a focus on demand weight to investigate and demonstrate the intrinsic value of such a model. Further, in this thesis, several assumptions were made in performing the experiments which increases the difficulty of providing statements derived from results. Therefore, the main limitation of this thesis is that the results only apply to the settings as specified in the experiment settings. Also, for model simplifications, demand uncertainty was not considered, meaning the experiments used deterministic demand data. In practice, there are always uncertainties and variations in demand. Lastly, all experiments were conducted on rather small datasets with only 13 customers to keep computation times within reasonability. Results from bigger datasets will create a more justified conclusion that would rely on statistically verified arguments. Therefore, for future work, it is interesting to combine an improved version of this model with metaheuristics. Next, the maximum driving time and vehicle speed were fixed based on a working day and research on vehicle speed in the capital of the Netherlands (Grooten & Kuik, 2010). An important limitation is that the calculation for distance and time was an approximation, which might result in lower or higher distances and time. Deviating from real distances and time can potentially result in more customers served or fewer customers served, higher or lower total energy use.

7. CONCLUSION

City logistics are affected by new regulations to avoid any fossil fuel-driven vehicles in city centers to decrease traffic congestion and pollution. The so-called zero-emission zones are forcing a shift in companies' fleets from fossil fuel-driven vehicles to electrical driven vehicles to continue operations. To cope with the challenges that EVs bring, the area of energy consumption is an important subject. This thesis addresses the challenging area of energy consumption of EVs for food distribution in urban logistics. First, by changing compartment configurations the total energy used for a dataset of 13 customers can be reduced by 4% to 20%, and the corresponding number of vehicles deployed to serve the customers can be reduced by 20%, meaning that in a real-life situation in the city center potentially more customers could be served. Next to that, the results show that by emphasizing more on the weight in the load-dependent discharging function, the customer sequence can be affected resulting in more accurate results. On the contrary, it must be acknowledged that the proposed model only started to show some behavioral changes when weight was considered heavily. This implies that there is room for improvement of the proposed model, specifically in the newly introduced energy function. Thereby, several negative impacts of city logistics such as carbon dioxide emission, noise, congestion, and space occupation can be directly reduced using smaller electrical driven vehicles. To conclude, the results of this thesis show that introducing load-dependent discharging possibly can result in more efficient routing when the objective of routing is using less battery capacity, but the magnitude of this improvement remains unknown. To explore the model's improvement potential, the model should take a different approach to the interpretation of customer demand weight, possibly in combination with different compartment configurations.

REFERENCES

Akçelik, R., & Besley, M. (2007). *Operating cost , fuel consumption , and emission models in aaSIDRA and aaMOTION. December 2003*, 3–5.

Attema, I. (2021). *Collaboration in last mile food deliveries : a multi-compartment vehicle routing problem.*

Barth, M., & Boriboonsomsin, K. (2009). Energy and emissions impacts of a freeway-based dynamic eco-driving system. *Transportation Research Part D*, *14*(6), 400–410. https://doi.org/10.1016/j.trd.2009.01.004

Barth, M., Younglove, T., & Scora, G. (2005). *Development of a Heavy-Duty Diesel Modal Emissions and Fuel Consumption Model.*

Bektas, T., & Laporte, G. (2011). *The Pollution-Routing Problem Tolga Bektas. 45*, 1232–1250. https://doi.org/10.1016/j.trb.2011.02.004

Bidfood. (2022). *Bidfood*. https://www.bidfood.nl/over/wie_we_zijn.jsp

Boussaïd, I., Lepagnot, J., & Siarry, P. (2013). A survey on optimization metaheuristics. *INFORMATION SCIENCES, February*. https://doi.org/10.1016/j.ins.2013.02.041

Braekers, K., Ramaekers, K., & Nieuwenhuyse, I. Van. (2015). The Vehicle Routing Problem : State of the Art Classification and Review The Vehicle Routing Problem : State of the Art Classification and Review. *COMPUTERS & INDUSTRIAL ENGINEERING*. https://doi.org/10.1016/j.cie.2015.12.007

Brown, G. G., & Graves, G. W. (1981). *Real-Time Dispatch of Petroleum Tank Trucks. August 2015.*

Charisis, A., Kaisar, E., & Du, L. (2020). *Logistics Hub Location-Scheduling Model for Inner-City Last Mile Deliveries. 10*(April). https://doi.org/10.7708/ijtte.2020.10(2).04

Chen, J., & Shi, J. (2019). Computers & Industrial Engineering A multi-compartment vehicle routing problem with time windows for urban distribution – A comparison study on particle swarm optimization algorithms. *Computers & Industrial Engineering*, *133*(November 2018), 95–106. https://doi.org/10.1016/j.cie.2019.05.008

Dablanc, L. (2007). *Goods transport in large European cities : Difficult to organize , difficult to modernize. 41*, 280–285. https://doi.org/10.1016/j.tra.2006.05.005

Dantzig, G. B., & Ramser, J. H. (1959). *The Truck Dispatching Problem. 6*(1).

Davis, B. A., & Figliozzi, M. A. (2013). A methodology to evaluate the competitiveness of electric delivery trucks. *Transportation Research Part E: Logistics and Transportation Review*, *49*(1), 8–23. https://doi.org/10.1016/j.tre.2012.07.003

Derigs, U., Gottlieb, J., Kalkoff, J., Piesche, M., Rothlauf, F., & Vogel, U. (2011). *Vehicle routing with compartments : applications , modelling and heuristics*. 885–914. https://doi.org/10.1007/s00291-010-0194-3

E-Canter specsheet. (2020). *E-Canter specsheet*.

Elshaer, R., & Awad, H. (2020). Computers & Industrial Engineering A taxonomic review of metaheuristic algorithms for solving the vehicle routing problem and its variants. *Computers & Industrial Engineering*, *140*(December 2019), 106242. https://doi.org/10.1016/j.cie.2019.106242

Eshtehadi, R., Demir, E., & Huang, Y. (2019). Solving the vehicle routing problem with multi-compartment vehicles for city logistics. *Computers and Operations Research*, 104859. https://doi.org/10.1016/j.cor.2019.104859

Febriandini, F., Yuniaristanto, & Sutopo, W. (2020). *Multi-Compartment Vehicle Routing Problem to Find the Alternative Distribution Route of Petroleum Product Delivery Multi-Compartment Vehicle Routing Problem to Find the Alternative Distribution Route of Petroleum Product Delivery*. https://doi.org/10.1088/1757-899X/943/1/012039

Grooten, J., & Kuik, F. (2010). *Mobiliteit in en rond Amsterdam*. https://www.fietsberaad.nl/CROWFietsberaad/media/Kennis/Bestanden/mobiliteitamsterdamhistorisch.pdf?ext=.pdf

Henke, T., Speranza, M. G., & Wäscher, G. (2015). *The multi-compartment vehicle routing problem with flexible compartment sizes*. *246*, 730–743. https://doi.org/10.1016/j.ejor.2015.05.020

Hübner, A., & Ostermeier, M. (2018). *A Multi-Compartment Vehicle Routing Problem with Loading and Unloading Costs A Multi-Compartment Vehicle Routing Problem with Loading and Unloading Costs*. *April*.

Iwan, S., Nürnberg, M., Jedliński, M., & Kijewska, K. (2021). Efficiency of light electric vehicles in last mile deliveries – Szczecin case study. *Sustainable Cities and Society*, *74*(July). https://doi.org/10.1016/j.scs.2021.103167

Juan, A. A., Goentzel, J., & Bektas, T. (2014). *Routing fleets with multiple driving ranges : Is it possible to use greener fleet configurations ?* *21*, 84–94. https://doi.org/10.1016/j.asoc.2014.03.012

Kin, B., Verlinde, S., & Macharis, C. (2017). Sustainable urban freight transport in megacities in emerging markets. *Sustainable Cities and Society*. https://doi.org/10.1016/j.scs.2017.03.011

Laporte, G. (2009). Fifty Years of Vehicle Routing. *Transportation Science*, *43(4)*(April 2017), 408–416. https://doi.org/10.1287/trsc.1090.0301

Lin, J., Zhou, W., & Wolfson, O. (2016). *Electric Vehicle Routing Problem*. *12*(June 2015), 508–521. https://doi.org/10.1016/j.trpro.2016.02.007

Marshall, D., McCarthy, L., Heavey, C., & McGrath, P. (2015). Environmental and social supply chain management sustainability practices: Construct development and measurement. *Production Planning and Control*, *26*(8), 673–690. https://doi.org/10.1080/09537287.2014.963726

Martins, S., Ostermeier, M., Amorim, P., Hübner, A., & Almada-lobo, B. (2019). Product-oriented time window assignment for a multi-compartment vehicle routing problem. *European Journal of Operational Research*, *276*(3), 893–909. https://doi.org/10.1016/j.ejor.2019.01.053

Mendoza, J. E., Castanier, B., Guéret, C., Medaglia, A. L., & Velasco, N. (2010). Computers & Operations Research A memetic algorithm for the multi-compartment vehicle routing problem with stochastic demands. *Computers and Operation Research*, *37*(11), 1886–1898. https://doi.org/10.1016/j.cor.2009.06.015

Musavi, M., & Bozorgi-amiri, A. (2017). Computers & Industrial Engineering A multi-objective sustainable hub location-scheduling problem for perishable food supply chain. *Computers & Industrial Engineering*, *113*, 766–778. https://doi.org/10.1016/j.cie.2017.07.039

Nesterova, N., Quak, H., Balm, S., Roche-Cerasi, I., & Tretvik, T. (2013). *Project FREVUE deliverable D1. 3: State of the art of the electric freight vehicles implementation in city logistics*. *19*(5).

Nijkamp, J. E., & Mobach, M. P. (2020). *Developing healthy cities with urban facility management management*. https://doi.org/10.1108/F-11-2019-0128

Nolz, P. C., Absi, N., Cattaruzza, D., & Feillet, D. (2020). Two-echelon distribution with a single capacitated city hub. *EURO Journal on Transportation and Logistics*, *9*(3), 100015. https://doi.org/10.1016/j.ejtl.2020.100015

Quak, H., Nesterova, N., & Rooijen, T. Van. (2016). *Possibilities and barriers for using electric-powered vehicles in city logistics practice*. *12*(June 2015), 157–169. https://doi.org/10.1016/j.trpro.2016.02.055

Rastani, S., Yüksel, T., & Çatay, B. (2020). Electric Vehicle Routing Problem with Time Windows and Cargo Weight. *Smart and Sustainable Supply Chain and Logistics – Trends, Challenges, Methods and Best Practices*, 175–190. https://doi.org/dx.doi.org/10.1007/978-3-030-61947-3_12

Reddy Kancharla, S., & Ramadurai, G. (2020). Expert Systems with Applications Electric vehicle routing problem with non-linear charging and load-dependent discharging. *Expert Systems*

With Applications, *160*, 113714. https://doi.org/10.1016/j.eswa.2020.113714

Russo, S. M., Voegl, J., & Hirsch, P. (2021). A multi-method approach to design urban logistics hubs for cooperative use. *Sustainable Cities and Society*, *69*(July 2020), 102847. https://doi.org/10.1016/j.scs.2021.102847

Sakai, T., Kawamura, K., & Hyodo, T. (2015). Locational dynamics of logistics facilities : Evidence from Tokyo. *Journal of Transport Geography*, *46*, 10–19. https://doi.org/10.1016/j.jtrangeo.2015.05.003

Savelsbergh, M., & Woensel, T. Van. (2016). *50th Anniversary Invited Article — City Logistics : Challenges and Opportunities City Logistics : Challenges and Opportunities. March.*

Schneider, M., Stenger, A., Goeke, D., Schneider, M., Stenger, A., & Goeke, D. (2014). *and Recharging Stations The Electric Vehicle-Routing Problem with Time Windows and Recharging Stations. August.*

Solomon, M. M. (1987). *Algorithms for the Vehicle Routing and Scheduling Problems with Time Window Constraints WITH TIME WINDOW CONSTRAINTS. May 2017.*

Solomon, M. M., & Desrosiers, J. (1988). *Survey Paper — Time Window Constrained Routing and Scheduling Problems. June 2014.*

Tsang, E., & Voudouris, C. (1997). *Fast local search and guided local search and their application to British Telecom ' s workforce scheduling problem. 20*, 119–127.

van Duin, J. H. R., Quak, H., & Muñuzuri, J. (2010). *The Sixth International Conference on City Logistics New challenges for urban consolidation centres : A case study in The. 2*, 6177–6188. https://doi.org/10.1016/j.sbspro.2010.04.029

Wang, C. L., & Li, S. W. (2018). *Hybrid fruit fly optimization algorithm for solving multi - compartment vehicle routing problem in intelligent logistics*. 466–478.