Electric Vehicles Performing Home Deliveries

Leroy Merlin Case Study

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Abstract: As e-commerce flourishes, companies like Leroy Merlin (LM) grapple with surging demand for home deliveries, prompting a restructuring of logistics networks under mounting pressure to curb carbon emissions. Focusing on the practical case of LM in the Lisbon region, this study addresses the integration of electric vehicles (EVs) into fleets tasked with delivering heavy items. While challenges like limited range and high purchase costs are commonly highlighted, this research emphasizes the often-overlooked factor of load capacity. A mixed integer linear programming (MILP) model was devised to optimize LM's home delivery routes with dual objectives: minimizing costs and reducing CO2 emissions. The model maintains a fixed fleet size but explores various compositions of both electric and internal combustion vehicles (ICVs). Incorporating a single depot, a heterogeneous fleet (HF), and multi-trip (MT) capabilities, the model utilizes a clustering method for medium to large-scale instances, followed by vehicle allocation. Results indicate the feasibility of integrating up to 3 EVs into the existing fleet without compromising service levels. In this scenario, carbon emissions could drop by 20%, and total feeding costs (fuel and electricity) would decrease by 13%. Furthermore, based on the Total Cost of Ownership metric (TCO), acquiring 3 EVs is financially advantageous over 3 ICVs after an 8-year period. Notably, a solution achieving a 40% reduction in emissions compared to the current scenario is attainable when prioritizing carbon emission reduction.

Keywords: Electric and conventional vehicle, heterogeneous fleet, vehicle routing problem, multi-trip, last mile delivery, home delivery, total cost of ownership.

1. Introduction

The European Union's ambitious goal of achieving carbon neutrality by 2050 grounded significantly on the transportation sector as 25% of greenhouse gas emissions come from both passenger and freight transport within the EU. Meanwhile, the last-mile delivery sector has experienced notable growth in recent years, following the developing trend of e-shopping and the widespread adoption of technologies. As companies witness a substantial shift from traditional brick-and-mortar retail to online sales, the demand for home deliveries has surged (Siragusa et al., 2022). This transition has, in turn, amplified the complexity of last-mile logistics, requiring meticulous stock management, order preparation, and shipping efforts. Delivering products to customers' doorsteps is traditionally a logistical challenge, making it one of the most expensive and environmentally damaging stages of supply chains. Urbanization is also impacting the home delivery sector as city residents are natural users of the online channel due to factors such as limited time, better internet connectivity, a lack of storage space and parking facilities (DHL, 2019). The population migration offers opportunities and challenges as leveraging this high demand could prove economically advantageous. However, this trend has led to an increase in traffic congestion within city centers, presenting environmental challenges which governments and city planners constantly try to counteract. Within the sphere of last-mile logistics, several innovative solutions and trends have emerged, such as the deployment of autonomous vehicles, the establishment of proximity pickup points or the crowdsourcing. Among these trends, EVs stand out as a promising solution due to their lower emissions profile. While emissions during the manufacturing phase of EVs may be relatively higher, their operational phase's reduced emissions more than compensate for this discrepancy (European Environment Agency., 2022). However, despite the evident advantages and the EU's ambitious environmental goals, the adoption of EVs in the transportation sector remains modest. In 2022, approximately 23% of new vehicle registrations in the EU were electric cars, but only a share of just 3.1% for new van registrations (European Environmental Agency, 2023). This dissertation addresses the application of electric vans in the home delivery segment, by handling a case study from one of Portugal's largest retail companies.

2. Problem definition

2.1. Supply chain overview

LM is a French retail chain specialized in home improvement and “Do It Yourself” products. From a management point of view, it is divided into 8 areas - *Zonas de Vida* (ZDV). In Portugal, there are 50 stores supplied by a national warehouse and 5 regional warehouses. Product flows occur between all these facilities as well as with suppliers. Stores sales are for LM the main source of income, as in 2022, more than 70% of total sales revenue came from in-store sales, where the customer leaves the store with the desired products. Despite that, the company operates as an omni-channel, complementing the store service with online and telephone sales. They also offer in-store pick-up services and home deliveries, which are important for reaching a larger number of customers and for when products are not available in store or are ordered online. When it comes to home deliveries, there are three types of flows, whose classification depends on the origin of the products and are independent of the channel used to make the purchase: shipped from warehouse (SFW) where orders satisfied by regional warehouse’s stock; shipped from store (SFS) where products are sent from a store to a regional warehouse before being sent to customers and shipped from partner (SFP). The SFW flow is prioritized, when possible, but due to the limited stock, over 10% of total sales were classified as SFS, and only about 1% for the other two flows. Therefore, the focus of this work is on the SFS flows which are carried out by subcontracted carriers, each with an exclusive fleet allocated to LM. Orders are categorized according to weight into three groups: parcels (up to 30 Kg), bulky items (30 to 300 Kg), and heavy bulky items (over 300 Kg). While parcel home deliveries are highly efficient, with same or next-day service available through the national postal company (CTT) with a considerable use of alternative fuel vehicles, the process for heavier categories is significantly less developed and requires a different approach (multiple operators, larger vehicles, etc.), leaving plenty of room for improvement.

2.2. Problem identification

This study focuses on the integration of EVs into the home delivery operations aiming to reduce emissions. Although the company relies on carriers for deliveries, any additional costs incurred by carriers due to EV integration may lead to higher expenses. Therefore, the extent of this dissertation is narrowed down to the West Lisbon ZDV, where a single carrier handles deliveries for the bulky and heavy bulky categories. LM transports the products to the carrier's warehouse, centered on its area of activity, which has recorded the highest number of deliveries. The daily operations of the carrier involve route planning, product consolidation, and customer notification of expected delivery time interval. This carrier’s current exclusive fleet for the deliveries of LM consists of 7 heterogeneous ICVs. Deliveries exceeding 1500Kg are handled by subcontracted heavy-duty trucks. This works’ focus lies in studying the operational and financial impacts of replacing these large-sized vans in LM's fleet with EVs. Apart from the usually identified challenges, such as the limited range, the possible need for time-consuming in-route recharging or high acquisition costs, the primary concern lies on the potential reduction in payload capacity and volume, as the carrier handles heavy orders near the vehicles' maximum load limit. A linear optimization model is introduced to incorporate these EVs into the carrier's route planning, with the goal of obtaining insights into operational costs, emission reduction, and the fleet's capacity to manage daily deliveries, particularly during peak periods. This research seeks to set a benchmark for similar high-density home delivery areas and help reaching the goal of reducing 50% the emissions to the atmosphere in its home delivery operation by 2025.

3. Literature Review

3.1. Electric Vehicles

The transition to EVs in last-mile logistics is a growing trend across various sectors, with ongoing research regarding their viability compared to ICVs reaching divergent conclusions, also depending on the sector or type of usage they have. Anosike et al. (2021), in a detailed literature review on the challenges of adopting EVs on last-mile deliveries, identified four main categories that affect their adoption: operational, infrastructure, battery technology and costs.

At the operational level, these vehicles are more exposed to the impacts of extreme weather conditions, such as heat (above 45°C) or cold (below 10°C), affecting battery efficiency. The use of climate control systems also seriously affects the maximum range (Margaritis et al., 2016). In addition, these vehicles have a lower charging capacity, and the penalty is harsher the larger the vehicle or the batteries used. EVs are more efficient in urban environments, where it is possible to take advantage of regenerative breaking and where drivers do not reach high speeds (Christensen et al., 2017). Range anxiety is also a widely discussed factor, since operators don't want to risk running out of battery and often maintain large battery buffers particularly in home delivery scenarios.

Infrastructure wise, it is practically unanimous that to increase the adoption of EVs for both personal and business use, it is necessary to improve the public charging infrastructure which remains insufficient, lacking flexibility, and facing issues of station availability and high costs. Upgrades to the distribution network are also needed to deal with increased demand and charging behaviors. Furthermore, the energy mix used for electricity generation, which often relies on fossil fuels, remains a concern. Transitioning to renewable energy sources is crucial for reducing emissions (Schiffer et al., 2021).

On the battery side, lithium-ion batteries are the dominant technology for EVs due to their high energy and power density. However, production technologies still need to be improved, as well as battery capacity and recharging, which at the moment still greatly damages lifespan if fast charging is used. Prolonging battery lifespan is essential, especially for high-usage scenarios like delivery services (Al-dal’ain et al., 2021).

Acquisition costs remain a significant barrier to EV adoption. TCO metrics are used to estimate the overall costs of EV ownership, considering factors like purchase price, fuel/electricity consumption, insurance, maintenance, ownership taxes, and tolls (Siragusa et al., 2022). Maintenance costs are generally considered lower for EVs, but the availability of these services and uncertain repair costs can be obstacles. Electricity and fossil fuel prices are influenced by multiple factors, such as energy policies, changes in the energy mix, as well as inflation rates and geopolitical issues, making it difficult to predict the long-term cost competitiveness of EVs (White et al., 2022). In addition, battery deterioration must be considered, and the lack of long-term data and battery replacement costs can affect TCO. Business models such as battery swap stations can reduce these uncertainties and make EVs both more affordable and convenient (Schiffer et al., 2021).

3.2. Electric-Vehicle Routing Problem (E-VRP)

Integrating EVs into fleets requires replanning the routes formed and the models used. The literature review presented concentrates on an extension: Heterogenous Fleet Vehicle Routing Problem with Multi Trips (HFVRPMT) and follows the framework established by Kucukoglu et al. (2021).

Problem features

Within this context, two main types of problems are addressed: Fleet Size and Mix (FSM) and Fixed Fleet Models (FF). Schiffer et al. (2021) tackle FSM problems, focusing on investment decisions regarding EVs or conventional ICVs. They explore scenarios considering individual vehicle characteristics and operating costs, aiming to determine the optimal time and vehicle type for investment. Zhang et al. (2023) go further by incorporating different vehicle categories based on load capacities. Ewert et al. (2021) introduce an indeterminate fleet, representing a case where the investment burden is shifted to logistics service providers.

Al-dal’ain et al. (2021), explore different FF compositions and develop a model to calculate operating costs for each composition. This information is then used as input for a replacement model, considering a time horizon of several years. Sethanan et al. (2020) focus only on planning routes for a FF, including, in addition to deliveries, inbound flows (pick-up). They also consider the MT feature, where vehicles can make multiple round trips within a planning period. This concept, sometimes referred to in the literature as multi-tour, can be introduced as an arbitrary number of trips in certain problems (Ewert et al., 2021; Sethanan et al., 2020; Zhao et al., 2019; Zhou et al., 2021) or be limited to a maximum in each planning period (Setiawan et al., 2019; Zhen et al., 2020). Zhen et al. (2020) incorporate the multi-Depot feature and release dates in their model.

The energy consumption is a crucial factor, primarily influencing computational complexity. In the articles reviewed energy consumption, whether for diesel or electricity, is considered proportional to the distance traveled, following a linear and deterministic pattern. However, to bring the models closer to reality, it is crucial to develop non-linear consumption patterns that depend on factors such as the weight transported, the elevation of the terrain or the speed of the vehicle Kucukoglu et al. (2021).

Moreover, given that recharging EVs is still time-consuming and less available when compared to refueling ICVs, charging planning a pivotal aspect of E-VRPs. Charging policies include full or partial charging, where EVs must recharge battery to the maximum capacity (Zhao et al., 2019) or can leave at any point respectively (Schiffer et al., 2021; Zhou et al., 2021). Other authors consider the EVs maximum range but do not allow for recharging during the planning period (Al-dal'ain et al., 2021).

Time constraints are a fundamental element as in home delivery planning, companies provide time windows to customers. In addition, it is necessary to consider at least time limits or maximum working periods for drivers, reflecting legal limitations (Sethanan et al., 2020). Most models include time limits and time windows for deliveries to customers. Time windows are usually treated as rigid constraints, meaning deliveries must occur within specified time periods but their violation can also be allowed by introducing penalty costs (Zhao et al., 2019; Zhou et al., 2021).

Objective Functions

E-VRP objective functions primarily revolve around minimization objectives. Whitin single objective functions, (Sethanan et al., 2020) minimize the distance traveled, (Zhen et al., 2020) focus on minimizing vehicle travel time rather than distance, offering a more realistic approach. (Setiawan et al., 2019) focus on the minimization of feeding costs.

Multiple objective functions capture a wider array of costs and environmental factors, commonly incorporating costs associated with emissions from usage (Al-dal'ain et al., 2021) and even adopt the well-to-wheel methodology, encompassing GHG emissions related to fuel production and usage (Ewert et al., 2021; Zhang et al., 2023). In contrast, residual vehicle value or less frequently included as an objective.

Solution Approaches

E-VRPs are inherently NP-hard problems, making the attainment of exact solutions for medium or large-scale instances highly challenging. Consequently, the literature predominantly relies on heuristic and metaheuristic solution methods and exact methods are exclusively employed, with a limited focus on small instances. Schiffer et al. (2021) combines optimal investment decisions with metaheuristics for route planning. Zhang et al. (2023) uses Particle Swarm Optimization (PSO) with chaos elements for improved optimization. Zhen et al. (2020) enhances PSO with Local Search with Variable Neighborhood Descent. Sethanan et al. (2020) creates a hybrid optimization algorithm by combining Genetic Algorithm, Differential Evolution Approach, and fuzzy logic.

4. Methodology

4.1. Model characterization

The problem at hand can be modeled as HFVRPMT, involving optimizing routes for a FF of vehicles with diverse characteristics (both EVs and ICVs). While previous research on integrating EVs into route planning has focused on charging constraints, this study's primary focus is the limited payload and volume capacity of this vehicles. In the formulation vehicles begin each trip with fully charged batteries or full tanks, rejecting in-route recharging and considering that every time the depot is visited the vehicles are able to perform trips up to its maximum range. The problem involves vehicles starting at a single depot location, loading products, delivering them to customers, and returning to the depot. Vehicles can undertake more than one trip during the planning period, but the number of trips is limited to a maximum. The transported items also vary in weight and volume. It is not mandatory for all vehicles to undertake trips, and the number of trips for each vehicle may be unbalanced. Time features are also included such as the time for unloading at customer locations, warehouse loading and a time maximum time to perform the deliveries. The mathematical formulation is based on the model proposed by Zhou et al. (2021).

Sets and indexes

N	Set of customers $(i, j, l \in N)$
K	Set of vehicles $(k \in K)$
W	Set of trips $(w \in W)$

Parameters

DV_i	The demand of customer i in volume
DP_i	The demand of customer i in weight
TT_{ij}	Travel time between customers i and j
D_{ij}	Distance between customers i and j
TO_i	Travel time between customer i and the depot
OT_i	Travel time between the depot and customer i
DO_i	Distance between customer i and the depot
OD_i	Distance between the depot and customer i
TS_i	Service time at customer i
TC_k	Service timeof vehicle k at depot
QV_k	Volume capacity of vehicle k
QP_k	Payload capacity of vehicle k
R_k	Maximum range of vehicle k
H	Time horizon
M	Large number

Variables

$ST_{k,w}$	Start time of trip w of vehicle k
$RT_{k,w}$	Return time of trip w of vehicle k
$Aac_{k,i,w}$	Arrival time at customer i location with vehicle k on trip w
$Lad_{k,w}$	Load carried by vehicle k on trip w
$Vad_{k,w}$	Volume carried by vehicle k on trip w
$y_{k,w}$	Binary equals one if vehicle k performs trip w; otherwise, equals zero
$x_{ij,k,w}$	Binary equals one if vehicle k visits customer j immediately after visiting customer i on trip w; otherwise, equals zero
$z_{k,i,w}$	Binary equals one if vehicle k visits customer i on trip w; otherwise, equals zero
$f_{k,i,w}$	Binary equals one if customer i is the first to be visited by vehicle k on trip w
$l_{k,i,w}$	Binary equals one if customer i is the last to be visited by vehicle k on trip w

Mathematical model

$$Min \sum_{k \in K} \sum_{w \in W} \sum_{i \in N} \sum_{j \in N} TT_{i,j} x_{i,j,k,w} + \sum_{k \in K} \sum_{w \in W} \sum_{i \in N} TO_i l_{k,i,w} + \sum_{k \in K} \sum_{w \in W} \sum_{i \in N} OT_i f_{k,i,w} \tag{1}$$

$$\sum_{k \in K} \sum_{w \in W} z_{i,k,w} = 1 \qquad \forall\, i \in N \tag{2}$$

$$f_{k,i,w} + \sum_{i \in N} x_{i,l,k,w} = l_{k,i,w} + \sum_{j \in N} x_{l,j,k,w} = z_{k,i,w} \qquad \forall\, l \in N, \forall\, k \in K, \forall\, w \in W \tag{3}$$

$$\sum_{i \in N} f_{k,i,w} = \sum_{i \in N} l_{k,i,w} = y_{k,w} \qquad \forall\, k \in K, \forall\, w \in W \tag{4}$$

$$y_{k,w+1} \leq y_{k,w} \qquad \forall\, k \in K, \forall\, w \in W \tag{5}$$

$$\sum_{i \in N} z_{k,i,w} \leq y_{k,w} N \qquad \forall\, k \in K, \forall\, w \in W \tag{6}$$

$$Lad_{k,w} = \sum_{i \in N} z_{k,i,w}\, DP_i \qquad \forall\, k \in K, \forall\, w \in W \tag{7}$$

$$Vad_{k,w} = \sum_{i \in N} z_{k,i,w}\, DV_i \qquad \forall\, k \in K, \forall\, w \in W \tag{8}$$

$$Lad_{k,w} \leq y_{k,w} QP_k \qquad \forall\, k \in K, \forall\, w \in W \tag{9}$$

$$Vad_{k,w} \leq y_{k,w} QV_k \qquad \forall\, k \in K, \forall\, w \in W \tag{10}$$

$$Aac_{k,i,w} \leq z_{k,i,w} H \qquad \forall\, i \in N, \forall\, k \in K, \forall\, w \in W \tag{11}$$

$$ST_{k,w} \geq z_{k,i,w} TC_k - M(1 - y_{k,w}) \qquad \forall\, i \in N, \forall\, k \in K, \forall\, w \in W \tag{12}$$

$$ST_{k,w+1} \geq RT_{k,w} + TC_k - M(1 - y_{k,w}) \qquad \forall\, i \in N, \forall\, k \in K, \forall\, w \in W \tag{13}$$

$$Aac_{k,i,w} \geq ST_{k,w} + OT_i - M(1 - f_{k,w}) \qquad \forall\, i \in N, \forall\, k \in K, \forall\, w \in W \tag{14}$$

$$RT_{k,w} \geq Aac_{k,i,w} + TS_i + TO_i - M(1 - l_{k,w}) \qquad \forall\, i \in N, \forall\, k \in K, \forall\, w \in W \tag{115}$$

$$Aac_{k,j,w} \geq Aac_{k,i,w} + TS_i + TT_{ij} - M(1 - x_{ij,k,w}) \quad \forall i \in N, \forall j \in N, \forall k \in K, \forall w \in W \tag{16}$$

$$RT_{k,w} \leq y_{k,w}H \quad \forall k \in K, \forall w \in W \tag{17}$$

$$\sum_{i \in N} \sum_{j \in N} x_{ij,k,w}D_{ij} + \sum_{i \in N} f_{k,i,w}\, OD_i + \sum_{i \in N} l_{k,i,w}\, DO_i \leq R_k \quad \forall k \in K, \forall w \in W \tag{18}$$

$$y_{k,w} \in \{0,1\} \quad \forall k \in K, \forall w \in W \tag{19}$$

$$x_{ij,k,w} \in \{0,1\} \quad \forall i \in N, \forall j \in N, \forall k \in K, \forall w \in W \tag{20}$$

$$z_{k,i,w}, f_{k,i,w}, l_{k,i,w} \in \{0,1\} \quad \forall i \in N, \forall k \in K, \forall w \in W \tag{21}$$

The problem is formulated as a minimization problem. Objective function (1) minimizes the total travel time, including customer visits, outbound and return depot trips. Equation (2) mandates each customer being visited exactly once. Constraint (3) states a customer is either visited first on a trip or follows another customer. Similarly, the last customer is either visited last or immediately followed by another. (4) controls the number of customers as first and last on a vehicle's route. Each vehicle and route have exactly one first and last customer, and none for unperformed trips. (5) allows trip w+1 if trip w is done on the same vehicle. (6) permits serving a customer only if included in that trip. (7) and (8) are demand constraints, ensuring loaded weights and volumes match customer orders on the route. (9) and (10) prevent exceeding vehicle capacity. (11) links a customer's arrival time to a vehicle's trip. (12) and (13) relate to depot loading times. Equations (14), (15), and (16) address customer time for first, last, or intermediate customers. (17) ensures vehicles return to the depot within the time limit. (18) limits vehicle use to their maximum driving range on each trip. (19) to (22) establish the decision variables' domain.

Another objective function (22) was also adopted, which aims to minimize the total emissions produced and thereby give greater prominence to less polluting vehicles.

$$Min \sum_{k \in K} \sum_{w \in W} \sum_{i \in N} \sum_{j \in N} D_{i,j}x_{i,j,k,w}e_k + \sum_{k \in K} \sum_{w \in W} \sum_{i \in N} DO_i l_{k,i,w}e_k + \sum_{k \in K} \sum_{w \in W} \sum_{i \in N} OD_i f_{k,i,w}e_k \tag{22}$$

4.2. Solution approach

The model has been tested, and as expected, it is only sufficient for solving small instances in reasonable time frames. Therefore, a heuristic method was developed to break down the problem and allow results to be obtained for medium and large-scale instances. The data is prepared and fed to the model as a first attempt to solve the instance. If results are found and the optimality gap after 1 hour of simulation is lower than 5%, these are saved, and the process is finished. If no results are found, the data of the instance has to be divided into several instances, using a clustering method to find groups of geographically close points. The vehicles are then assigned to the clusters and the model run for each of the clusters separately. If acceptable results are not obtained for all the clusters formed, the number of clusters is increased by 1 and the process is repeated.

Clustering

Clustering was done using the machine learning method K-means used for grouping related objects into clusters. It's commonly applied in unsupervised problems where historical data is not considered. In K-means, each observation is assigned to one of the *k* clusters created from *n* observations based on the closest centroid. The goal is to minimize the squared Euclidean distance between each observation and the cluster's centroid, thereby grouping data points into clusters where they are more similar to others in the same group and dissimilar to those in different groups. In this case, the clustering is performed based solely on the longitude and latitude coordinates of the customer locations based on the framework proposed by (Xue, 2023). However, it requires specifying the *k* value in advance for which the elbow curve method is applied to find an optimal balance between the number of clusters and the quality of grouping. Clusters with fewer than 5 items or a total orders weight lower than the smallest vehicle's capacity were integrated into the next cluster with the lowest total weight of orders to be distributed. This prevented assigning overly underutilized vehicles for such deliveries.

Assign vehicles to clusters

First, assign the highest-capacity vehicles to clusters with the heaviest orders to reduce the probability of reaching infeasibility due to lack of time to perform the deliveries. If a vehicle cannot handle the orders in its cluster, it is swapped with one of the already assigned, starting with the last assigned vehicle, to ensure capacity limits are met. If infeasibility persists, the results are not extracted. After initial allocation, the workload is balanced by assigning vehicles to clusters based on weight-to-capacity ratio, ensuring even distribution of work (Figure 1).

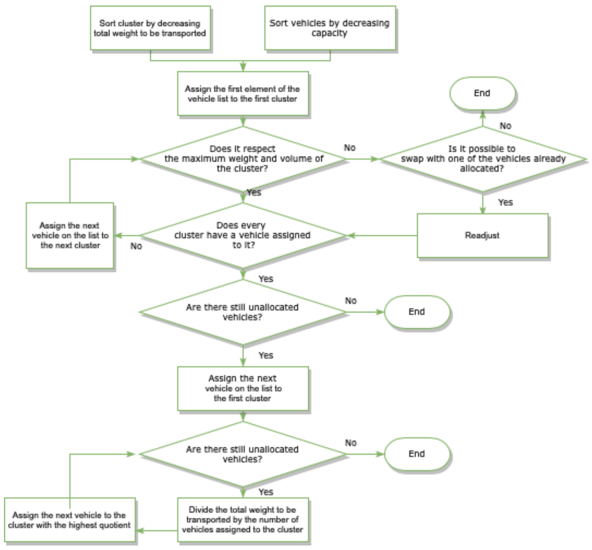

Figure 1 - Process to assign vehicles to clusters

5. Results

5.1. Baseline and data

The simulation was conducted over a 2-week period, during which 716 orders were delivered. Following the methodology proposed by Al-dal'ain et al. (2021), various scenarios were created, involving the replacement of ICVs from the current fleet with EVs. In Scenario 1 (baseline), as the vehicles are heterogeneous, a replacement order was determined according to the carrier's plans. Each subsequent scenario involves the introduction of one EV (Table 1). The EV was selected by the company and is not a variable in this study. The main differences compared to ICVs (Table 2) in the fleet include a nearly halved payload capacity, some reduction in volume, and zero emissions for EVs.

Table 1 - EVs properties

Identi-fication	Price	Pay-load (Kg)	Volume (m^3)	Consum-ption (KWh/100Km)	Range (Km)
Maxus eDeliver 9	84.000	860	11	31,03	296

Table 2 - Current fleet properties

Id	Fuel consumption (L/100km)	Maximum volume (m^3)	Emissions (gCO_2/Km)	Maximum payload (Kg)
0	13,5	15	186	1443
1	12,5	12	186	1443
2	13,1	12	186	1443
3	11,4	12	186	1443
4	9,9	12	186	1443
5	12,9	15	191	1521
6	12,9	12	191	1521

A total of 63 clusters were generated, but 10 of them did not meet the weight or order quantity criteria, so they were merged with other clusters. The results for the baseline scenario are displayed in Table 3.

Table 3 - Simulation results for the baseline scenario

Day	Clusters (actual/ invalid)	Objective Function (min)	Max Gap (%)	Computation Time (s)
1	3 (1)	494,94	0,00	2638
3	7 (2)	865,27	0,00	3294
4	4	599,97	0,00	20
5	4 (1)	552,57	0,00	324
6	4 (1)	595,13	0,00	3528
7	4 (1)	720,00	0,00	1626
8	4	372,49	0,00	13
10	4 (1)	626,51	4,01	3915
11	4 (1)	591,33	0,77	3656
12	3	421,43	0,00	34
13	5	626,72	0,00	4627
14	7 (2)	699,80	0,00	16

5.2. Scenario analysis

Figure 2 illustrates the variations in the objective function for the remaining scenarios. It has been deduced that, at most, to ensure the satisfaction of all customers, up to 3 EVs can be introduced. Scenario 5 would be optimistic, as it is only achievable on 8 of the days. Infeasibility occurs when the vehicles assigned to the clusters lack the required capacity to transport certain orders within a cluster, either due to their limited load or volume.

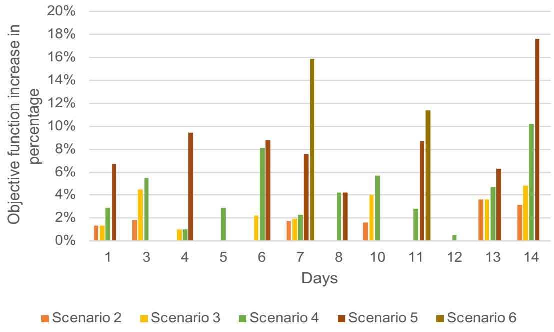

Figure 2 - Simulation results for the baseline scenario

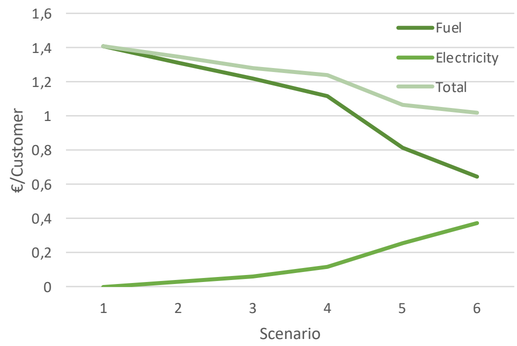

Figure 3 – Fuel and electricity and total costs in each scenario

Table 4 provides data on fuel consumption for deliveries, considering individual vehicle distances performed. Scenario 4 achieves a 21% reduction in fuel consumption and emissions. While scenarios 5 and 6 may not be practical, they show the potential substantial reductions in emissions and diesel consumption per customer, with scenario 5 achieving a 42% reduction in situations where EVs perform a greater part of the deliveries.

Table 4 - Fuel consumption and emissions in each scenario

Scenario	Fuel Consumption (L/ customer)		Emissions (gCO_2)/ customer)	
1	0,904	0%	1359,317	0%
2	0,842	-7%	1284,888	-5%
3	0,781	-14%	1213,679	-11%
4	0,716	-21%	1078,504	-21%
5	0,520	-42%	779,229	-43%
6	0,414	-54%	615,815	-55%

Figure 3 shows customer-specific feeding expenses in various scenarios. EV charging costs rise less than fuel costs drop, resulting in overall savings. In scenario 4, fuel costs per customer reduce by 0,29€, with an additional 0,11€ spent on electricity, leading to a 0,18€ decrease per order (13%). Scenarios 5 and 6 promise even greater savings, at 24% and 27% reduction compared to the baseline.

The vehicle fleet usage is skewed towards ICVs due to the objective of minimizing travel time and maximizing load capacity. Figure 4 highlights this imbalance. Furthermore 28% of the available EVs were not utilized, compared to only 2% of ICVs. The daily distance performed by EVs remain within their range, suggesting that the company can rely on overnight slow charging without significant infrastructure investments.

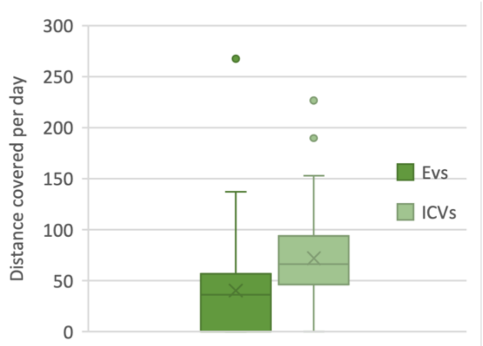

Figure 4 – Box plot distances covered per day

Since EVs are not used to the same extent as ICVs, it made sense to see the impact of the objective function focused on minimizing emissions. The emissions factor e_k for EVs was set at 0,1 to ensure route optimization while minimizing emissions. This factor, though not zero, is effective in minimizing emissions since it's far lower than the emissions of the most efficient ICVs. Utilizing 3 EVs and 4 ICVs in the new formulation for emissions and cost optimization, a 40% reduction in emissions and a 12% reduction in feeding costs per customer were achieved, with electricity costs comprising 32% of the total expenses. Even though the emission factor for EVs was not considered 0 to solve the model, the results presented assume 0 emissions from EVs.

5.3. Methodology analysis

The clustering method employed in this study, was identified as the primary source of uncertainty. To evaluate the choice of the number of clusters using the elbow curve method, the results of the baseline scenario were compared with the results obtained by varying k by one unit. It was concluded that when reducing the number of formed clusters, it is rare to obtain results, but when possible, they tend to be better (lower objective function value). On the other hand, when increasing k, results are generally worse, leading to the conclusion that the method used provides a good guideline for determining the appropriate value of *k*, consistently suggesting reasonable cluster numbers.

The readjustment of clusters considered invalid due to low weight or order numbers by assemble them to the clusters with the lowest weight to transport was also assessed. Merging these clusters with the geographically closest ones did not yield significant changes in the results, making it challenging to determine which method performs better over extended periods. These results were further compared to a scenario where vehicles were exclusively assigned to these clusters, and it was confidently concluded that the outcomes in that case would be considerably worse.

5.4. Total Cost of Ownership

The TCO analysis was performed to evaluate the economic viability of the EVs. The methodology used by Siragusa et al. (2022) was followed. The analysis considers factors like purchasing prices, depreciation rates, insurance costs, maintenance costs, registration fees, state subsidies, and ownership costs. The annual distances traveled by the vehicles in each scenario are based on the previous model's results. To make the comparison fair, it is assumed that the company is a scenario where it will have to replace 3 of its current vehicles with: A (3 ICVs), B (2 ICVs and 1 EV), C (2 EVs and 1 ICV), D (3 EVs), and E (3 EVs with emissions minimized). The ICV used for comparison is similar to the largest vehicle used in the current fleet and has an initial purchase price of 54.000€.

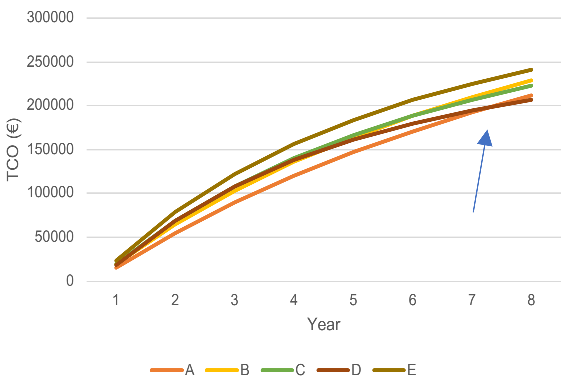

Figure 5 – TCO per year on the different scenarios

Results (figure 5) show that scenarios B, C, and E lead to higher TCO compared to scenario A throughout the period. Scenario D is the only one where a lower TCO can be achieved compared to scenario A, if the vehicles are kept for at least 8 years. Scenario E, despite higher TCO (11% more), enables significant emissions reduction. These findings provide valuable insights for the company to balance emission reductions and the cost associated with the transition to EVs.

6. Conclusions and Future Work

The rising demand for home deliveries due to technology, environmental concerns, and the e-commerce boom are a major challenge for companies aiming to cut supply chain emissions and control costs. This dissertation details a real case study in collaboration with LM Portugal, a major player in the do-it-yourself market which set the goal of reducing the emissions from its home deliveries by 50% until 2025 compared to the levels of 2022. The strategy includes replacing traditional ICVs with EVs. For this transition to an environmentally friendly fleet, the limited range, the potential need for recharging during routes the high acquisition costs are traditional concerns. However, when dealing with bulky and heavy bulky items payload capacity, the loss on payload capacity becomes a critical factor. To evaluate this transition, a mathematical model was developed, named the Heterogeneous Fleet Vehicle Routing Problem with Multi Trips, which contemplates vehicle differences and the possibility of multiple routes carried out by the same vehicle, limited to a maximum distance per time period. However, as the model is unable to solve medium or large-scale instances, the K-means clustering based on the geographical coordinates was performed followed by an assignment procedure of the vehicles to clusters which are then solved separately.

Results from the scenarios formulated indicate that on the fleet under consideration, which operates in the area of the country with the highest density of orders, at most, 3 out of the 7 ICVs of the current fleet could be replaced by EVs without jeopardizing service levels. Emissions would be reduced by 21% and feeding costs by 13%. However, as the objective function was minimizing the travel times the potential of EVs was not fully exploited. A scenario aimed at reducing emissions, using the same number of EVs, achieves a remarkable 40% emissions reduction while maintaining the 13% reduction in feeding costs. Furthermore, a TCO analysis reveals that the total costs of 3 EVs can outperform those of 3 ICVs after at least 8 years of operation. This is because the initial costs are higher but are offset by reduced fuel and maintenance expenses over time.

Future research could enhance the developed model by considering real-world factors, such as operators' lunch breaks or the need for route replanning to integrate non-available customers at the scheduled time of the deliveries. The model might benefit from more realistic energy consumption profiles specially in hilly urban environments like Lisbon and assessing long-term battery degradation effects is also valuable. Exploring new assigning methodologies could also be explored (e.g., few ICVs performing the deliveries of the heavier orders and EVs performing the remaining). Furthermore, examining the feasibility of other EV models, including those with smaller batteries but higher load capacity, could be explored. Expanding the study to lower-density areas is essential for a comprehensive understanding of EV integration in various fleet contexts.

References

Al-dal'ain, R., & Celebi, D. (2021). Planning a mixed fleet of electric and conventional vehicles for urban freight with routing and replacement considerations. *Sustainable Cities and Society*, *73*, 103105. https://doi.org/10.1016/J.SCS.2021.103105

Anosike, A., Loomes, H., Udokporo, C. K., & Garza-Reyes, J. A. (2021). Exploring the challenges of electric vehicle adoption in final mile parcel delivery. *Https://Doi.Org/10.1080/13675567.2021.1978409*, *26*(6), 683–707. https://doi.org/10.1080/13675567.2021.1978409

Christensen, L., Klauenberg, J., Kveiborg, O., & Rudolph, C. (2017). Suitability of commercial transport for a shift to electric mobility with Denmark and Germany as use cases. *Research in Transportation Economics*, *64*, 48–60. https://doi.org/10.1016/J.RETREC.2017.08.004

DHL. (2019). *DHL Supply Chain - Spain*. Retrieved September 21, 2023, from https://www.dhl.com/es-en/home/supply-chain/insights-and-trends/meeting-the-challenges-of-urbanization/registration/thank-you.html

European Environment Agency. (2022). *Transport and environment report 2022.* Retrieved September 21, 2023, from https://www.eea.europa.eu/publications/transport-and-environment-report-2022/transport-and-environment-report/view

European Environmental Agency. (2023). *Electric vehicles*. Retrieved September 21, 2023, from https://www.eea.europa.eu/en/topics/in-depth/electric-vehicles

Ewert, R., Martins-Turner, K., Thaller, C., & Nagel, K. (2021). Using a Route-based and Vehicle Type specific Range Constraint for Improving Vehicle Routing Problems with Electric Vehicles. *Transportation Research Procedia*, *52*, 517–524. https://doi.org/10.1016/J.TRPRO.2021.01.061

Kucukoglu, I., Dewil, R., & Cattrysse, D. (2021). The electric vehicle routing problem and its variations: A literature review. *Computers & Industrial Engineering*, *161*, 107650. https://doi.org/10.1016/J.CIE.2021.107650

Margaritis, D., Anagnostopoulou, A., Tromaras, A., & Boile, M. (2016). Electric commercial vehicles: Practical perspectives and future research directions. *Research in Transportation Business & Management*, *18*, 4–10. https://doi.org/10.1016/J.RTBM.2016.01.005

Schiffer, M., Klein, P. S., Laporte, G., & Walther, G. (2021). Integrated planning for electric commercial vehicle fleets: A case study for retail mid-haul logistics networks. *European Journal of Operational Research*, *291*(3), 944–960. https://doi.org/10.1016/J.EJOR.2020.09.054

Sethanan, K., & Jamrus, T. (2020). Hybrid differential evolution algorithm and genetic operator for multi-trip vehicle routing problem with backhauls and heterogeneous fleet in the beverage logistics industry. *Computers & Industrial Engineering*, *146*, 106571. https://doi.org/10.1016/J.CIE.2020.106571

Setiawan, F., Masruroh, N. A., & Pramuditha, Z. I. (2019). On Modelling and Solving Heterogeneous Vehicle Routing Problem with Multi-Trips and Multi-Products. *Jurnal Teknik Industri*, *21*(2), 91–104. https://doi.org/10.9744/JTI.21.2.91-104

Siragusa, C., Tumino, A., Mangiaracina, R., & Perego, A. (2022). Electric vehicles performing last-mile delivery in B2C e-commerce: An economic and environmental assessment. *International Journal of Sustainable Transportation*, *16*(1), 22–33. https://doi.org/10.1080/15568318.2020.1847367

White, L. V., Carrel, A. L., Shi, W., & Sintov, N. D. (2022). Why are charging stations associated with electric vehicle adoption? Untangling effects in three United States metropolitan areas. *Energy Research & Social Science*, *89*, 102663. https://doi.org/10.1016/J.ERSS.2022.102663

Xue, S. (2023). An adaptive ant colony algorithm for crowdsourcing multi-depot vehicle routing problem with time windows. *Sustainable Operations and Computers*, *4*, 62–75. https://doi.org/10.1016/J.SUSOC.2023.02.002

Zhang, S., Guan, C., Qiu, Y., & Wu, N. (2023). Multi-objective route optimization of urban cold chain distribution using electric and diesel powered vehicles. *Research in Transportation Business & Management*, *49*, 100969. https://doi.org/10.1016/J.RTBM.2023.100969

Zhao, M., & Lu, Y. (2019). *A Heuristic Approach for a Real-World Electric Vehicle Routing Problem*. https://doi.org/10.3390/a12020045

Zhen, L., Ma, C., Wang, K., Xiao, L., & Zhang, W. (2020). Multi-depot multi-trip vehicle routing problem with time windows and release dates. *Transportation Research Part E: Logistics and Transportation Review*, *135*, 101866. https://doi.org/10.1016/J.TRE.2020.101866

Zhou, Y., Huang, J., Shi, J., Wang, R., & Huang, K. (2021). The electric vehicle routing problem with partial recharge and vehicle recycling. *Complex and Intelligent Systems*, *7*(3), 1445–1458. https://doi.org/10.1007/S40747-021-00291-3/TABLES/8