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The role of municipalities in the adoption of electric mobility: case study from Lisbon, Portugal

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Summary

Taking into consideration the growing need to decarbonize transports, the electrification of propulsion systems has gained relevance in the last years. Municipalities have played an important role in the adoption of electric mobility, with this work focusing on the fleet of the Lisbon municipality, Portugal, which shifted to electric passenger vehicles, at the end of 2018, as part of the Sharing Cities project. The objective of this work was to estimate the environmental and economic impacts of transitioning to an electric fleet in a commercial fleet context. Data from the trips and battery charges of each vehicle were collected, using a smart management platform. Subsequently, the vehicles were grouped by similarities, and 5 clusters with different usage patterns and charging periods were identified. Electric vehicles are already economically viable for periods longer than 7 years, with a cost reduction of up to 20% in 10 years being possible for vehicles with higher annual mileage. Taking into account the replaced vehicles, each electric vehicle reduces exhaust emissions between 2.2 to 4.1 tonnes per year.

Keywords: electric vehicle; usage patterns; recharging; clustering; emission savings

1 Introduction

In an effort to reduce global warming by 2ºC, EU member states have set a CO_2 emission reduction target of at least 55% by 2030 relative to emissions in 1990 [1]. The higher efficiency of new vehicles coming into the market has not been enough to overturn the increased demand for the transportation of goods and passengers [3]. Government action is needed to stop the increase of GHG emissions and hinder global warming. Consequently, in December 2020, the European Commission decided "greening mobility" must be mandatory for the transport sector to grow. Similar to the ideas pushed by the European Commission and the European Green Deal, there has been a worldwide effort to create policies that boost the growth of EVs in the transport sector, to instruct drivers into adopting eco-driving, incentivizing the use of public transport fleet instead of personal vehicles, changing older for newer models that produce far less GHG [4].

Although BEV and PHEV market shares in Europe have been increasing, from 0,2% in 2012 to 3.3% in 2019 it is still quite small to have a major impact in reducing pollution levels [5]. The growth in vehicle registration of EVs in Portugal is double of the EU in 2018 [6]. In the Lisbon Metropolitan Area (AML), commercial fleets operate around 22% of the existing light passenger vehicles and 54% of the light goods vehicles. Companies buy a large portion of the new LD vehicles, for example in the United Kingdom, commercial fleets buy around half of the new LD vehicles [7]. Such numbers make it possible to ascertain that company fleets can be the leaders of EV adoption and this shift can potentially have a sizable impact on reaching the targets proposed for 2030 and 2050, improving air quality in cities. Companies have been leading in the adoption of BEVs in large fleets and in the installation of recharging stations in the workplace for multiple cars, which represents a lower cost burden when compared to the purchase private users make, of a home recharging station for a single EV. In more detail, it is expected that the transition of companies or government fleets to EVs will lead to a growth of privately owned EVs. For example, a survey of 100 fleet managers in Germany found that over 70% plan to acquire EVs in the near future, a much higher intention of acquiring an EV than the private sector [8].

Literature using actual results from EVs in commercial fleets is scarce, mainly because the majority of EVs being sold on the market are quite new and only now companies are finding EVs capable of performing their driving needs. Rolim monitored 25 electric vehicle users for one year in the city of Lisbon. A vast reduction in both energy consumption (58%-63%) and CO_2 emissions (35-43%) using a WTW life cycle approach was discovered when compared to ICEVs [9]. Another study in Portugal evaluated commercial fleets in business campuses simulating different recharging routines for BEVs that travel roughly 35,000km a year. By using off-peak hours, it was possible to obtain a return of investment (of choosing EV instead of ICEV) in 2 to 3 years and to reduce emissions by 4.2 tons CO_2 per vehicle annually, taking into account Portugal's emission factor (on a WTW perspective) [10]. For the USA, in Columbus, by substituting their city fleet for EVs, they saved between 1.7 to 4.9 tonnes of CO_2 (depending on the car model) per vehicle per year in a TTW life cycle analyses for an annual mileage of 17,700km [11].

In this context, this work quantifies the energy, environmental and economic impact associated with the transition to a BEV fleet, taking as a case study the Lisbon municipal (CML) fleet.

2 Data and Methods

2.1 Case study description

The H2020 Sharing Cities lighthouse program [14] aimed to achieve a wide scale deployment of smart cities solutions, shifting the thinking to decarbonized and local renewables and to make the active engagement of citizens a reality, demonstrating and assessing how the innovative use of technologies and new products can improve city life and the lives of its inhabitants, creating safer, cleaner, smarter and more social cities.

The Lisbon Municipality has been actively engaged in implementing several measures that will contribute not only to an integrated mobility system in Lisbon but also to increase the energy efficiency of urban mobility and, consequently, the quality of life in the city of Lisbon. These measures include the promotion and deployment of sharing services (e.g. car-sharing systems, bike-sharing systems), electrification of mobility (deployment of electric vehicles and electric vehicle recharging network). Within the European Lighthouse Program Sharing Cities, CML introduced 160 BEVs to its fleet in late 2018, all leased. Of those, 140 are for personal use or fixed to a specific sector. They are typically referred to as private vehicles in the study however, some can be used by multiple people in the same sector, granted for vehicles used to transit from home to work there exists a clear main driver, and 20 BEVs are utilized in a sharing system, where any municipal employee can drive them upon request. Quantitative data was gathered (from the CML monitoring platform) with information relative to vehicle trips, vehicle battery recharges, and recharging stations. Data covered a period from late 2018 until December 2020.

2.2 Data collection

Vehicle monitoring data was collected for 160 vehicles through a Mobility Device Connector (uMDC) installed in the vehicles. The installation of these devices developed by CEiiA enables monitoring in real-time the vehicles gathering data related with vehicle usage (number of trips, duration of trips, km travelled, energy consumed and recharged, etc.). Access to the CML mobility platform allowed collecting this data. Overall, 322,000 trips were recorded for the vehicles under analysis. Also, information regarding the recharging events was obtained from the same platform some basic values presenting the size of the data sample are presented in Table 1.

Table 1: Trips and recharges volume

Vehicle	BEVs	Trips	Trip hours	km	Recharges	Recharged hours	kWh recharged
Total	160	322,036	100,349	2,776,951	29,661	452,922	332,209

Figure 1 depicts the principal steps performed in the methodology. All steps (except the environmental and economic analysis) were performed in Python, since it allowed filtering the data to remove errors, (such as missing values, repeated values in multiple sequenced trips or charges, and unfeasible values) and correct them if possible, for the purpose of improving data quality.

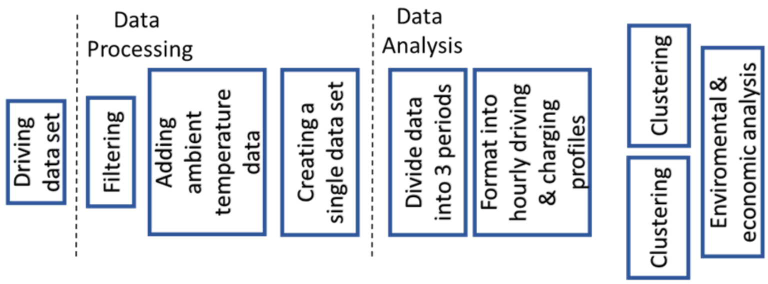

Figure 1: Flowchart of methodology

Trips shorter than 200 meters were excluded from the study. Since vehicles trips and charges were provided from different sources in multiple data sets, a single data set was created for each vehicle with the charges data added to the first trip made after the recharging. Also, the data was divided into 3 periods:

- **Learning Period -** Most of the employees, didn´t have experience with EVs, they had to adapt their previous driving patterns and cope with the limited range. The amount of practice needed varies and on average takes 3 months to adapt to EV range. As such, the first 3 months of EV usage were termed the learning period.

- **Regular Period -** After the learning period, a normal period begins. The driving patterns observed in this period have more in common with future usage of the EVs than the previous period. This period will have the largest importance, and most analyses will consider this period.

- **Pandemic Period -** The first state of emergency in Portugal was declared on 18 of March 2020 due to the COVID-19 rapid spread. More states of emergency followed with driving restrictions imposed that altered previous driving patterns. A part of society started working from home not using as much their private vehicles, and some quit the public transport system and started using more their private vehicles for fear of catching the virus while in public.

To aggregate vehicles based on their driving pattern a period needed to be selected, which was the regular period since it is the one that better reflects vehicle usage. To study the usage of the vehicles, 3 possible modes were defined: traveling, recharging, or parked. Although the vehicle is parked while recharging, that time only counts as recharging. The data computed using only weekdays or weekends excludes holidays, the usage during holidays is atypical when compared to normal weekdays and weekends.

2.3 Clustering

To cluster the vehicles, the first step was to select the features pertinent for the clustering model. Since these must reflect the driver's usage of the vehicle in the working periods, only trips and charges executed during the weekdays were used and, consequently, hourly time usage and hourly time charging periods were created. The usage times in non-working hours do not reflect the driving patterns while working, as such driving hours between 9 PM and 6 AM were discarded. However, commuting to work is also vital for the analysis and, as such the periods of for 6 AM to 8 AM and 5 PM to 9 PM were selected for the model. All hours of charging times were selected for the study, on the grounds that charging is mainly done in the workplace, and high night charging rates mean the vehicle stays in the workplace and is not used to commute to and from work. In total, 16 usage times features and 24 charging times features were selected and relative usage and charging times were used instead of the absolute value in seconds. These were calculated using Equation 1, where i stands for the hour of the day ($0<i<23$), Usage $time_i$, Charge $time_i$ and Park $time_i$ stand for the time in seconds, the vehicle drove, charged, and was parked in hour *i*, respectively. To reduce the number of variables a principal component analysis was performed (PCA), a dimensionality reduction method, able to reduce the number of features and increase interpretability. It does so by creating uncorrelated variables called principal components (PCs) the more PCs are created the ampler the variance, a minimum of 90% variance was chosen, similar to other studies [14], and 8 PCs were needed to achieve it.

$$Usage_i = \frac{Usage\ time_i * 100}{Usage\ time_i + Charge\ \ time_i + Park\ time_i};\ Charge_i = \frac{Usage\ time_i}{Usage\ time_i + Charge\ \ time_i + Park\ time_i}$$

Equation 1

Second, the clustering model called K-means was selected. Used in most literature on clustering vehicles based on driving patterns, the value K is needed to be chosen first, this was done based on 2 important analyses, the elbow method and the examination of the initial clusters driving patterns. The usage profiles of the three K-means results were performed and K=5 was chosen since all clusters had considerable differences. The K-means algorithm ran 10000 times and the end result was the best output in terms of inertia. The individual variance of each principal component was computed by using the PCA algorithm, the results for the first 10 PCs, individual and total variances, are shown in Table 2. The importance of keeping a high variance was paramount, so 8 principal components (PC) were needed to reach 90% total variance reducing the number of variables fed to the clustering algorithm by 80%, (from 40 to 8).

Table 2: Total and individual variances of each PC

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Individual Variance	37.4	20.7	13.4	7	4	3.2	2.7	2.1	1.7	1.4
Total Variance	37.4	58.1	71.5	78.5	82.5	85.7	88.4	90.5	92.5	93.6

With the 134 BEVs with available data for personal/sector use, since 6 were excluded for a lack of data an anomaly removal process was conducted called local outlier factor (LOF) and 3 vehicles were concluded to have a larger than usual LOF of: -2.28; -2.05; -1.72. The vehicle with the highest LOC was removed from the clustering study, because it presents an uncommon and unique driving pattern. Figure 2 presents the vehicles displayed in a 3-dimensional plot with the 3 most important principal components as the axis, representing 71.5% of the total variance (Table 2), each dot represents a vehicle while the color represents their respective cluster.

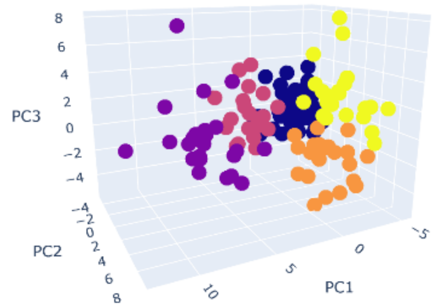

Figure 2: 3-D plot of the 5 clusters

To perform the K-means Algorithm a k number of clusters must be defined as “a priori” and the elbow method was chosen to help find the right number of clusters. The “elbow point” was pondered to be either 3, 4 or 5 and the usage profiles of the three K-means results were performed. The clustering algorithm aggregated the vehicles into 5 clusters based on usage profiles, with the maximum having 43 vehicles and the minimum 21. All 5 clusters were given a name based on the usage profiles, the recharges analysis, and trips analysis:

- Cluster 1 – Commuting (C) – contains 21 EVs
- Cluster 2 – Labor, high recharging rates (LHC) – contains 25 EVs
- Cluster 3 – Labor, medium recharging rates (LMC) – contains 22 EVs
- Cluster 4 – Low usage (LU) – contains 43 EVs
- Cluster 5 – High usage (HU) – contains 22 EVs

2.4 Total Cost of Ownership

For the economic analysis, a total cost of ownership (TCO) analysis was performed, using equation 2, considering 3 time periods: 3 years,7 years, and 10 years. Furthermore, 5 scenarios of vehicle replacement were defined in which the TCO was compared:

•**B BEV –** 160 bought BEVs (Renault Zoe E.V. 40 R110), utilizing the model in use by the municipal fleet;

•**L BEV –** 160 leased BEVs (Renault Zoe E.V. 40 R110), utilizing the model in use by the municipal fleet;

•**NEW ICEV –** 160 bought ICEVs (Renault Clio TCe 90);

•**B HEV –** 160 bought hybrid electric vehicles HEVs (Toyota Yaris 1.5 HSD), existent in the CML fleet;

•**OLD ICEV–** not replacing the old vehicle fleet (Citroen Saxo 1.5D).

$$TCO = (1+TA) * \left(PP - S + \sum_{n=1}^{N} \frac{FC*(1+t_f)*C*AM}{(1+r)^n} + \sum_{n=1}^{N} \frac{MR*AM+AT}{(1+r)^n} + \sum_{n=1}^{N} \frac{12*LC}{(1+r)^n}\right) - \frac{RP}{(1+r)^N} \qquad \text{Equation 2}$$

S – subsidies	C – consumption	TA– autonomous taxation	RP – resail price
FC – fuel cost	AM – annual mileage	t_f –fuel price annual change rate	n – year
LC – leasing costs	PP – purchasing price	MR – maintenance and repair costs	r – interest rate
AT – annual taxes	N – total No. of years	TCO – total cost of ownership	

Where S is the subsidies given for purchasing a BEV (in 2018 the value was 2250 € and companies could only use it for a maximum of 5 vehicles). Since most companies won´t change their entire fleet at once, won't probably buy more than 5 vehicles for the first time, and more incentives for EVs are probable, subsidies were considered for all BEVs. N is the total number of years in the TCO study. PP encompasses the vehicle cost (VC) and associated taxes (with BEVs being exempt). Civil responsibility insurance is required by law, its value may be difficult to estimate since there is no fixed value and any insurance company dictates their prices, companies have most insurances in a bundle which makes deducing the cost of the insurance hard. For these reasons the insurance costs won´t be accounted for in the TCO. Maintenance/repair costs (MR) are assumed to be 39% less for BEVs than the ICEVs this value was taken from the Letmathe 2017 study [16], in which the maintenance and repair costs were calculated for the Renault Zoe, the petrol model Renault Clio TCe and the petrol Toyota Yaris, MR costs were transformed into a cost per km. The consumption (C) of the BEV comes from the data analysis, for the ICEV the consumption will be computed using WLTP values and city average fuel consumption, normalized with our BEV consumption results. In Portugal, the vehicle annual taxes cost (AT)) depends on the vehicle engine's cubic capacity (cc), emissions, and fuel type [15]. BEVs don't pay IUC, and HEV and PHEV have no discount rates, but end up paying a smaller AT than ICEV since they produce fewer emissions. All the rest of the TCO variables values are presented in Table 3. The scenario of keeping the old fleet is just used to compare fuel costs, keeping the old fleet for 3 or more years could be unrealistic since the vehicles are quite old as most are near their life cycle end, their MR value should be the highest since the vehicle as more than 20 years, the VC was taken from the respective brands' websites and reflect the prices in early 2021. The price of petrol has increased 20% in Portugal from 2009 to 2019 while diesel increased even further, by 40%, for this reason, t_f will be 4% for the diesel vehicle and 2% for the petrol [17]. It is assumed the t_f for electricity is 0, electricity has been more or less constant and the price in 2019 is similar as in 2014. Fuel costs will be the values of 2019 since the acquisition of BEVs started in late 2018, and 2020 fuel costs values are unreliable for future trends since they sharply decrease as a consequence of the COVID-19 pandemic, the electricity costs depend on which charging post was used and may vary drastically depending on location and power rate, with the data collected a value of the electricity cost was computed; LC costs are around 470 €/month.

Table 3 TCO variables of the 5 possible scenarios

Variable name	BEV		NEW ICEV	OLD ICEV	HEV
	Owned	Leased			
VC	32 240 € [18]	-	17 650 € [18]	-	26 020 € [19]
ISV	0 €	-	231.46 €	-	1171.56 €
S	2 250 €	-	0 €	0 €	0 €
TA	0 %		10 %	10 %	10%
C	15.4 kWh/100km		5.3 l/100km	6.4 l/100km	4.3 l/100km
Fuel	Electricity		Petrol	Diesel	Petrol
AT	0 €		103.12 €	32.41 €	137.14 €
t_f	0 %/year		2 %/year	4 %/year	2 %/year
FC	0.201 €/kWh		1.58 €/l	1.41 €/l	1.58 €/l
MR	0.021 €/km	-	0.035 €/km		0.37 Km

RP is the resale value, due to being a recent technology and a new model it is hard to estimate the potential resale value, and so an UK deprecation calculator was used to find the resale value of the Renault Zoe, the Renault Clio TCe 90 and the Toyota Yaris 1.5HSD, based on vehicle model, annual mileage and age [20]. To calculate the price of electricity, an average price was calculated for all the 4 municipal fleet recharging locations, and a value of 0.22€/km was used for both home charging post and public post since the average Portuguese household electricity price was almost the same [21]. The data of the energy charged comes from the electric vehicle and does not account for energy losses from the transformation of electric energy coming from the charging post to chemical energy, stored in the battery. 1120 charging post data were crossed referenced with their respective charges from the vehicle charging logs, to find efficiency of 85%, a typical recharging efficiency value. One of the location addresses was not getting stored in the charged data, since the GPS coordinates were always stored for each charge, the building locations were mapped by their latitude and longitude and their perimeter was expanded 200 meters, the amount of charges outside the municipal facilities went from 30.6% to 19.5%.

3 Results

Table 4 shows vehicle mileage in the learning period was 32.6 km/day and increased 23% in the regular period, while the pandemic period has the lowest mileage of 29.11 km/day. Overall, the vehicles are mostly used on the weekdays with an average of 52.8 km/day and only 11.8 km/day on weekends. The daily trips follow the same trend as the daily mileage, the regular period had 4.73 trips/day the highest of the three and the pandemic period had the lowest with 2.88 trips/day. The consumption has decreased from 0.164 kWh/km in the learning period to 0.153 kWh/km. By comparing the learning period with the regular period, drivers made more trips per recharge and recharged the battery further as they gain more experience, the consumption also has decreased for all vehicles. These findings are in line with the argument that range anxiety decreases, as EV experience increases [22]. The average energy spent per trip is around 1.26 ± 1.37 kWh and did not vary considerably between each period.

Table 4 Trips Analysis Data of personal BEVs

Name	Period	Global/Weekdays /Weekends	Average	Standard Deviation
km/day	Full	Global	32.48	15.52
km/day	Learning	Global	32.62	23.36
km/day	Regular	Global	39.6	18.89
km/day	Pandemic	Global	29.11	17.22
km/day	Regular	Weekdays	52.82	25.36
km/day	Regular	Weekends	11.78	12.04
Trips/day	Full	Global	3.75	1.5
Trips/day	Learning	Global	3.96	2.81
Trips/day	Regular	Global	4.73	1.82
Trips/day	Pandemic	Global	3.19	1.6
Average speed (km/h)	Regular	Global	24.96	11.17
Average speed (km/h)	Regular	Weekdays	24.61	10.97
Average speed (km/h)	Regular	Weekends	28.22	12.32
Consumption (kWh/km)	Full	Global	0.154	0.076
Consumption (kWh/km)	Learning	Global	0.164	0.062
Consumption (kWh/km)	Regular	Global	0.153	0.084
Consumption (kWh/km)	Pandemic	Global	0.153	0.065

Table 5 shows, the number of trips per battery recharge has increased as drivers get more experience, the average energy recharged also increased, which suggests range anxiety is decreasing and drivers wait longer for the battery to run lower before recharging. Daily energy recharged has grown in the regular period, in the pandemic period there was a sharp decline in the amount of daily energy recharged. During the regular period, 7.84kWh/day was recharged during the weekdays and only 1.36kWh/day on weekends. On average 93.5% of the energy is recharged on weekdays.

Table 5 - Recharges Analysis Data of personal BEVs

Name	Period	Global/Weekdays /Weekends	Average	Standard Deviation
No. of trips per recharge	Full	Global	8	------------
	Learning	Global	6.94	------------
	Regular	Global	7.84	------------
	Pandemic	Global	8.62	------------
Energy recharged (kWh)	Full	Global	11.45	7.33
	Learning	Global	10.09	6.72
	Regular	Global	10.84	7.04
	Pandemic	Global	12.77	7.72
Daily energy recharged (kWh/day)	Full	Global	4.68	2.19
	Learning	Global	4.93	3.78
	Regular	Global	5.78	2.67
	Pandemic	Global	4.07	2.39
	Regular	Weekdays	7.84	3.71
	Regular	Weekends	1.36	1.6

3.1 Cluster analysis

The usage profiles of each cluster on the weekdays during the regular period are shown in Figure 3. The most evident features of each cluster are:

- Cluster C (1)- Vehicles are mostly used in the morning from 7:00 to 9:00 and in the afternoon, from 16:00 to 20:00. The majority of recharging is performed from 8:00 to 19:00.

- Cluster LHC (2)- Has two major utilization spikes, the first from 8:00 to 12:00 and the second from 13:00 to 17:00. The majority of recharging is performed mostly at night, from 17:00 to 6:00.
- Cluster LMC (3)- The usage profile is similar to cluster LHC however the recharging duration from 17:00 to 6:00 appears to be half the time of cluster LHC.
- Cluster LU (4)- The majority of the utilization is performed between 7:00 to 20:00, without any apparent utilization spike. The majority of recharging is performed from 8:00 to 19:00.
- Cluster HU (5)- Similar to cluster C however it has higher utilization, the utilization spikes are the same as cluster C and the utilization between them is substantial and oscillates from 20 to 30%.

The Cluster results are presented in Table *6* . Clusters 2 and 3 daily mileages during the weekdays are 50.4 and 42.5km respectively and their driving peaks are on working hours, it can be concluded both clusters are mainly used for working purposes. The major difference between them is the higher recharging rates in cluster 2 and, for this reason, cluster 2 was named labor high recharging rates (LHC), and cluster 3 was named labor medium recharging rates (LMC).

Table 6 Trips Analysis Data of BEVs cluster

Name	Period	Global/ Weekdays /Weekends	Cluster C (1)	Cluster LHC (2)	Cluster LMC (3)	Cluster LU (4)	Cluster HU (5)
Nº of Vehicles	---------	-----------	21	24	23	43	22
km/day	Full	Global	46.48	30.96	27.26	25.74	59.47
	Learning	Global	38.39	23.94	23.25	26.21	50.43
	Regular	Global	56.41	38.5	31.34	31.99	71.54
	Pandemic	Global	34.23	28.19	25.85	21.45	43.57
	Regular	Weekdays	74.96	50.39	42.5	42.52	96.59
	Regular	Weekends	17.06	14.09	9.45	9.69	17.56
Trips/day	Full	Global	4	3.95	3.28	3.54	6.36
	Learning	Global	3.46	3.09	2.99	3.48	5.98
	Regular	Global	4.95	4.99	4.18	4.68	7.68
	Pandemic	Global	2.83	3.53	2.76	2.76	4.46
	Regular	Weekdays	6.47	6.5	5.67	6.23	10.2
	Regular	Weekends	1.74	1.89	1.29	1.41	2.28
Average velocity (km/h)	Regular	Global	29.09	24.32	24.88	24.12	23.83
	Regular	Weekdays	28.74	23.93	24.77	23.77	23.4
	Regular	Weekends	31.85	27.62	26.14	27.56	27.8
Consumption (kWh/km)	Full	Global	0.155	0.156	0.155	0.155	0.153
	Learning	Global	0.162	0.170	0.162	0.164	0.164
	Regular	Global	0.152	0.154	0.154	0.153	0.152
	Pandemic	Global	0.157	0.155	0.152	0.152	0.150
Stops/km	Regular	Global	0.92	1.35	1.35	1.41	1.25
	Regular	Weekdays	0.96	1.4	1.37	1.46	1.3
	Regular	Weekends	0.63	0.96	1.04	0.95	0.71
km/Trip	Regular	Global	11.39	7.72	7.52	6.79	9.27
	Regular	Weekdays	11.44	7.73	7.51	6.76	9.29
	Regular	Weekends	10.81	7.60	7.71	7.12	9.30

The clusters with the highest daily energy recharged are also the ones with the highest daily mileage with 59.47 and 46.48km/day for the High usage (HU) and Commuting (C) clusters respectively. These 2 clusters also have the most trips per day and the highest mileage per trip, however, cluster C travels more per trip since it is mainly used for commuting. The average speed is similar in most clusters, around 24km/h, and rises approximately 2 km/h in the weekends. Cluster C has a higher speed with 29km/h since the trips associated with commuting use highways and intercity roads, that are linked with higher speeds and continuous traveling. The vehicles don´t recharge during the night, suggesting they don't spend the night in the workplace. For this reason, it was named the commuting (C) cluster. The consumption does not vary considerably between clusters and is around 0.155kWh/km, however, the learning period has higher consumptions with an average of 0.164kWh/km. Cluster 5 usage profile indicates it has the largest overall utilization, and daily mileage with 96.59km/day during the weekdays, double of the total average. Cluster 5 was named high utilization (HU) cluster for these factors. Cluster 1 is the second most used with vehicles driving during peak hours, which are correlated with commuting from home to work and vice versa. Cluster 4 is composed of the vehicles with the least overall utilization and tied with cluster LMC for daily mileage in the regular period on the weekdays. It has no major driving peaks and recharges mostly during the day, it was named the low utilization (LU) cluster.

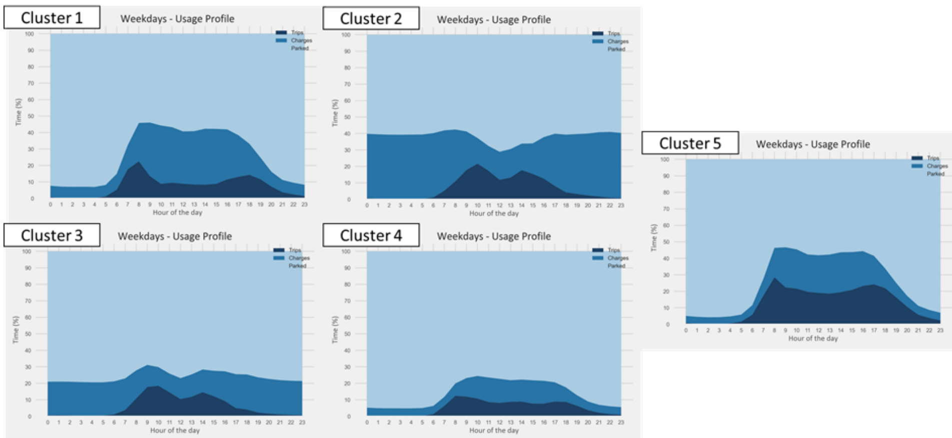

Figure 3 Usage profiles during the weekdays for the 5 clusters

The working clusters are mainly used during work hours, recharge mostly during the night, and have the biggest number of hours per day connected to the recharging posts with 10.53 and 7.01 hours for the LHC and LMC respectively, as seen in Table 7.

Table 7: Recharges analysis data of BEVs cluster

Name	Period	Global/ Weekdays /Weekends	Cluster C	Cluster LHC	Cluster LMC	Cluster LU	Cluster HU
No. of Vehicles	---------	-----------	21	25	22	43	22
Recharging (h/day)	Full	Global	5.98	9.36	6.25	4.15	5.16
	Learning	Global	9.93	19.95	5.62	3.77	11.97
	Regular	Global	9.53	16.23	10.32	7.77	8.91
	Pandemic	Global	2.94	5.61	3.52	2	2.26
Efective recharging (h/day)	Full	Global	1.92	2.26	1.6	0.93	1.38
	Learning	Global	2.11	2.2	1.61	1.66	6.33
	Regular	Global	2.44	3.14	2.05	1.14	1.62
	Pandemic	Global	1.22	1.77	1.3	0.72	0.93
Recharging (kWh/day)	Regular	Global	8.12	5.78	4.65	4.83	9.98
	Regular	Weekdays	11.13	7.42	6.27	6.69	13.75
	Regular	Weekends	1.7	2.4	1.21	0.83	1.87
Average recharging duration (h)	Full	Global	10.9	28.45	24.19	15.55	7.7
	Learning	Global	7.51	21.86	18	7.98	4.91
	Regular	Global	12.34	33.57	30.63	20.91	6.22
	Pandemic	Global	9.83	22.19	16.58	10.45	3.18
Average recharging energy (kWh)	Full	Global	11.06	12.38	13.54	12.85	8.92
	Learning	Global	9.71	11.17	11.84	11.82	8.09
	Regular	Global	10.52	11.99	13.76	12.66	8.46
	Pandemic	Global	13.47	13.66	14.19	13.99	9.9
Recharging efficiency (h)	Full	Global	68.41	51.18	58.33	68.95	67.95
	Learning	Global	67.91	56.13	62.63	65.8	71.77
	Regular	Global	68.48	52.77	59.91	67.89	67.73
	Pandemic	Global	69.96	47.38	56.93	69.81	66.6

Cluster C is in third with 6 hours per day. In terms of energy recharged per day the HU and C clusters have the highest amount with 9.98 and 8.12kWh/day respectively. The average recharging duration is larger in the clusters

LHC and LMC, since the vehicles are recharged mostly during the night, they stay for long periods unattended, in contrast, cluster C and HU mostly recharge during the day, the only possible time since the EVs are used for commuting from work to home, and because vehicles are used mostly during the day these vehicles tend to spend smaller times connected to the recharging posts. On average a battery recharge of cluster LHC is 3.7 and 2.6 times longer than cluster LU and C, respectively. As for average recharging energy, the average is between 11 and 13.5kWh except for cluster LU that has the lowest, with 8.46kWh. The recharging model predicted that LHC and LMC have the lowest recharging efficiency with 51 and 58% respectively, meaning only 58% of the time the vehicle is connected to the recharging post it's actually recharging, and the rest is "wasted" time. Because the model associates each recharge with the most efficiency possible the actual efficiency can be substantially lower.

3.2 Economic Analysis

Regarding the TOC analysis, results reveal that for the short-term period the cheapest scenario is buying ICEVs, since they cost 0.37€/km while buying HEVs were 19% more and buying BEVs 39% more. These results are to be expected given the high purchasing cost coupled with the high depreciation associated with BEVs. Leasing for the short-term period was found to be 21% cheaper than purchasing a BEV. For the medium-term period of 7 years the results start shifting, leasing BEVs is now the most expensive scenario, worse than buying BEVs or HEVs, the ICEV is still the cheapest option, with 0.27€/km, however, bought BEV now cost 0.30€/km, 42% cheaper than the short-term period, meanwhile, ICEV TCO only decreased 27%. Purchasing BEVs became cheaper than HEV by 11%. For the long-term of 10 years, buying BEVs is now the cheapest option (0.23€/km) followed by ICEV (0.24€/km), HEV did not become cheaper than ICEV with a cost of 0.29€/km. Fuel costs played a massive role in getting BEVs as the best long-term option, the new ICEV spent 172% more on fuel, the old model even more with 205%, and even the HEV spent 125% more on fuel than the BEV.

The results indicate that it is economically viable for companies to purchase BEVs in the long term. Annual mileage was a major factor in TCO, not only influenced by fuel costs but also by maintenance costs and resale value. For the medium-term period, only vehicles with more than 21,000km/year were cost-competitive. The results are more favorable than Weiss, 6 years TCO of 0.13 ± 0.14€/km higher cost for BEVs when compared to ICEVs, compared to this work 7 years of 0.01 ± 0.02€/km [13]. Nonetheless, it is important to point out some limitations in this study. For example, the lease BEV TCO is only important for the short term since it is a 3-year contract, and if it were to be renegotiated after the lease expires its cost would substantially drop. The HEV chosen for the TCO is from a different brand than the BEV and ICEV, however, the cost is similar in both brands. No insurance costs were added to the study except for the lease BEV since it comes included in the contract.

4 Conclusions

In accordance with the financial incentives for companies provided by the Portuguese government and the operational costs, it is possible to ascertain that BEVs are the cheapest option for a medium to a long period of operations. The most influential characteristic of the economic viability of BEVs is the annual mileage. For the short term, leasing is a valid solution with lower costs than purchasing, and the risk of battery degradation is irrelevant since the vehicle isn't owned by the company.

For the BEV fleet of CML, the clustering algorithm identified 5 clusters with distinct recharging and driving periods. The 2 clusters with a low night recharging rate, possibly were used to drive the user from work to home. These clusters had double the annual mileage of the others, around 26,000 km/year, and were the only ones with a medium-period lower TCO than ICEVs. Using the vehicle to commute from work to home is a major factor in the BEV's economic viability. The clusters with the majority usage during working hours had the least mileage (11,000-14,000 km/year) but spent 1 to 6 hours more each day recharging than the other clusters, concluding the utilization of the recharging posts by high mileage vehicles was done more efficiently with higher power without any meaningful battery degradation encountered in the data. Between the learning and the regular period, as EV experience increased users became more energy efficient and consumption decreased an average of 7%. The Covid-19 pandemic also had an impact on the driving patterns, vehicles drove much less, and AM decreased by

24% hurting the economic viability of the EVs since they depend mostly on the fuel savings that are proportional to the AM.

Regarding the cost analysis, the main findings from the work are that the annual mileage and the period of time used are the most influential variables in the TCO, EVs are more cost-competitive than ICEVs in the long-term even for the lowest mileage if the subsidies are included. For the high utilization groups in the CML, the payback period was less than 7 years. As such, the results suggest that commercial vans might be cost-competitive by having a higher annual mileage than LD vehicles.

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