Impacts of EV transition in municipal fleet

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Abstract

Taking into consideration the growing need to decarbonize transports, the electrification of propulsion systems has gained relevance in the last years. In Portugal, the Lisbon City Council (CML) has played an important role in the adoption of electric mobility with a fleet of electric passenger vehicles, acquired 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 comparison to a conventional one. Data from the trips and battery charges of each vehicle were collected through devices installed in the vehicles, using a smart management platform. Subsequently, the vehicles were grouped by similarities, and 5 clusters with different usage patterns and charging periods were identified. Based on this information, both the CML fleet and scenarios of wide national adoption in the light commercial fleets were assessed.

In conclusion, 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 CML vehicle reduces exhaust emissions between 2.2-4.1 tonnes per year. For the national commercial fleets adoption scenarios, it was estimated that the replacement of 27% of vehicles would only reduce road transportation CO2 emissions by 2.4% but would bring more electric vehicles to the second-hand vehicle market increasing environmental benefits.

Keywords: Battery electric vehicles; total cost of ownership; municipal fleet; Well-to-Wheel emissions; clustering; ambient conditions.

1 Introduction

To combat global warming, EU member states have set multiple CO2 emission reduction targets, the transport sector is one of the biggest emissions contributors, responsible for 27% of total EU-28 greenhouse gases (GHG) emissions in 2017, with road transportation having the most emissions [1]. According to a study by the World Health Organization (WHO) in 2016, 84% of the population in big cities were exposed to particulate matter (PM) levels above air quality guidelines [2]. Government action was 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 [3], a transition to electric vehicles (EVs) in urban areas would decrease exposure quite significantly. In 2018 low-emission vehicle registrations were 7.4% in Portugal, 3.17% were battery electric vehicles (BEVs), ranking in the middle in terms of adoption when compared to the rest of the European Union (EU) [4]. 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 vehicles, for example in the United Kingdom, commercial fleets buy around half of the new light-duty vehicles [5]. Since commercially owned cars are resold faster than privately owned, the acquisition of EVs for commercial fleets will trickle down into the second-hand car market, which will boost private adoption. Commercial fleets can potentially have a sizable impact on improving air quality in cities, BEVs produce zero emissions from a Tank-to-Wheel (TTW) perspective, however from a Well-to-Tank (WTT) perspective, they produce emissions mainly from the production of electricity, and their values can vary drastically depending on each country's electricity carbon intensity. A study by Moro and Lonza assessed the GHG savings from the use of BEVs in each of the 28 EU countries and concludes that BEVs can produce more GHG than ICEVs in countries that produce most of their electricity from coal and gas power plants, however, in general most of the EU-28 countries including Portugal (58-80 g. CO_2/km) show a reduction of emissions by switching to BEVs [6]. 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. Nonetheless, three studies of real-world fleets were found. Rolim monitored 25 electric vehicle users for one year in the city of Lisbon. A vast reduction in both energy consumption (58%-63%) and CO2 emissions (35-43%), using a Well-to-Wheel (WTW) life cycle approach, was discovered when compared to ICEV [7]. Another study in Portugal evaluated commercial fleets in business campuses simulating different charging 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 ICE) in 2 to 3 years and to reduce emissions by 4.2 tons CO2 per vehicle annually, taking into account Portugal's emission factor (on a WTW perspective) [8].

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 [9]. The vehicle total cost of ownership (TCO) is the fees of owning a vehicle starting with its purchase for a specific period of time, it encompasses the costs of fuel, insurance, maintenance, repairs, and any taxes associated with owning the vehicle. Technological improvements, mass production together with low running costs are making BEVs TCO converge with those of conventional vehicles, Weldon calculated the TCO of a small size vehicle for a 10 year period, with an annual mileage (AM) of 10,000km, the best case scenario would be a payback period within 8 years and, in the worst case EVs would not be cost-effective, for high usage with an AM of 16,000 km the payback period was between 6 and 8.5 years [10].

The BEV consumption is influenced by weather factors, the most prominent are wind speeds and ambient temperature, wind speed increases drag which increases fuel consumption. Extreme low or high temperatures hurt energy efficiency mostly due to the use of climate systems. Donkers found the optimum temperature is around 20ºC [11], and extreme low temperatures have a larger impact than extreme high temperatures on energy consumption, Stutenberg corroborated low temperatures have a higher impact on consumption, by performing different test cycles [12]. Taggart used real-world fleet data and also concluded high consumption rate at extremely low temperatures and the optimum temperature is around 23ºC [13].

The thesis objectives were quantifying the energy, environmental and economic impact associated with the transition to a BEV fleet, taking as a case study the Lisbon municipal (CML) fleet. Constructed on collected data, a large sample of vehicles was analyzed. Based on the hourly time-series data, vehicles were aggregated into clusters with similar driving and charging patterns, a distinctly new approach of clustering vehicles to identify different operational behaviors. Furthermore, the potential adoption and environmental impacts of BEVs in commercial fleets in Lisbon, Porto, and the remaining country were also quantified. Another objective was finding the influence of ambient temperature on BEVs consumption.

2 Data and Methods

Within the European Lighthouse Program Sharing Cities, CML introduced 160 BEVs to its fleet in late 2018, all leased. From those, 140 are for personal use or fixed to a specific sector, and 20 BEVs are utilized in a sharing system, where any municipal employee can drive them upon request. This BEV fleet is the case study, quantitative data was gathered (from the CML monitoring platform, through a Mobility Device Connector) with information relative to vehicle trips, vehicle battery charges, and charging stations. Data covered a period from late 2018 until December 2020. Ambient temperature during each trip was added (from an IST weather station). Qualitative data was also collected by interviews with the fleet manager. A basic overview of the data size is shown in *Table 1*.

Table 1 Trips and charges information

Vehicle	No. of BEVs	No. of trips	No. of trip hours	No. of km	No. of charges	No. of charged hours	No. kWh charged
Sharing	20	10 091	3 143	72 160	799	31 946	9 171
Personal	140	311 945	97 206	2 704 791	28862	420 976	323 038
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 the steps except the environmental & economic analysis were performed in Python, the data was filtered 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. Trips shorter than 200 meters were excluded from the study, a day of the week variable was created to ensure data analysis of both weekdays and weekends driving patterns, ambient temperature of each trip was added to study the possible fuel consumption dependencies. Vehicles trips and charges were given 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 occurred to save both trips and charges in the same data set, this was executed in the following way, a charge is detected when the trip initial battery is at least 2% higher than the final battery of the previous trip and, consequently, a charging event is considered to have occurred between these two trips, then it seeks in the charges data set of the vehicle, for a charging that occurred between the beginning of the trip and the ending time of the previous trip, to understand if the matching was done correctly, the matching error was calculate based on equation 1.

$$Error = |CFB_i - TIB_i| + |CIB_i - TFB_{i-1}| \tag{1}$$

CFB_i, TIB_i, CIB_i and TFB_{i-1} stand for charge final battery, trip initial battery after the charging as occurred, charge initial battery, and trip final battery before charging occurred, respectively. The variable i represents the line in the data set, $(i-1)$ represents the trip before and i the trip after, the data of the charge is saved in the same line in the data set has the first trip performed after the charge took place. Of the 140 BEVs in the city fleet for personal use, 6 were eliminated from the study for faulty or insufficient data. 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, the first 3 months were termed the learning period.
- **Regular Period -** After the learning period, a normal period begins the driving patterns observed in this period will have more in common with future usage of the EVs than the previous period. This period will have the largest importance, and most future analyses will use this period.
- **Pandemic Period -** The first state of emergency was declared on 18 of March 2020 because of 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.

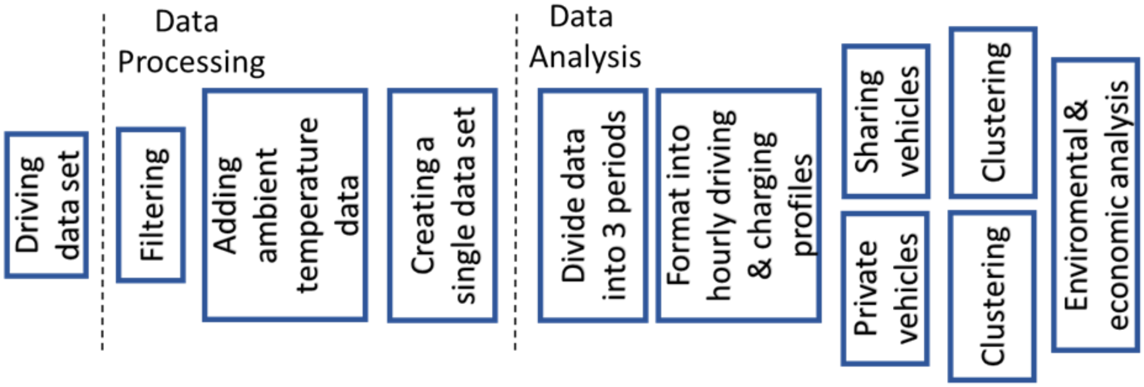

Figure 1 Methodology Flowchart

Vehicles were aggregate based on their driving pattern during the weekdays of the regular period since it reflects normal working days. To study the usage of the vehicles, 3 possible modes were defined, traveling, charging, or parked, both or all of these modes are not possible to be performed at the same time, this data was computed and stored in an excel file for further use. The data computed using only weekdays or weekends excludes holidays, the usage during holidays is atypical when compared to normal weekdays and weekends. Most of the trips made by sharing vehicles during the pandemic period have errors in the data and a major part of the charges made in this period have no data, due to these factors the pandemic period analysis can't be performed for the sharing vehicles. To cluster the vehicles, first the features pertinent for the clustering model were chosen, they must reflect the driver's usage of the vehicle in the working periods, as such only trips and charges executed during the weekdays were used, 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, the act of commuting to work is vital to the study, and the reason for 6 AM to 8 AM and 5 PM to 9 PM to be 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, relative usage and charging times were used instead of the absolute value in seconds, they were calculated using equation 2. 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.

$$Usage_i = \frac{Usage\ time_i * 100}{Usage\ time_i + Charge\ \ time_i + Park\ time_i};\ Charge_i = \frac{Charge\ time_i}{Usage\ time_i + Charge\ \ time_i + Park\ time_i} \quad (2)$$

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 elbow method is a plot where the x-axis is the K value and the y-axis is the sum of the squared errors of the cluster for each K value, the line plot usually resembles an arm, the "elbow point" of that arm is the ideal number of clusters. Based on Figure the elbow point is either 3,4, or 5. The usage profiles of the three K-means results were performed, K=5 was chosen since all clusters had drastic differences. The K-means algorithm ran 10000 times, the end result was the best output in terms of inertia, if the number of iterations is low the solution may converge to different results each time it's executed. To obtain the influence of ambient temperature on the consumption of BEVs, trips using the data of all BEVs in the Lisbon municipal fleet were fitted into a generalized linear model (GLM). The link function was obtained by analyzing the scatter plot of the consumption vs ambient temperature in Figure , A line was drawn in black over the scatter plot that represents the consumption mean for each temperature degree from 5 ºC to 34 ºC. The distribution resembles a polynomial distribution $g(\mu) \cong\ const + coef_1 * \mu + coef_2 * \mu^2$, this link function was used to fit the data. The data was filtered to included trips only above certain distance thresholds and also portioned into different average velocities, similar to Taggart's approach [13].

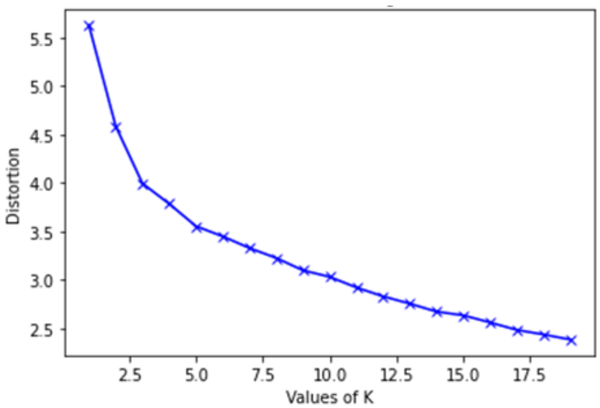

Figure 2 The Elbow Method

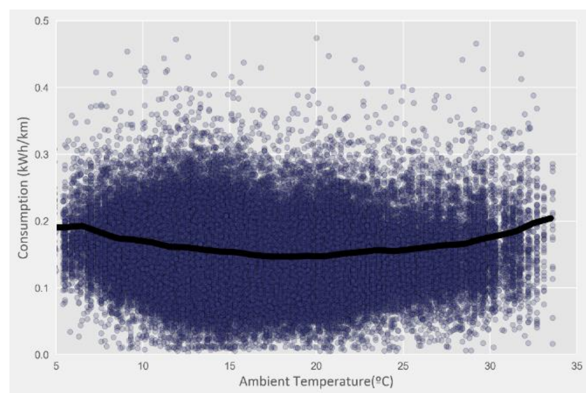

Figure 3 Scatter plot of EVs consumption and ambient temperature

For economic analysis, the total cost of ownership (TCO), which encompasses the costs from acquisition to disposal of the vehicle, was calculated for 3 time periods, 3 years,7 years, and 10 years using equation 2. Comparing the TCO of 5 possible scenarios, which are replacing the old vehicles with:

- **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).

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

S – subsidies	C – consumption	TA– autonomous taxation	RP – resale 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 where ISV (*imposto sobre veículos*) is a fee paid once to license a vehicle, it depends on vehicles engine cubic capacity (cc), CO_2 emissions, and fuel type [15]. BEVs don't pay ISV while HEVs have a discount rate of 40%. 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], where 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) is called IUC (imposto único de circulação) 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 2. The scenario of keeping the old fleet is just used to compare fuel costs and because it is also used in the environmental analysis, 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 2 TCO variables of the 5 possible scenarios

Variable name	**BEV** Owned	Leased	**NEW ICEV**	**OLD ICEV**	**HEV**
VC	32 240 € [24]	-	17 650 € [24]	-	26 020 € [25]
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 resail value, 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 [18]. Besides calculating the global TCO of the entire fleet, the TCO of the sharing vehicles, of each cluster, and only the private/personal fleet will also be calculated. 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 [19]. 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%. The environmental analysis is performed for the same scenarios except there is no difference between bough our leased BEV, the emissions were divided into 3 sectors: Well-to-Tank (WTT); Tank-to-Wheel (TTW); Cradle-to-Gate (CTG) emissions associated with the vehicle production. The WTT emissions were associated with the fuel production, for petrol and diesel, its values came from the European Commission JRC [12], the carbon intensity used was 310 $CO2$/kWh, the rate in 2018 for Portugal according to the European environment agency (EEA) [20]. The TTW emissions were estimated using COPERT 5.4.52, most of the inputs variables were taken from the national inventory report 2021 Portugal (NIR) [21], except the circulation data, since vehicles are mostly used in the city it was assumed urban driving had 80% and rural and highway driving had each 10%. The CTG was calculated based on research by Ford and LG scientists, where they discovered producing batteries emits 140 Kg $CO2/kWh$ [22]. Also, a broad study was performed for 3 regions in Portugal, the Lisbon metropolitan area (AML), Porto metropolitan area (AMP), and the regions outside the two previous areas (RO), calculating the TTW emissions reductions associated with switching a large portion of company light passenger vehicles to BEVs, using COPERT, the inputs were similar to the ones used in the case study except for the circulation data which came from NIR and the data of existing vehicles in Portugal 2020 was acquired from Londublis [23].

Company vehicles' high annual mileage makes it impossible for all ICEV to be substituted for BEVs and since diesel vehicles have a larger annual mileage no more than 80% of diesel vehicles were substituted. Vehicles were grouped by vehicle class and Euro standards, only half of the large-size vehicles were substituted due to our vehicle model not satisfying all requirements large vehicles need to accomplish their function, 2 possible scenarios were created:

A. **Low transition scenario** – The substitution followed the general scheme listed above, no vehicles with euro 5 standard were substituted while for euro standard 4 only 75% of petrol vehicles and 60% of diesel vehicles were substituted.

B. **High transition scenario –** The euro 4 standard vehicles had the same substitution rate as other vehicles with older norms, for vehicles with euro 5 standard it followed the same substitution rate as euro 4 vehicles did in the low transition scenario.

3 Results and Discussion

The first step was to validate the placement of the battery charges, done in the data pre-processing calculated using equation (1). 98.2% show an error of less than 1%. 87% of the trips the program detected had a match in the charge data set, 77% of the charges with no data have a charge of less than 6%. Daily energy charged has grown in the regular period, from 4.93 to 5.78kWh/day. However, the pandemic period has seen a sharp decline in the amount of daily energy charged (4.07kWh/day). During the regular period, 7.84kWh/day was charged during the weekdays and only 1.36kWh/day on weekends. On average 93.5% of the energy is charged on weekdays. Vehicle mileage in the learning period was 32.6km/day and increased 23% in the regular period, the pandemic as the lowest mileage of 29.11km/day, the daily trips follow the same trend, 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, consumption as decreased from 0.164kWh/km in the learning period to 0.153kWh/km. By comparing the learning period with the regular period, it was noticed drivers made more trips per charge and charged the battery further as they gain more experience.

Since most of the driving is performed during the weekdays, the weekdays user profile for the 3 existing periods were compared. In *Figure 2*a), the highest hourly mileage is between 8 AM to 11 AM, at 7 PM it starts to plummet, and from 0 AM to 5 AM almost no trips took place. Charging profiles were made based on the time and energy-charged, a conservative approach was made to extrapolate what type of charging power was select, matching the power output to the best time efficiency of the charging post. *Figure 2*f) shows the charging posts are more used during the day, peaks from 9 to 11 AM, the approach suggests the most used power mode is the 7.4kW (*Figure 2*c)), however, the real results will tend to more high-power energy charges, for the charging posts less than 25.5% of their usage was actually charging the battery the rest of the time vehicles were connected to the charging post while fully charged. The sharing vehicles during the learning period had a much lower usage (7km/day), the consumption was higher than the private fleet (0.191kWh/km), during the regular period the mileage increased to 30km/day but was still below the private fleet and consumption dropped to 0.162kWh/km. The clustering algorithm aggregated the vehicles into 5 clusters, its usage profiles are depicted in *Figure 3*: **5a) Cluster commuting (C)** vehicles drive mostly before and after working hours mainly for commuting from home to work, the majority of charging is performed during working hours, contains 21 EVs; **5b) Cluster labor high charging rates (LHC)** vehicles drive only during working hours, charges mostly during the night, contains 25 EVs; **5c) Cluster labor medium charging rates (LMC)** similar driving pattern to LHC, however, its charging time is almost half of LHC**,** contains 22 EVs; **5d) Cluster low usage (LU)**, vehicles drive between 7:00 to 20:00 with no apparent usage peaks, charges mostly during the day, contains 43 EVs; **5e) Cluster high usage (HU)** higher utilization during commuting hours however it as a sizable usage during working hours, the majority of charging is performed during the day, contains 22 EVs. Sharing vehicles spent the most time recharging, their usage profiles resemble cluster LHC. To validate the clustering process most sharing vehicles were expected to fall in the LHC cluster, weighted K-means was used, giving less importance to the sharing vehicles as to not alter the original cluster centroids, the results were satisfying, 74% of the sharing vehicles joined the LHC.

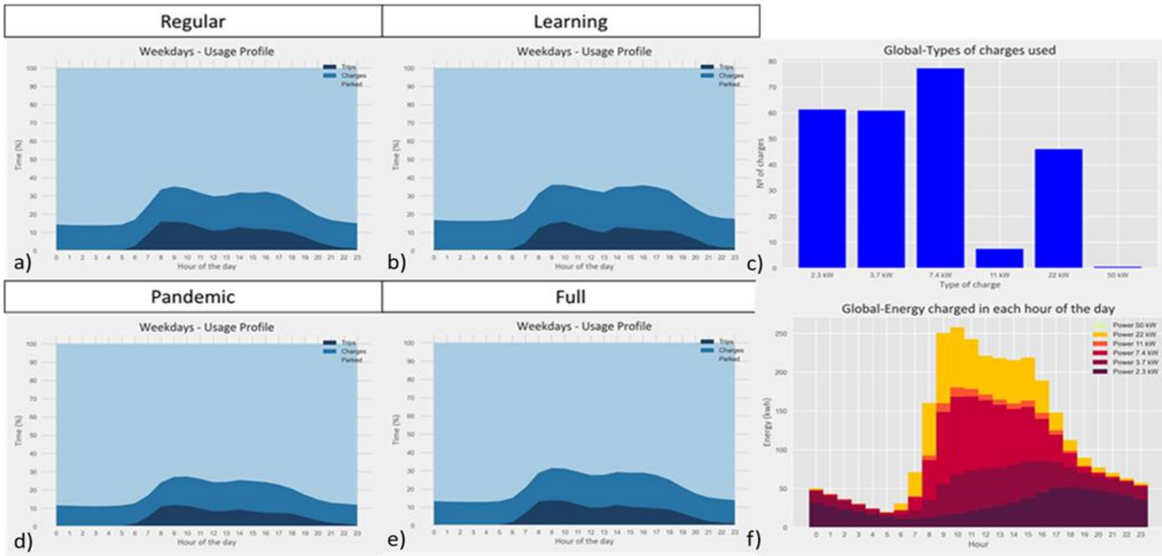

Figure 2 Weekdays usage profile for: a) Regular period; b) Learning period; d) Pandemic period; e) Full period. c) Charges Profile f) Amount of each type of charge

The BEVs are most efficient when the ambient temperature is around 20ºC, the ideal temperature increases for longer trips, for trips larger than 20km the ideal temperature was 21.8ºC. The influence of ambient temperature is lower for longer trips, deviance of 10ºC from the most efficient temperature leads to on average 17% increase in energy consumption, while trips with 10 or more km the influence drops to 14.4% and for trips longer than 20km the ambient temperature influence has an even lower increase of 11%.

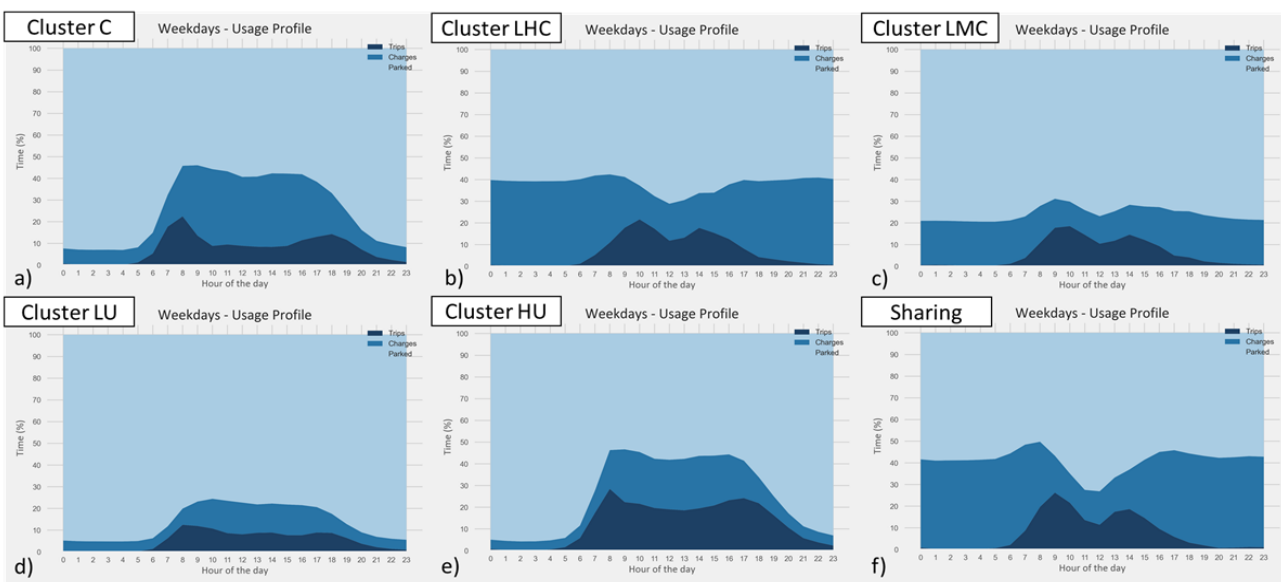

Figure 3 Usage profiles during the weekdays for Weekdays usage profile for: a) Cluster C; b) Cluster LHC; c) Cluster LMC ; d) Cluster LU; e) Cluster HU; f) Sharing vehicles

The TCO for the 3 time periods are shown in *Table 3*, the OLD ICEV TCO is not important since it's not a viable option due to their age and advanced deterioration. Analyzing the total fleet, for the short-term period the cheapest alternative is buying ICEVs, they had a 0.37€/km TCO while HEVs were 19% more and buying BEVs a whopping 39% more. Leasing for the short-term period was found to be 21% cheaper than purchasing a BEV. For the medium-term period of 7 years, ICEVs are still the cheapest option, with 0.27 €/km, however, BEV now costs only 10% more. For the long-term period buying BEVs is now the cheapest option, while HEV is still more expensive than ICEV. The fuel costs of ICEV were 172% higher than BEVs, making the AM the most important variable for BEV economic viability. BEVs were competitive in the long-term for all clusters including sharing vehicles, private vehicles and cluster LHC have similar TCO to the total fleet, while sharing, cluster LMC and LU had the poorest results. For the medium-term period, only vehicles with 21 000 plus km/year were cost-competitive. Pinto's payback period of less than 3 years was not met by any of the clusters, however, he used a higher AM of 35,000km/year [8]. The emissions associated with the 4 scenarios of the CML fleet are presented in Table 4, BEVs have the largest WTT CO2 emissions of the 4 possible scenarios, 48% more than the OLD ICEV and 20% more than NEW ICEV, for the TTW, BEVs produce no tailpipe emissions, between 285.1 and 545 tonnes of CO2 would be emitted in the city if the municipal didn't purchase a BEV fleet. WTW BEV emissions were 77% less than the old fleet and used 63-79% less energy than the other 3 options. BEVs emitted 1.4-3.3 less CO2 tonnes per year per vehicle, their emissions per mile were 56g*CO2/km, lower than Moro and Lonza assessed for Portugal [6].

Table 3 TCO of the 5 clusters, the sharing vehicles, and the private vehicles

3 Years TCO [€/km]								
Scenarios	**total**	**private**	**sharing**	**cluster C**	**cluster LHC**	**cluster LMC**	**cluster LU**	**cluster HU**
BEV	0.52	0.51	0.57	0.42	0.52	0.55	0.54	0.35
L BEV	0.41	0.40	0.51	0.29	0.41	0.50	0.49	0.23
NEW ICEV	0.37	0.37	0.41	0.32	0.37	0.41	0.40	0.28
OLD ICEV	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14
HEV	0.45	0.44	0.50	0.37	0.45	0.49	0.49	0.32
7 Years TCO [€/km]								
Scenarios	**total**	**private**	**sharing**	**cluster C**	**cluster LHC**	**cluster LMC**	**cluster LU**	**cluster HU**
BEV	0.30	0.29	0.34	0.23	0.30	0.33	0.33	0.20
L BEV	0.37	0.36	0.46	0.26	0.37	0.45	0.45	0.21
NEW ICEV	0.27	0.27	0.30	0.23	0.27	0.30	0.29	0.21
OLD ICEV	0.13	0.13	0.13	0.12	0.13	0.13	0.13	0.12
HEV	0.33	0.33	0.37	0.27	0.33	0.37	0.36	0.24
10 Years TCO [€/km]								
Scenarios	**total**	**private**	**sharing**	**cluster C**	**cluster LHC**	**cluster LMC**	**cluster LU**	**cluster HU**
BEV	0.23	0.22	0.26	0.17	0.23	0.26	0.25	0.14
L BEV	0.35	0.34	0.43	0.25	0.35	0.42	0.42	0.20
NEW ICEV	0.24	0.23	0.26	0.20	0.24	0.26	0.26	0.18
OLD ICEV	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
HEV	0.29	0.28	0.32	0.23	0.29	0.32	0.31	0.21
km/year	**14041**	**14454**	**11151**	**20590**	**14053**	**11439**	**11676**	**26112**

BEV production emits 5.3 more tonnes of CO2 according to the CTG analysis, BEV would need to travel 27,000km to achieve less overall pollution than ICEV, which the total fleet achieves in less than 2 years, if the AM stays low because of the pandemic, it would take an extra 3 months. HU cluster only needs 1.1 years and the sharing vehicles need 2.4 years. The BEV fleet only reaches the carbon emissions of HEVs after 4.5 years. The majority of the fleet has a payback period similar to Weldon's research [10].

The environmental impact of mass adoption of light passenger BEVs into Portuguese company fleets is shown in *Figure 4*, AML had the lower impact since it has a younger fleet, only 11-19% of the fleet was substituted compared with the AMP 20-31% and the RO 28-41%. CO2 emission reduction is linear, for example, scenario A changes 19.8% of the AMP fleet and reduces CO2 emission by 18%, scenario B changes 31% and reduces 31.6%. NMVOC (non-methane volatile organic compounds) and CO (carbon monoxide) emissions are the most reduced, the AML fleet in scenario A changes 10.7% of its fleet and reduces 39% the CO and NMVOC emissions, these two pollutants are associated with petrol vehicles. While NOx and PM reduction values are identical and are mainly associated with diesel vehicles, in scenario A the AML fleet reduces 15% of NO_X and PM emissions.

Table 4 WTW fleet yearly CO2 emissions for the 4 scenarios

Scenarios	Fuel	WTT [t]	TTW [t]	WTW [t]	Diff [%]
Old ICEV	Diesel	84.7	456.5	541.2	-
New ICEV	Petrol	104.2	545.0	649.2	20%
HEV	Petrol Hybrid	61.3	285.1	346.4	-36%
BEV	Electricity	125	0	125	- 77%

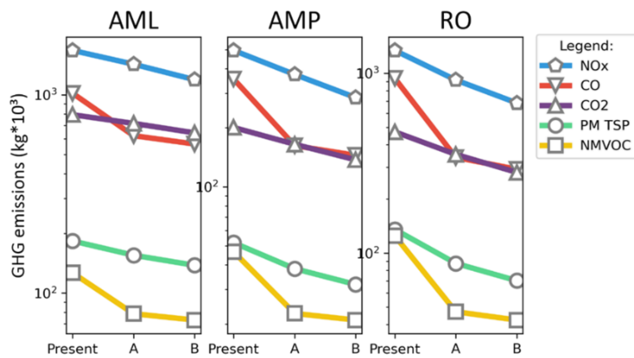

Figure 4 TTW GHG emissions for the 3 regions, with low and high substitution scenarios, CO_2 in kg$*10^6$

4 Conclusions

In accordance with the financial incentives for companies provided by the Portuguese government and the operational costs, it can be claimed BEVs are the cheapest option for a medium to a long-term 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 charging and driving periods. The 2 clusters with a low night charging rate, possibly were used to drive the user from work to home, these clusters had double the annual mileage of the others, and were the only ones with medium-term period lower TCO than ICEVs. It's concluded that using the vehicle to travel from work to home is a major factor in the BEV's economic viability. The cluster with the majority usage during working hours had the least mileage but spent 1 to 6 hours more each day recharging than the other clusters, concluding the utilization of the charging posts by high mileage vehicles was done more efficiently with a higher power. Average recharging took longer and substantially charged more energy for low mileage clusters. By clustering based on daily driving and recharging habits, the vehicles other driving characteristics also resembled themselves creating clear distinct groups, with remarkable similarities within each group. Between the learning period and the regular, as EV experience increased users became more energy efficient and consumption decreased 7%. The sharing vehicles typically used by less experienced users had 16% higher fuel consumption in the learning period and continued with a 6% higher consumption, another evidence EV experience had an immense influence on the consumption rate. The Covid-19 pandemic 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. Energy savings of 63-79% were identified.

Other key conclusions are, the ideal ambient temperature is around 20ºC, its influence is higher especially in low-speed trips which are customary in city centers where the CML fleet spends most of its time, for high-speed trips the influence was lower, these findings were expected and exhibit similar results to the other studies on this subject, deeper understanding of extreme low and high temperatures was not possible, because of Lisbon geographical location the weather is mild and extreme temperatures are very unusual. EVs are more cost-competitive than ICEVs in the long-term even for the lowest mileage if the subsidies are included. For the high mileage groups in the CML, the payback period was less than 7 years. Even if we consider BEVs production pollutes more than ICEVs, this study concludes BEVs end up reducing emissions in the long run. By switching their older conventional vehicles for electrics, the CML is expected to emit 406 fewer tonnes of CO2 annually.

Considering the national adoption, the replacement of 192 500 vehicles, would reduce tailpipe emissions of CO_2 by 28%, CO by 57%, and NOx by 38%. The results of the national adoption could be more impactful since the 406kt CO_2 reduction corresponds only to a 2.4% reduction of the national road transportation emissions. Nonetheless, it will bring more electric vehicles to the second-hand vehicle market increasing the environmental benefit further.

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