Assessing feasibility and potential application of alternative technologies on urban mobility

André Silva
Andrecrsilva@tecnico.ulisboa.pt
Instituto Superior Técnico, Universidade de Lisboa, Portugal
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Abstract

Considering that most of the population lives in urban areas, the management of energy and emission of pollutants associated to transport sector in cities is fundamental. In this context, there is a need to assess the impacts associated with the usage of alternative propulsion technologies, while electric mobility arises as an interesting solution due to its high efficiency and zero local emissions. In this context, the objective of this work was to assess the energetic and environmental impacts of electric vehicles, based on a real-world driving data in comparison to a conventional vehicle with a simulation of a potential usage of an electric vehicle, having as a case study 62 drivers in the Metropolitan area of Lisbon. Firstly, the drivers were separated into two different groups (G1 and G2), according to its vehicle's typology, and then, 27 scenarios were set, to simulate structural and behaviour constraints, affecting the charging opportunities, in order to evaluate their electric mobility feasibility in each scenario. Taking only into account the feasible drivers, it was possible to define the driver's day-to-day mobility characteristics in each scenario and assess their charging impacts , depending on the electricity generation mix (in this specific case, in the year 2017), at different times of the day, and at different periods of the year, comparing their emissions with the ones emitted by a conventional vehicle. Results revealed that the structural constraints were more influential to determine the feasibility. This one defines the scenario group's characteristics, while behaviour constraints mainly act as a sensibility analysis. The feasibility is lower at the scenarios with only charging opportunities during the day, on average 77%, and on the scenarios with only opportunities on weekends, on average 70%, when comparing with those with high feasibility, and this ones only include the drivers with the lowest travelled distances with the lower average speed. Concerning to the CO2 emissions, the impacts were highly dependent on the electricity generation mix. In winter period, they were 24% lower, due to the contribution of renewable energies. The CO2 reduction opportunity was also more expressive at that period. In Winter period, the reduction peaks appeared at 9h and 19h, and showed reductions in the order of 82% (G1) and 87% (G2), while in Summer period, the peak only happened at 20h, and showed reductions in the order of 77% (G1) and 84% (G2). However, some drivers might not take advantage of the bigger opportunities for reduction of CO2 because in some cases, that would mean that they need to change their mobility characteristics and that might not be possible.

Keywords: Naturalistic driving data, Electric mobility feasibility, Mobility characterization, energy mix, impacts

1. Introduction

The transportation sector is one of the main consumers of final energy (about 33.2% in 2016 [1]) and its deeply connect to our society's way of life. The sector has a key role in our economy and is fundamental to our logistics chain as well as for our living standard, by approaching places, peoples and goods. Inside this sector, the road transportation is the most energy intensive mode, and its contribution has been rising due to lack of investments in other type of fluvial and railway alternatives as well as in public transports, which lead to the private automobile domination [2]. The energy consumption of the sector is mainly powered by burning fossil fuels and as a result, it's a source of pollutant emission gases, such as nitrogen oxides (NOx), particulate matter (PM), non-methane hydrocarbons (NMHCs) and sulphuric oxides (SOx). The characteristics and quantities of the emissions depends on several factors such as the quantities and quality of the burned fuel, the technology used for combustion and for the tail-pipe gases treatment (such as the 3-way catalytic converter and particle filters), load factor, maintenance, etc. The road mode is also the main polluter inside of cities. Considering that most of the population lives in urban areas, the management of energy and emission of pollutants associated in cities is fundamental. The EU commission has set goals that aim a 50% shift away from conventionally fuelled cars by 2030, phasing them out in cities by 2050 [3]. In this context, the electric vehicle (EV) appears as an interesting solution, since it has a greater efficiency [4], when compared to the internal combustion engine vehicle (ICEV) and produces zero local emissions. This study aims to assess the electric mobility feasibility of a group of drivers and then, assess the impacts of the feasible, if they change to the electric mobility.

2. Data and methods

A generic overview of the methodological approach is presented in Fig. 1. Firstly, naturalistic driving data was collected using an onboard data logger (i2D device). This data was automatically sent by the device to a dedicated Online platform called "i2D". From the data, was possible to define the day-by-day mobility characterization of each driver, as well as estimate an energy consumption of a potential application of the electric vehicle, regarding the time distribution per power mode. From these 2 known factors, is possible to set a group of scenarios with different charging behaviours and assess the electric mobility feasibility to each driver, in every created scenario. After testing the feasibility, it's possible to assess the impacts of the charges by the feasible drivers, regarding the electricity generation mix.

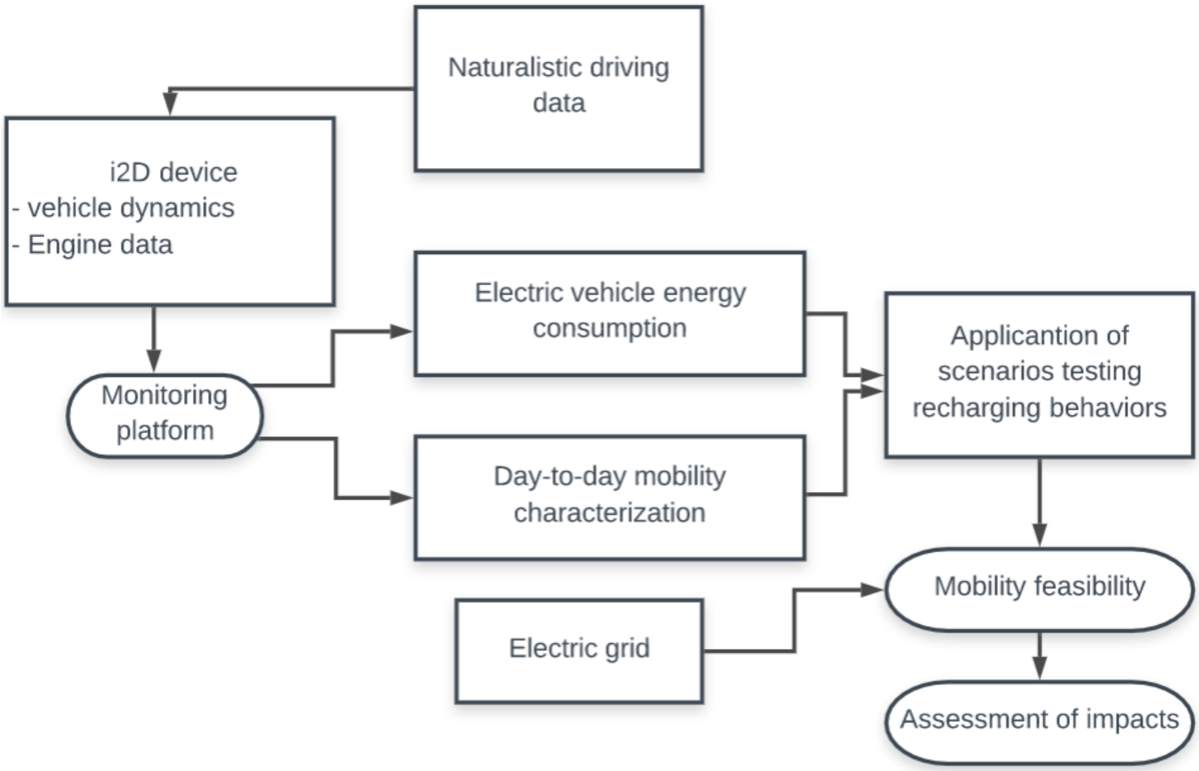

Fig. 1 Generic overview of the methodological approach

2.1. Data collection

For the acquisition of the real-world driving data, an onboard data logger named "i2D" was used. This device connects to the vehicle's OBD port allowing a non-invasive monitoring system installation. This device collects and measures and automatically transmits to the dedicated platform, with a 1 Hz frequency, vehicle driving data, including driving dynamics (speed, acceleration) and engine data (mass or air flow, engine rpm and load, throttle position, etc.) [4]. It was assumed only driver per vehicle. In this study, a sample of 62 drivers were monitored using the "i2D" device.

Table 1 – Characterization of monitored vehicles by fuel, type and number of drivers

Fuel	*Type*	*Number of drivers*
Gasoline	Light duty passenger	12
Diesel	Light duty commercial	9
	Light duty passenger	41

The drivers were separated into two different groups (G1 and G2), according to its vehicle's typology. Light duty passenger vehicles were grouped to G1, and Light duty commercial and pickups were grouped to G2.

2.2. Data analysis

In order to define the driver's day-to-day mobility characterization (fixed value for each driver), its necessary to obtain first the hourly distribution of travelled distances on average, in each type of weekday (Weeks and weekends), for each driver. From the real-world driving data, an average was used from every trip made since the beginning of the monitorization process. In order to ensure that the trip was meaningful and to ensure normal driving conditions, a minimum of 200 meters travelled are needed to guarantee the trip validation. The average speed, even if constant for each driver, can be obtained in the same monitoring file as the travelled distances. Other distribution that must be taken int account, it's the time distribution per power mode, which measures how much time each driver spends in each power mode, on a valid trip.

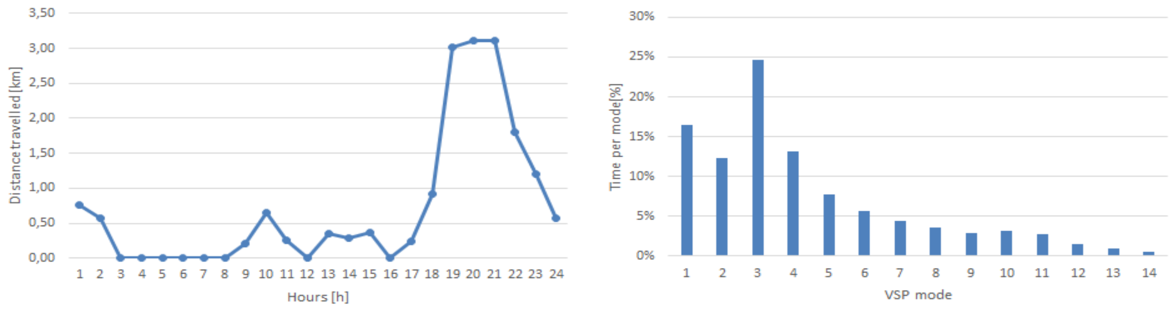

Fig. 2. Example of an hourly distribution of travelled distances – driver 8 (left) and distribution per power mode – driver 19 (right)

2.3. VSP modes

The Vehicle Specific Power (VSP) [5] methodology was presented initially as an alternative methodology for pollutant emissions studies and is defined as instantaneous power per unit of mass of the vehicle. This methodology gives a provides a simplification of the forces applied to the vehicle. When using this methodology, it is possible to compare vehicles with different propulsion technologies, based on the power required at each moment. It can be defined by:

$$VSP = \frac{\frac{d}{dt}\left(E_{cinética} + E_{potencial}\right) + F_{rolamento} \cdot v + F_{aerodinâmica} \cdot v}{m} =$$

$$= v \cdot [a \cdot (1 + \varepsilon_i) + g \cdot declive + g \cdot C_r] + \frac{1}{2}\rho_a \cdot \frac{C_d \cdot A}{m} \cdot (v + v_w)^2 \cdot v \qquad (1)$$

In this study, the approached methodology used a VSP distribution divided in 14 groups, considering that the first 2 modes dedicated to negative power modes. The distribution per power mode that was obtained by the real-world data comes represent in 82 different modes, comprehended between]-21;60]. To be able to use this data, it was necessary group it into 14 modes, according to Table 2.

Table 2. VSP binning and ranges of w/kg for each mode

Modo VSP	*W/kg*	*Modo VSP*	*W/kg*
1	VSP <-2	8	13≤VSP<16
2	-2≤ VSP<0	9	16≤VSP<19
3	0≤VSP<1	10	19≤VSP<23
4	1≤VSP<4	11	23≤VSP<28
5	4≤VSP<7	12	28≤VSP<33
6	7≤VSP<10	13	33≤VSP<39
7	10≤VSP<13	14	VSP > 39

Depending on the type of vehicle (Table 1), each group was modelled by a different vehicle. G1 was modelled by the Nissan Leaf and G2 was modelled by the Renault Kangoo ZE.

Table 3. Technical Specs of the modelled vehicles

	Nissan Leaf	*Renault Kangoo ZE*
Power [kW]	80	44
Torque [Nm]	254	226
Traction	Front	Front
Battery capacity [kWh]	24	22
Typo de battery	Li-ion	Li-ion

Since vehicle has its own technical specs, they will have a different energy consumption per power mode.

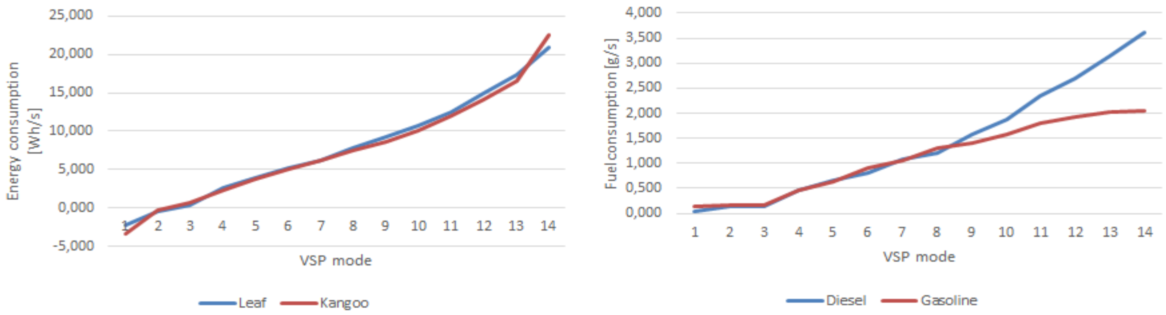

Fig. 3. EV Energy consumption [Wh/s] per VSP mode (left) and ICEV Fuel consumption [g/s] per VSP mode (right)

2.4. Analysis Tool

The developed tool, as inputs as de Average speed, the hourly distribution of travelled distances and the time distribution per power mode. As output, for every driver in each scenario defined, the electric mobility feasibility, the hourly distribution of energy available and the hourly distribution of energy actually charged for every type of weekday, the user profile of each of the 7 days of the week on an average base minute-to-minute, the energy consumption as well as according to the type of fuel of the original ICEV, the hourly distribution of CO_2 emissions.

2.4.1 Electric modelling and determination of the energy consumption

Firstly, the type of vehicle is chosen according to Table 1. The battery capacity of the batteries of the Nissan Leaf and Renault Kangoo are respectively 24 kWh and 22 kWh. However, only 83.75% of the total capacity are available to the user. The maker reserves the surplus capacity to essential services, for protection of the batteries during charges and for minimizing the visible effects of batterie capacity decay due to the charging cycles, prolonging their lifetime [6]. Another factor to consider, defined by the type of vehicle, it's the VSP modal consumption.

Table 4. VSP modal energy consumption [Wh/s]

	Energy consumption Wh/s													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Leaf	-2,241	-0,434	0,275	2,567	3,976	5,260	6,122	7,876	9,217	10,656	12,553	14,862	17,365	20,957
Kangoo	-3,401	-0,329	0,658	2,284	3,765	4,989	6,159	7,420	8,681	10,132	12,025	14,079	16,553	22,513

In order to compute the energy consumption per travelled kilometre, the time distribution per power mode was used, accordingly:

$$Wh/s = \sum_{i=1}^{14} (\%\ time\ per\ VSP\ mode)_i \times (Wh/s\ \ per\ VSP\ mode)_i \qquad (2)$$

$$Energy\ [Wh/s] \times \frac{1}{Average\ velocity\ [km/h]} \times 0{,}001 \times 3600 = Energy\ consumption\ [kWh/km] \quad (3)$$

By applying the energy consumption at the hourly distribution of travelled distances, it was possible to assess the amount of energy that was spent by each driver, on average, at each hour on a given type of day.

2.4.2 Charging opportunities

In order to be able to charge the battery, as in the ICEV, the EV must be stopped. Using the hourly distribution of travelled distance, it was possible to check if the vehicle has travelled any distance at any given moment. However, to be closer to the real user behaviour, it was only considered a valid opportunity to charge if the vehicle is stopped for at least 2 hours in a row. The opportunity that only takes in consideration the operation of the vehicle, was called operational charging opportunity. It must be considered that with this conservative approach, the number of opportunities was greatly reduced, but it is more intuitively closer to the real behaviour, considering the existing structures. Again, with a conservative approach, it was only considered the slow charge method. In Portugal, electricity is distributed with 200 V and 10 A. with a slow charge, only 2.2 kWh could be charged per hour.

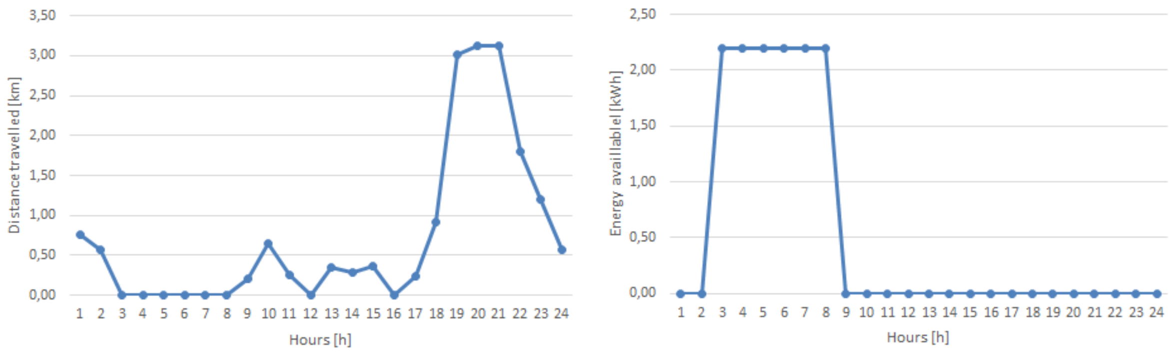

Fig. 4. Hourly distribution of travelled distance - driver 8 (Left) and Hourly distribution of charging opportunities - driver 8 (Right)

As seen in Fig. 3,even when the driver was stopped at 11h and 15h, these periods were not taken in account. However, the driver can only charge, if its State of charge (SOC) allows it, or if there aren't any other constraints applied.

2.4.3 Operation on the modelled vehicle

Once the hourly distribution of used energy and the hourly distribution of charging opportunities are available, there are conditions to start the simulation. On this simulation, several notes were considered:

- Continuous operation consists of 4 full weeks
- The day-to-day mobility characterization is fixed and never change between days of the same type
- Every driver starts the simulation at the same time, at the first Monday at 0h
- Every driver starts the simulation with a SOC of 100%

What it concerns to the charging, in order to simulate the charging tail effect, it's not linear since its changes depending on its SOC. If the SOC was:

- Between 0% and 92% - Charges normally, the same rate as defined by the grid
- Between 92% and 95% - Charges with a factor of 0.9
- Between 95% and 100% - Charges with a factor of 0,5

However, this phenomenon can only be observed on the next, more detailed analysis. Since it can charge 2.2 kWh per hour, that means 10.95% and 11.94% at Leaf's and Kangoo's battery, respectively. These values are too big, since the charging tail effect, as modelled, can only be seen on the last 8% of the SOC. Over the simulation, even with the fixed mobility characteristics, the effects of a continuous operations started to appear. this way, a more detailed analysis was made, one per each individual day of the week. In order to minimize the effects of the beginning of the simulation, only the last 3 weeks were considered.

2.4.4 Scenarios and feasibility

In order to study various conditions, 27 scenarios were set. These scenarios represent the effect of structural and behaviour constraints. The structural constraints were defined by the non-opportunity to charge at some types of weekday, or specific periods of the day. In each group of structural constraints were also defined 3 behaviour constraints that define the SOC from which the drive starts a charge, is opportunity occurs.

Table 5. General overview of Scenarios definitions

Period	Type of day	SOC	nº scenario
Night and day	Week + weekend	100	1
		60	2
		30	3
	week	100	4
		60	5
		30	6
	Weekend	100	7
		60	8
		30	9
Day	Week + Weekend	100	10
		60	11
		30	12
	Week	100	13
		60	14
		30	15
	Weekend	100	16
		60	17
		30	18
Night	Week + Weekend	100	19
		60	20
		30	21
	Week	100	22
		60	23
		30	24
	Weekend	100	25
		60	26
		30	27

The beginning of the period "daytime" was defined as 8h and lasts until 19h. In the same way, night-time starts at 20h until 7h. The feasibility analysis was made considering the SOC of each driver, in each scenario. if during the operation period, a driver's SOC reaches 0, he Is not feasible to the electric mobility. After this assessment, it was possible to compute the hourly distribution of charged energy for every scenario, only taking in consideration the feasible drivers.

2.4.5 CO_2 emissions

To compute CO_2 emissions, the same methodology was used as to one to compute the energy consumption and energy spent.

Table 6. VSP modal fuel consumption

	Fuel consumption g/s													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Diesel	0,046	0,131	0,147	0,473	0,648	0,817	1,073	1,198	1,581	1,868	2,349	2,695	3,133	3,608
Gasoline	0,130	0,153	0,167	0,471	0,627	0,899	1,069	1,306	1,409	1,588	1,810	1,930	2,015	2,047

$$Wh/s = \sum_{i=1}^{14} (\%\,time\ per\ VSP\ mode)_i \times (g/s\ \ per\ VSP\ mode\ )_i \qquad (4)$$

$$Fuel\ [g/s] \times \frac{1}{Average\ velocity[km/h]} \times 0{,}001 \times 3600 = Fuel\ consumption\ [g/km] \qquad (5)$$

Table 7. CO_2 emission factors for different fuels

	Gasoline	*Diesel*
CO_2 Emission Factor [g CO_2/km]	3,17	3,19

In order to compute the CO2 emissions, the factors of Table 7 were used. By applying CO2 emission factor to the hourly distribution of travelled distance, it was possible to assess the CO2 emissions for every ICEV, at any given moment.

2.4.5 Electrical Grid

The impacts of battery charging are directly connected to the electric grid characteristics. Due to politics, demand, and availability (in case of renewables), the energy generation mix is flexible, and so are its impacts.

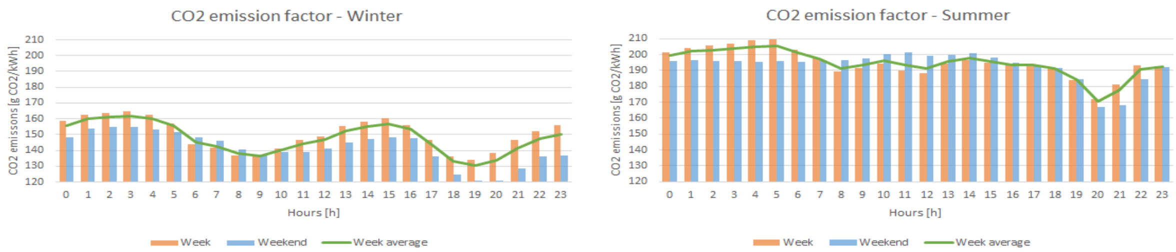

Fig. 5. Hourly distribution of CO2 emission factor - Electricity, Winter and Summer

3. Results and discussion

After the feasibility assessment results revealed that, the feasibility is lower at the scenarios with only charging opportunities during the day, on average 77%, and on the scenarios with only opportunities on weekends, on average 70%, and when comparing with those with high feasibility, and this ones only include the drivers with the lowest travelled distances with the lower average speed (Fig. 6,Fig. 7

Fig. 8)

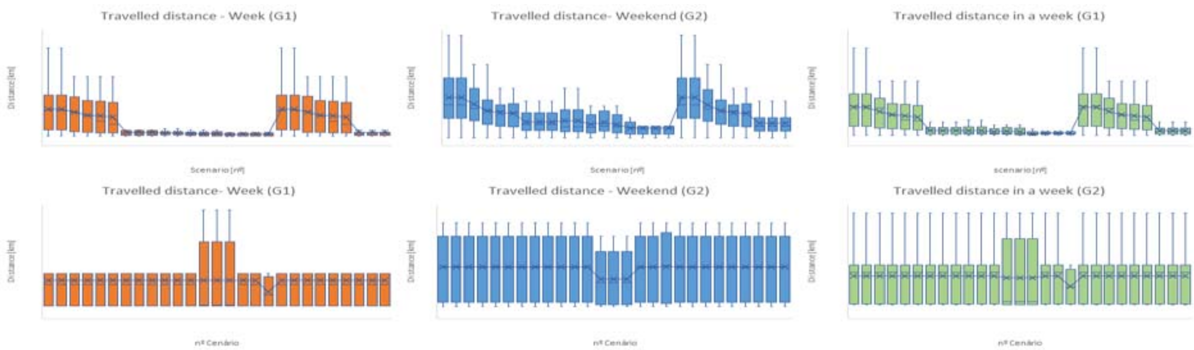

Fig. 6. Travelled distance by the feasible in different scenarios

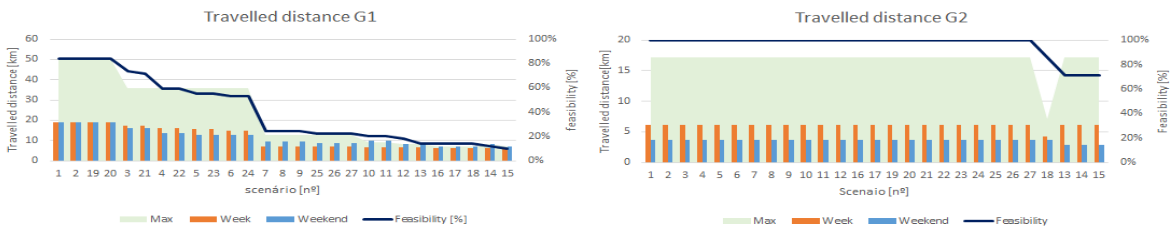

Fig. 7. Feasibility and travelled distance

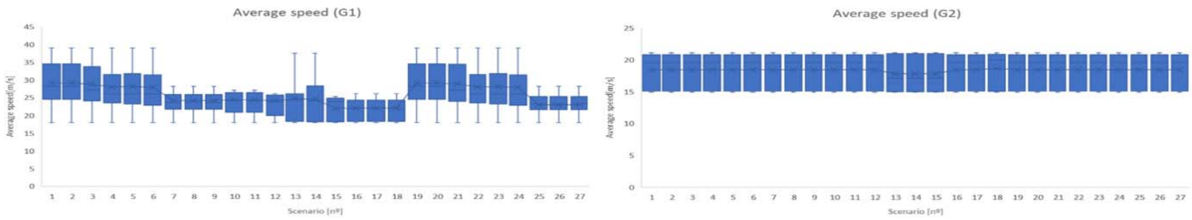

Fig. 8. Average speed

Fig. 9- Energy charged and opportunity to charge

The scenarios with charge opportunities only at weekends [25,26 e 27], as well as the scenarios [13,14], are also characterized by using more percentage of energy opportunities. On average, scenarios [25,26 e 27] used 38.8% and scenarios [13,14], used 31,5% of total available energy available (Fig. 9)

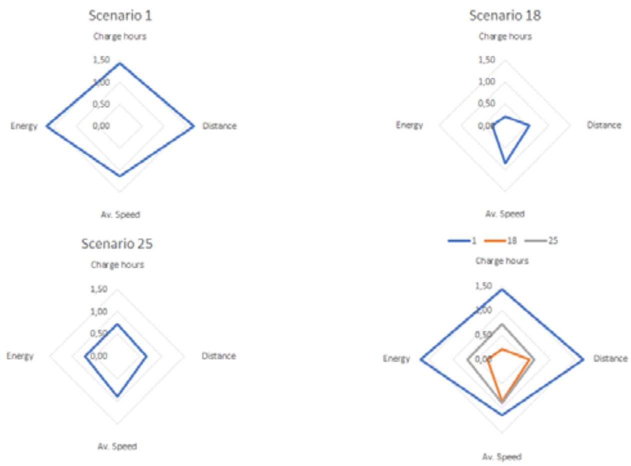

Fig. 10. Polar evolution (G1)

In order to make a comparison between scenarios, it's possible to use polar evolution diagrams. Fig. 10 . These polar evolutions were normalized to its average. As observed, structural constraints were more influential to determine the feasibility. This one defines the scenario group's characteristics, while behaviour constraints mainly act as a sensibility analysis.

Fig. 11. CO_2 emissions comparison, between ICEV and EV (G1)

As shown in Fig. 11, the EV's CO2 emissions are much smaller than the ICEV, however in winter the reduction is even greater. In Winter, G1 showed a reduction of 80.5% on average, and 74.4% in summer.

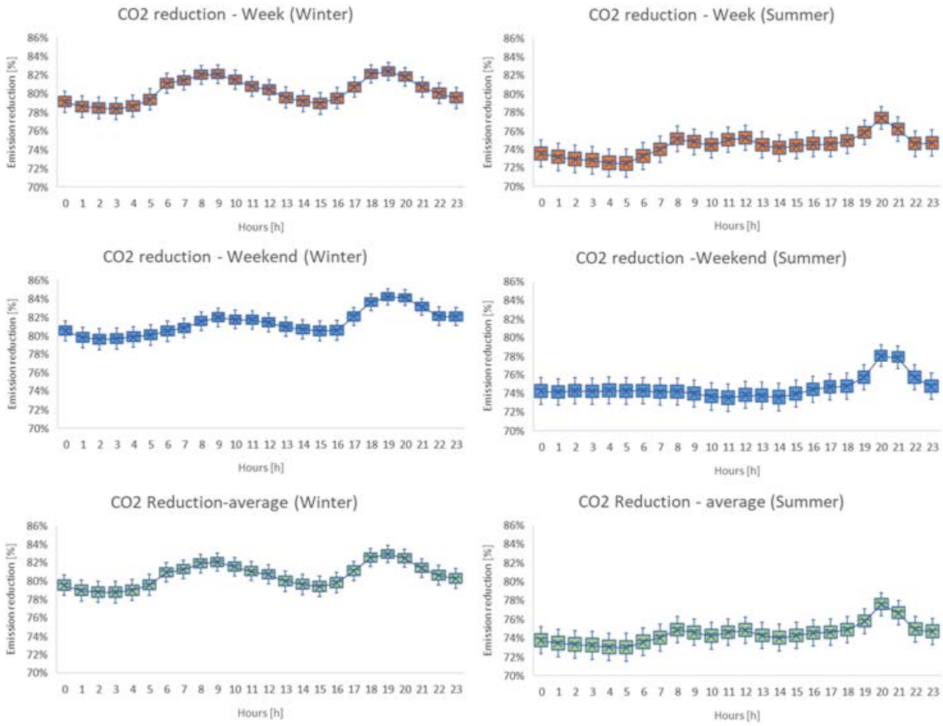

Fig. 12. Example of hourly CO_2 reduction opportunity- G1

As Fig. 5 and Fig. 12 represents, In Winter, there was 2 peaks at 9h and 19h and showed reductions in the order of 82%, while in Summer period, the peak only happened at 20h, and showed reductions in the order of 77%

4. Conclusions and further work

The main objectives of this work consisted in characterizing the driving profiles and simulate the operation in an EV, based on real-world driving data, and then assess the feasibility as well as energy and environmental impacts. Concerning the feasibility, results revealed that the structural constraints were more influential to determine the feasibility. This one defines the scenario group's characteristics, while behaviour constraints mainly act as a sensibility analysis. The feasibility is lower at the scenarios with only charging opportunities during the day, on average 77%, and on the scenarios with only opportunities on weekends, on average 70%, when comparing with those with higher feasibility, and this ones only include the drivers with the lowest travelled distances with the lower average speed. The scenarios with charge opportunities only at weekends [25,26 e 27], as well as the scenarios [13,14], are also characterized by using more percentage of energy opportunities. On average, scenarios [25,26 e 27] used 38.8% and scenarios [13,14], used 31,5% of total available energy available. Regarding the scenarios that only charges at weekends, the feasibility greatly depends on the operational opportunities to charge, because the energy charged at this period must be enough for all week of operation. It's also important to say that the analysis was made using the original versions of the Nissan Leaf and Renault Kango Ze. Newer versions present better efficiencies and better batteries with bigger capacities. If the new versions were used in this methodology, a considerable larger percentage of drivers would be considered feasible. In this analysis, rigid scenarios, with no changes between days of the same type, were considered, which doesn't happen in real-world. In this case, in the long term, the condition that really defines de feasibility it's not the capacity of the battery, but the quantity of energy that is charged weekly. If the effective energy charging opportunities are not at least equal to the energy consumed, the SOC will become energy deficient. Bigger the deficiency, sooner the need to break the operation characteristics to be able to charge. If not, the driver might lose its feasibility qualification. When considering the impacts, results reveal that they are very dependent on the time and on the year period, because of the flexibility of the electricity generation mix. It's also important to say that this analysis has taken in consideration the electricity generation mix related to the year 2017. Since the characteristics of production are constantly changing, this year might not be representative. Regarding de CO_2 emission factor, results evidenced that during the daily scenarios, this factor were usually lower (7.9% during Winter and 3.6% during summer). This phenomenon happens because the definition of daily period starts at 8h. Therefore, there is a charging peak at this hour and at the same time, the electricity generation mix has a high contribution of renewable energies, thus a very low CO_2 emission factor. Was also possible to verify that CO2 emissions are much lower in Winter period, when compared to the Summer (24%) due to the high contribution of renewable in the generation mix. Therefore, the reduction opportunities for CO2 emissions due to the EV battery charges, when compared to ICEV were also bigger. Each group of analysis showed different values regarding reduction of emission. In Winter, G1 showed a reduction of 80.5% on average, and 74.4% in summer, while G2, 86% and 81.6% in Winter and Summer respectively. The opportunities for reduction of emissions are deeply related with the factor of emission of the electrical grid. In Winter, there was 2 peaks at 9h and 19h and showed reductions in the order of 82% (G1) and 87% (G2), while in Summer period, the peak only happened at 20h, and showed reductions in the order of 77% (G1) and 84% (G2). However, some drivers might not take advantage of the bigger opportunities for reduction of CO2 because in some cases, that would mean that they need to change their mobility characteristics and that might not be possible.

Future work may include monitoring a bigger sample of drivers for a longer period, apply road level factor, eco-driving effects and study different types of charging methods.

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