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Abstract

Electric mobility with all of its advantages has gained momentum during the last decade with increasing utilization by many sectors of the society. However, professional fleets 19 operators (e.g. taxis) are still conservative in switching to this new mobility paradigm. In this paper, we empirically evaluate whether electric vehicles together with normal charging speeds could replace current internal combustion engine vehicles for taxi mobility and study the implications for the taxi business. To perform this study we resort to a detailed and large mobility dataset of a taxi fleet collected in a mid-sized European city. The results provide a first indication that such transition towards electric mobility is feasible for the vast majority of the vehicles of the fleet and that simple AC chargers at taxi stands could suffice to provide the necessary range autonomy.

Empirical Evaluation of the Performance of Electric Vehicles for Taxi Operation

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***Abstract*—Electric mobility with all of its advantages has gained momentum during the last decade with increasing utilization by many sectors of the society. However, professional fleets' operators (e.g. taxis) are still conservative in switching to this new mobility paradigm in many parts of the world. In this paper, we empirically evaluate whether electric vehicles together with conventional charging stations could replace current internal combustion engine vehicles for taxi mobility and study the implications for the taxi business. To perform this study, we resort to a detailed mobility dataset of a taxi fleet collected in a mid-sized European city. The results provide a first indication that such transition towards electric mobility is feasible for the vast majority of the vehicles of the fleet and that simple AC chargers at taxi stands could suffice to provide the necessary range autonomy.**

***Index Terms*—Electric vehicles, Taxi mobility, Energy consumption, Empirical data, Charging Infrastructure**

I. Introduction

The electrification of car-based transportation has been increasing rapidly over the last few years as the development of technology has allowed a substantial decline on the cost of batteries. In Europe, Internal Combustion Engine (ICE) cars are set to disappear soon: all new registered vehicles are to be zero-emission from 2035 [1] and many manufacturers have already adjusted their strategies to meet this target. Electric Vehicles (EVs) offer important advantages, namely in terms of air pollution mitigation [2] or lower running costs of car ownership [3]. These advantages have already influenced many countries to define fiscal policies that further motivate the migration from ICE vehicles to EVs.

Despite the noticeable success of this migration that is revealed by the increasing share of EVs, professional fleets are still very conservative in adhering to this type of mobility. The main concerns are related to the limited range, high acquisition cost and the long battery charging times, that are seen as important disadvantages in terms of the economic efficiency of a real-time transportation business. A limited (dedicated) infrastructure of electric charging stations and the high costs of using fast chargers (similar to diesel or petrol costs) further contribute to a minimal share of EVs in taxi fleets[1].

The recent increase in the cost of diesel and petrol is substantially reducing the profit margin of professional fleets that travel several thousands of kilometers per month. On the more than 3000 taxis that are powered by Taxi-link, supporting the study on this paper, this fuel cost normally represents between 20 to 30% of the total taxi revenue. Theoretically, EVs could reduce this cost to less than 10% of the revenue generated, making it difficult to understand the current residual share of EVs in taxi fleets. Furthermore, the mobility pattern of taxis, with average speeds of 30 km/h and significant idle times at taxi stands, seem suitable for the paradigm of electric propulsion, contrary to what happens for instance in fleets that essentially travel on highways at the maximum allowed speed.

The parking time at taxi stands also seems very suitable for charging EVs, not with fast DC chargers, but with much more common and less expensive AC chargers, identical to those installed domestically. This alternative would have the advantage of battery lifetime maximization and could prove sufficient to the charging needs of taxi fleets. This paper intends to study - based on a detailed, large-scale dataset of a taxi fleet collected throughout a month - whether the 24 h mobility of a taxi, together with the paradigm of AC chargers at taxi stands is completely suitable for the current autonomy and charging characteristics of EVs.

Prior works have addressed several topics in the transition towards electric mobility (e.g. charging station planning [4] [5]). Studies studying the technical [6] [7] or economic [8] feasibility of fully electric taxi fleets are still scarce. Most of these studies are either simulation-based [6] containing several simplifying assumptions or make use of empirical data [7] but resort to simple energy consumption models. In this work, we combine real-world taxi operation data with a precise EV consumption model to study more precisely the suitability of EV and normal AC charging for everyday taxi operation.

[1] In September 2021, from the +3,000 taxis operated in Portugal using the *Taxi-link*'s taxi dispatch system, only 19 of these were EVs (0.53%).

The remainder of this paper is organized as follows. Section II presents the large-scale taxi mobility dataset collected in the city of Porto, Portugal. The methodology to determine the energy consumption of electric taxi fleets is given in Section III. The analysis of the implications to transition towards electric mobility is detailed in Section IV. Concluding remarks and future work directions are given in Section V.

II. Porto's Taxi mobility data

Data Acquisition. Mobility data is permanently being collected by a fleet of 407 taxis in the city of Porto, Portugal, for the operation of the taxi-link dispatch system. Vehicles equipped with on-board devices (e.g. smartphone) collect permanently taxi state information (e.g. *Busy*), and positioning and timing data with a frequency of 1 Hz resorting to the Global Positioning System (GPS), which are periodically transferred to a central server for further processing and storage. Specifically, each trip record has the following attributes: i) taxi identifier, ii) taxi state, iii) trip start timestamp, iv) trip end timestamp v) taxi stand identifier (only for *Stand* state) and v) position that consists of a polyline that contains (lat, lon) points of the vehicle trajectory. The taxi state is collected from the taximeter or is an input from the driver. The taxi can be in five main states, namely *Busy* (i.e. performing a service), *Free* (i.e. roaming for new service), *Pause* (i.e. driver is off-duty), *Pickup* (e.g. moving towards the assigned customer) and *Stand* (i.e. vehicle stopped at taxi stand).

For this study, we resort to data collected by the fleet of the largest taxi company in the city (18 vehicles) with only combustion engine vehicles. This company was chosen because all vehicles operate 24h per day (with 2 to 3 different taxi drivers) and all are explored intensively, with service arising mainly at taxi stands or from requests of private clients or assigned by the main taxi central in the city. The collected taxi trajectory data is then used to estimate the energy consumption of vehicles (Section III-B).

Use case characterization. In this study, we resort to data collected during the full month of October 2021, in a medium size European city in northern Portugal. Porto has approximately 232 k inhabitants within a territory of 41.4 km^2 lying in the center of a metropolitan area with 1.737 million inhabitants. Currently, there are 63 public charging stations in the city, totaling 130 plugs for EV charging.

There is a total of 66 taxi stands spread throughout the city but these are mainly concentrated in the city center and commercial and business districts. The capacity of taxi stands varies widely with the smallest and the largest holding 2 and 31 vehicles, respectively. Three main operational strategies are followed to pick-up passengers: i) waiting for passengers in a taxi stand, ii) responding to requests dispatched by a dispatch central or private customers, or iii) hailing by a passenger while roaming. Due to legal requirements, and as the demand for taxi services is generally lower than the supply, drivers mostly park (for significant amounts of time during some periods of the day) in the available taxi stands.

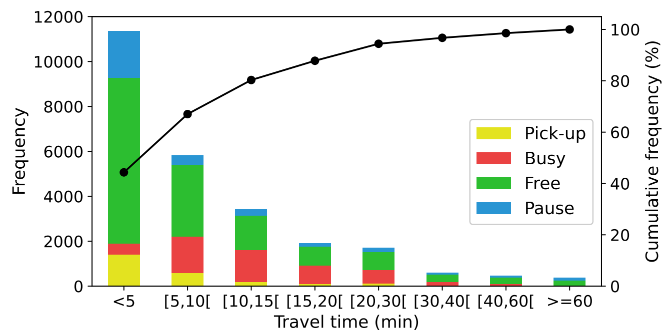


Fig. 1: Frequency distribution of travel time metric.

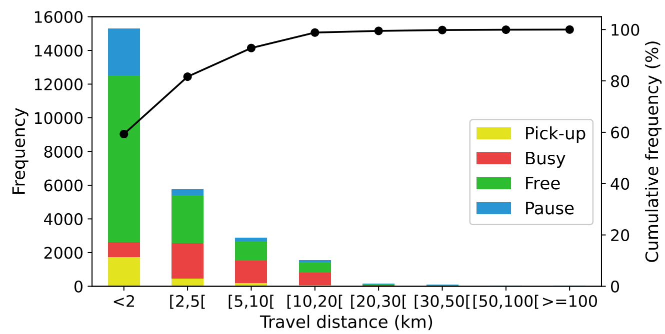


Fig. 2: Frequency distribution of travel distance metric.

Dataset characterization. In the following, we characterize the taxi service in the city of Porto for better understanding the business operation in the period under analysis, specially considering the operation of EVs. The dataset consists of 44838 trip records for different taxi states, which totals 5222 services for the 18 taxis, corresponding to an average of 290 services per taxi per month.

Two of the most important parameters to analyze (for electric mobility) are *travel time* (i.e. time spent in *Busy*, *Pickup* or *Free* state) and the *travel distance*, which are presented in Fig. 1 and Fig. 2, respectively. The average travel time in the *Busy*, *Pickup*, and *Free* states are approximately 14 min, 7 min and 10 min, respectively. The travel time with onboard passengers is smaller than 15 min for 67.4% of the trips. Note that these travel times are small as vehicles mostly respond to requests arising within the city boundaries. Vehicles are parked at taxi stands an average of 3.5 hours per day and the average waiting time at taxi stands was almost 20 min, which shows that taxi drivers are idle for large periods of time allowing vehicle charging during these periods.

During one month, each taxi travelled on average a total of 4516 km of which 52.57% were travelled without passengers. The average travel distance in the *Busy*, *Pickup*, and *Free* states are approximately 1818 km, 324 km and 1993 km, respectively. The results show that the travel distance with *Busy*, *Pickup*, and *Free* did not exceed 10 km for 83.6%, 96.3% and 94.8% of the trips, respectively.

To summarize, we observe that i) travel time and distance are relatively short, ii) the likelihood of performing long services is very small and iii) taxis are parked for long periods at taxi stands. These factors combined can potentially make the operation of EVs in this medium-sized European city very appealing.

III. Methodology

A. Goals & Setting

This work assesses the feasibility of resorting to electric mobility for operating taxi fleets. Specifically, we aim at assessing the impact that switching from combustion to EVs might have on the daily operation of taxis and their profitability. Furthermore, this work also has as objective to evaluate the suitability of using equipment with low or normal charging speeds (up to 22 kWh[2]) for charging taxis while they are parked in a stand. High-speed/rapid chargers are not considered, as previous studies [4] [5] [9] have shown that high currents and temperatures have detrimental effects on the longevity of batteries. Further, the required investments for installing and maintaining fast DC charging are considerably higher, with unfavorable Return of Investment (RoI) given that taxi stands cannot be accessed by other vehicles.

For avoiding or minimizing any inconvenience or loss on the daily taxi operation and business' results, we assume that time periods between services (during which the driver is waiting for the next passenger at the stand) can be harnessed for vehicle charging. Currently, most common charging solution for EVs require the driver to plug the vehicle to a charger port by means of an electric cable that is unplugged at the end of the process. For simplicity, in this research study, the time for (un)plugging the vehicle is not accounted for, being considered that the battery of the taxi is charged during the entire period the taxi is parked in the stand, i.e., between vehicle arrival and departure. This assumption is inline with the future trend of *wireless charging* of EVs [10] that is expected to become commercially available in the next decades. Another relevant adopted assumption is the consideration that multiple taxis can be being charged simultaneously at the same stand. Our approach also considers a full availability of charging stations in all stands of the network.

To accomplish the above mentioned goals, we resort to the vehicle trajectory information collected by the taxi-link dispatching system (Section II). Trajectory data is then processed to obtain velocity profiles; to account for sensor inaccuracies (e.g. GPS positioning errors) we apply a low-pass filter termed Savitzky-Golay filter [11] to remove instantaneous signal fluctuations contained in the velocity time series $v(t)$ prior to determining the acceleration profile $a(t)$. Acceleration and velocity profiles are then used to estimate the instantaneous energy consumption of EVs using a backward model.

B. Electric vehicle consumption model

In the last decades, several models to estimate the energy consumption of pure EVs have been developed. Those models

[2]No charging losses due to the battery or charger inefficiencies are considered in this study.

TABLE I: EV model parameters

Variable	Value	Unit	Description
$v(t)$		m/s	Instantaneous speed
$a(t)$		m/s^2	Acceleration
m	1521	kg	Mass of the vehicle
g	9.8066	m/s^2	Gravitational acceleration
θ	0	$^\circ$	Road grade
C_r	1.75		Rolling coefficient
c_1	0.0328		Rolling resistance coefficient
c_2	4.575		Rolling resistance coefficient
ρ_{Air}	1.2256	kg/m^3	Air mass density
A_f	2.3316	m^2	Frontal area of the vehicle
C_D	0.428		Aerodynamic drag coefficient
η_d	92	%	Drive line efficiency [18]
η_{em}	91	%	Electric motor efficiency [19]
η_b	90	%	Battery efficiency [19]

can be divided into two categories [12]–[16]: **forward** and **backward** models. The former is fed by driver inputs (e.g., brake or accelerator pedal position) to estimate the torque required to match the desired speed of the driving cycle. Although accurate, the forward models require long execution times. Backward models use as input the drive cycle $[v = f(t)]$ and the characteristics of the vehicle (e.g., mass) to calculate the energy at the wheels. Working "backward" the energy produced by the power unit is subsequently calculated. Backward models present trustworthy estimates and faster execution times when compared to forward models. The backward models consider *steady-state* (constant environment through time) or *quasi-steady* (environment changing slowly enough to be considered constant), which can be a limitation given the dynamics of the application. However, these models represent an appealing trade-off between computational time and accuracy [17]. Due these reasons, the quasi-steady backward approach by Fiori et al. [15] was adopted for this work.

The selected model is able to efficiently predict the energy consumed by an EV using only data retrieved by a smartphone. The model inputs are the instantaneous acceleration and speed profiles, and the EV characteristics (e.g. frontal area mass) as given in Table I. The output of the model are the energy consumption (kWh/km), the instantaneous power (kW) and the State-of-Charge (SoC) of the battery (%). The power at the wheels can be calculated using Eq. 1.

$$P_{Wheels}(t) = \left(ma(t) + mg * cos(\theta) * \frac{C_r}{1000}(c_1 v(t) + c_2) + \frac{1}{2}\rho_{Air} A_f C_D v^2(t) + mg * sin(\theta) \right) * v(t) \tag{1}$$

The consumed power is then calculated using P_{Wheels}:

$$P_{Consumed}(t) = \frac{P_{Wheels}(t)}{\eta_d * \eta_{em} * \eta_b} \tag{2}$$

where η_d, η_{em} and η_b represent the drive line, electric motor and a battery efficiency, respectively. These parameters have been set based on two previous studies [18] [19].

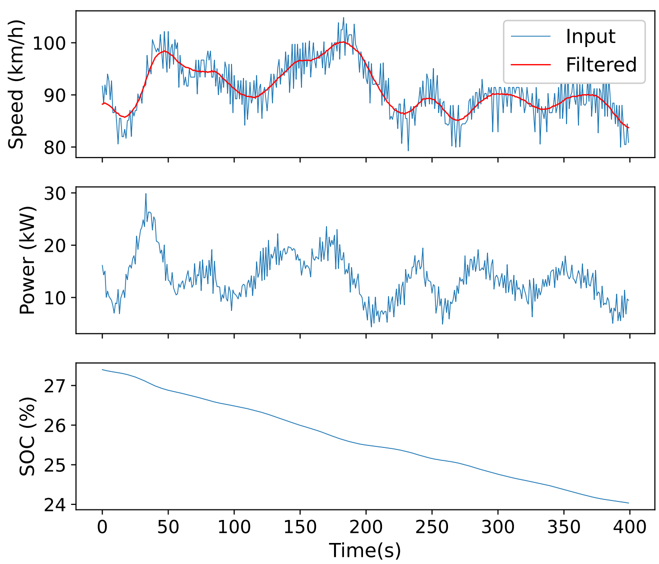


Fig. 3: Illustrative example of the energy consumption model. The noisy vehicle speed obtained from GPS data is first filtered to remove fast signal fluctuations. This smoothed speed curve is used to calculate the consumed power (middle plot) for subsequently updating the vehicle State of Charge (SoC).

The SoC is determined using Eq. 3. To represent the worst-case scenario, and given the different efficiencies of regenerative braking systems, this component is not considered.

$$SoC_{Final}(t) = SoC_0 - \sum_{i=1}^{N} \Delta SoC_{(i)}(t) \tag{3}$$

$$\Delta SoC_{(i)}(t) = SoC_{(i-1)}(t) - \frac{P_{Consumed\,(i)}(t)}{3600 * C_{bat}} \tag{4}$$

Model parameters. The settings of the main model parameters are given in Table I. The EV considered in this study was the Kia e-Niro equipped with a 64 kWh battery, whose advertised average consumption is 0.153 kWh/km. We consider this battery size adequate for taxi operation given its cost and considering the future prospects for the evolution of battery technology. Moreover, this vehicle type is already used by several taxi operators.

Illustrative Example. Fig. 3 presents an illustrative example (400 s trip) of the application of the energy consumption model. The top figure shows the speed profile obtained using GPS data (in blue), that is clearly noisy, and the signal resulting from the smoothing (in red), after filtering. As expected, the middle plot shows that the power is clearly correlated with the speed profile. The lower plot shows the reduction of the SoC due to energy consumption.

C. Model Validation

We employ three standard driving cycles (NEDC, WLTC, WMTC) to validate the model used in this paper. Our results

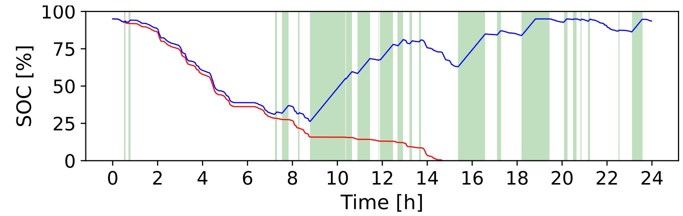


Fig. 4: State of Charge (SoC) for a given taxi and day. At the start of the day the SoC is 95%. The blue line represents the SoC for a vehicle charged during stops at taxi stands (green areas). The red line depicts the battery depletion curve if the vehicle is never charged during operation.

were compared against reference values from the Joint Research Centre (JRC) of the European Commission [20]. The results presented in Table II indicate that the implemented model accurately estimates the energy consumption with deviations varying between 1.7 and 8.4%, which are considered acceptable. Increasing the model complexity (e.g. considering additional factors and interactions) should help decrease the prediction error.

TABLE II: Model validation using standardized driving cycles

Driving Cycle	JRC [Wh/km]	Model [Wh/km]	Error (%)
NEDC	156.9	154.2	1.7
WLTC	178.4	182.2	2.1
WMTC	182.9	198.3	8.4

IV. Results

A. Autonomy analysis

We analyze and discuss the feasibility of transitioning towards electric taxi fleets resorting to large-scale empirical taxi operation data. For that purpose, the consumption model (Section III-B) is applied to the operational data of the 18 taxis, returning an estimate of the SoC level over time. As an example, Fig. 4 shows the SoC level variation of a selected taxi over a given day. The blue line represents the SoC assuming that the vehicle is charging while parking at a stand (in green), while the red line indicates the SoC level variation if the vehicle is never charged. This example highlights that periodic charging is required to satisfy the requirements of a working day, otherwise, the autonomy would be 0% after 14 h.

Fig. 5 graphically represents the SoC level of each taxi at the end of a given day. In the simulation, a SoC level of 95% was considered for all taxis at the beginning of the first day (Oct. 1st). For the majority of the vehicles, the SoC level at the end of the day remains close to the maximum level of 95%. The SoC level decreased to negative values only for 4 taxis (*d, h, n, r*), representing cases where the minimum conditions required for continuous operation are not met considering the current demand. Fig. 6 analyzes the travel distance of each service and the total number of trips executed by each taxi. We observe that the tails of the inverse Cumulative Distribution Function

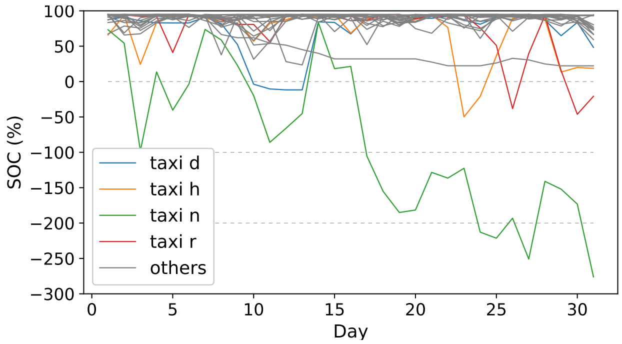
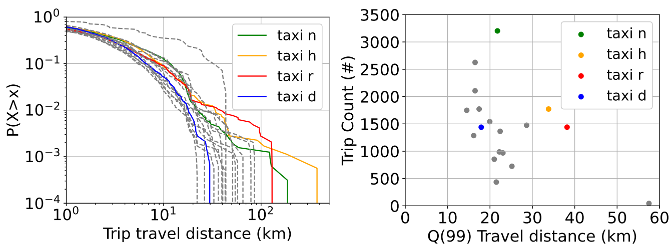


Fig. 5: Virtual State of Charge (SoC) for each individual taxi at the end of the day. The SoC for the vast majority of vehicles remains high. However, only a small subset of days and taxis do not have sufficient autonomy (negative SoC).



(a) ICDF (b) distance vs trip count

Fig. 6: Trip Travel distance for different taxis.

(iCDF) of the travel distance (Fig. 6a) are considerably longer for taxis h, n and r. Furthermore, Fig. 6b shows that these taxis perform a combination of services with larger travel distances [as measured by the 99^{th} quantile of the individual trip travel distance] (taxis h and r) and/or high number of performed services (taxi n), which increases the autonomy requirements.

Taxi n is clearly the one whose daily operation is least conducive to switching to electric mobility, attaining negative SoC values most of the days. The total travel distance of taxi n is 12912 km, which is almost three times higher than the average travel distance (4516 km). On the other hand, its average waiting time at taxi stands was just slight above 15 min, below the average value of all taxis (19 min 29 s). These two indicators help to understand the SoC values registered and lead us to believe that, in order to satisfy the current operating routines of this taxi, it would be necessary to adopt an EV with a greater autonomy, to use faster charging solutions, use hybrid operation models combining EVs and ICE vehicles, among others.

Due to the disparity of values recorded by taxi n when compared to the others, the information from that taxi was disregarded from a more general analysis of the SoC of the vehicles. Fig. 7 depicts the minimum, average and the maximum values of the SoC of all the remaining taxis at the end of each day. The results indicate that charging while parked (which is idle time) allows most of the taxis to guarantee enough autonomy to complete their operation.

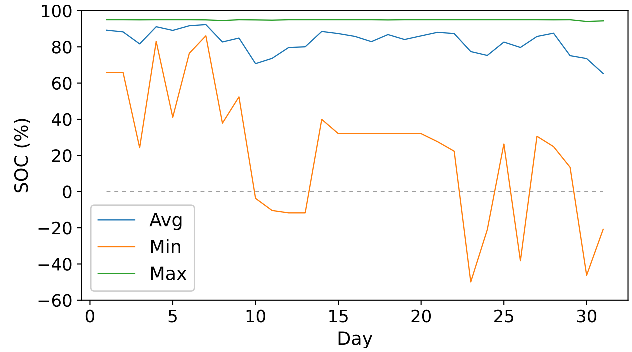


Fig. 7: Minimum, average and the maximum of SoC for all taxis (excluding taxi n)

Therefore, electric mobility of taxis is a valid alternative, allowing a considerable reduction in operating costs without loss of profitability.

B. Cost analysis

From the 407 vehicles that compose the taxi fleet operating in Porto, only 8 were pure EVs (corresponding to 1.97%) at the end of October 2021. At the end of 2020, this value was even lower at 1.50% of the EVs. This very low proportion of electric taxis in Porto is clearly far from the values recorded at the national level, where a more significant tendency towards the adoption of EV can be found. Indeed, in 2020, EVs represented a share of 5% of the light passenger vehicles sold in Portugal, while between January and October 2021 the EVs market share increased up to 8% [3]. The EV rate adoption gap (taxi fleet vs national market) can be traced to several different reasons. The high acquisition cost of EVs and the nonexistence of charging stations for exclusive use of taxis are, undoubtedly, two key factors delaying the electrification of the taxi fleet. Electric taxis currently operating are charged at the drivers' home or using a charger from the public network, whose availability varies considerable from day to day and location to location. When charging at home, drivers only pay for electricity but this period corresponds to off-duty periods that are non-existing to taxis that are explored fully, 24h a day, such as the taxis used on this study. Using chargers from the public network (mostly rapid charging stations) leads to higher charging costs, since in addition to the cost of electricity, additional service fees and taxes are charged by the operator.

Table III presents the average energy rates (diesel and electricity) in Oct. 2021, as well as a reference value for the usage of a public charging station. We also provide an estimate of the total cost for completing the average travel distance of 4516 km. This cost estimate was obtained considering an average consumption of 7 L/100 km in the case of combustion engine vehicle and of 0.153 kWh/km in case of EV. For public chargers usage, an average value of 0.40 €/kWh was assumed. These results show that, when using a home charger or low-cost charging points dedicated for taxis, the option for an

[3] https://www.uve.pt/pt

TABLE III: Cost estimate for the average travel distance (4516 km) for the month of Oct. 2021 and two energy sources

Energy Source	**Unit Price**	**Consumption**	**Total Cost (€)**
Diesel	1.604 €/L	7 L/100 km	507
Electricity	0.145 €/kWh	0.153kWh/km	100
Public Charger	0.400 €/kWh		276

EV is the most economically advantageous when compared to a combustion engine vehicle or even to the same EV being charged at public charging stations.

V. Conclusions

We studied the feasibility of using electric propulsion in combination with AC charging for taxi operation in a mid-sized European city. A data-driven evaluation has shown that conventional AC chargers installed at taxi stands would provide sufficient autonomy even for taxis operating uninterruptedly, while cutting the costs related to powering the vehicle by more than five times, compared to the cost of fossil fuel. These significant savings would support financing the replacement of ICE vehicles by new EVs just based on the operational saving related to energy costs. The assessment indicates that electric mobility is suitable for the vast majority of taxis, which clearly exhibit moderate requirements in terms of energy consumption given the current service demand.

We intend to continue studying the transition of taxi fleets towards electric mobility. The current work relies on a number of simplifying assumptions that will be relaxed in future works. The approach followed in this study contemplates the installation of charging stations in all stands. However, in practice, this approach may not be optimal due to the unnecessary excess capacity of the charging network and the corresponding higher operational costs, despite the availability of public subsidies to fund the installation of such network. We intend to study the optimal number and the location of the charging stations to be installed at the taxi stands.

Clearly, conveying the type of results reported in this paper to taxi drivers is a fundamental step towards the acceleration of the shift from ICE vehicles to EVs. Our future work will also aim at using on-board tablets and smartphones - currently the driver interface of the dispatch system - to implement a virtual dashboard of an EV, replicating the real dashboard of the current combustion engine taxis, but using metrics in the context of electric mobility, permanently displaying the SoC, the virtual charging behaviour at taxi stands, and the cost savings compared to fuel-based operation. We are convinced that graphically conveying through a virtual automotive dashboard the behaviour in terms of autonomy, charging times and energy cost savings of a typical EV will clearly show to taxi drivers the results herein reported.

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