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Machine learning approach for electric vehicle availability forecast to provide vehicle-to-home services

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Abstract

In this study, we propose a machine learning (ML) model to predict the availability of an electric vehicle (EV) providing vehicle to home (V2H) services. Electric vehicles are able to store and give back energy directly to consumers and/or the grid using V2H and/or vehicle to grid (V2G) technologies. However, there is a limited understanding of what impact vehicle availability has on the its capacity to engage in such services. Using five different vehicle usage profiles, classified by the number of trips made per week, the machine learning model proposed is used to predict the availability of an EV. An optimisation model is then used on each profile to obtain the minimum electricity bill for each profile class assuming V2H service provision. PV generation providing power to the house was also considered. The ML model had an accuracy of over 85% and R^2 value of 0.78 in predicting the location and distance travelled for the EV respectively. Final results showed that the less an EV is used for travelling, the greater its availability to participate in V2H services. Also, all categories of EV user benefited from reduced power bills when deploying V2H. An electricity cost reduction of at least 46% on average was obtained when V2H is implemented with an agile electricity price structure regardless of the level of vehicle usage.

Peer-review under responsibility of the scientific committee of the 5th Annual CDT Conference in Energy Storage & Its Applications, Professor Andrew Cruden, 2021.

Keywords: Electric vehicle; Optimisation; Machine learning; Vehicle-to-grid

1. Introduction

In 2019, the United Kingdom became the first major economy in the world to write into law targets to reduce greenhouse gas emissions to net zero by 2050 [1]. Data from 2018 showed that 33% of the greenhouse gas emissions in the UK were from the transport sector [2]. Therefore, decarbonisation transport represented a major challenge towards achieving this goal. The electrification of transport has been considered one of the most promising options to overcome this challenge. At the end of 2020, the UK government announced an initiative to ban the sales of new petrol and diesel vehicles by 2030 and push the adoption of electric vehicles (EVs) across the country [3,4].

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However, with the electrification of transport, electricity demand is expected to increase in the future as EV ownership grows with as many as 11 million EVs predicted to registered in the UK by 2030 and 36 million by 2040 [5]. This will likely require a significant investment to improve the electrical grid to cope with such increased demand [6].

Smart charging could play a key role in reducing the impact of charging a large number of EVs in the future, by charging EVs at off-peak times whilst also providing substantial benefits to energy consumers [5,7,8]. The use of this technology can also help the penetration of renewable energies by charging when there is abundant electricity generation from intermittent energy sources, such as wind and solar energy [5,9]. Furthermore, the use of Vehicle-toGrid (V2G) technologies can provide additional economic value over smart charging alone due to the possibilities of providing energy back to the electrical grid whenever is required and at the same time taking advantage of low prices in the electricity to charge when using a bidirectional charger [8,10]. Individual consumers may also take advantage of V2G on a smaller scale. For example, using Vehicle-to-home (V2H) technologies households may take advantage of periods of low demand and low cost electricity to charge their EV and later supply the household with the energy stored at periods of high electricity demand or price [11].

EVs can be considered as a type of energy storage system, albeit an intermittently available storage system, which is capable of supporting the electrical grid. Due to its intermittent availability, the integration of EVs into the electric grid must be treated differently to other energy storage systems. In order to take full advantage of V2G or V2H, the EV must be plugged into a bidirectional charger. In the UK, the average plug-in rate is below 30% which translates to four timers less revenue when compared to a 75% plug-in rate as currently there is no incentive to keep the car plugged for longer periods of time [10,12]. However, vehicles have been reported to be parked 95% of the time [13,14].

In the literature, most studies do not consider EV availability when providing V2G or V2H services, such as [15–18], even though its importance in the delivery of ancillary services is recognised [12]. Those that do consider EV availability are fairly conservative, mostly assuming availability at fixed times during the day such as a 9 to 5 schedule [19–22]. Another study used machine learning techniques to predict EV availability by using an automated machine learning model to predict the location of the EV and the likelihood of it being close to a bidirectional charger [23]. Yet another study used an ensemble machine learning-based algorithm to optimise the charging behaviour, however they did not consider any V2G or V2H services [24]. Therefore, there is a need to analyse the impact of EV availability in order to get a better perspective of the potential value of V2G and V2H.

In this study, we propose a machine learning model to predict the availability of an EV to perform V2H services [25]. An optimisation model using the Pyomo framework [26] and the Gurobi optimisation solver [27] is then used to optimise the charge/discharge behaviour of the EV in order to minimise the consumer's electricity bill. PV generation providing power to the house was also considered. A comparison between five different vehicle usage profiles and their capacity to participate in V2H services are explored.

2. Methods

A machine learning model was developed to predict the availability of an EV. The model was used to perform a comparison of different levels of vehicle usage and determine how effectively V2H services can be provided as the EV availability changes. An optimisation model was formulated and solved using the Pyomo framework [26] and the Gurobi optimisation solver [27] to minimise the electricity bill for the consumers. Transport data taken from the UK's National Travel Survey (NTS) [28] was used to train the machine learning model and predict availability of the EV. For this work we used the Nissan Leaf 2018 parameters, with a battery capacity of 38 kWh, 6 kW battery power with a 0.24 kWh/mi consumption and a charge/discharge efficiency of 93%. A fast-charging V2H enabled charger was considered for the EV simulations, with a bidirectional power flow up to a maximum of 6 kW [29].

For this work, we used the electricity consumption data [30] for 100 different households in London and PV generation readings [31] for a Greater London Household from the UK Power Networks project. Each household modelled had the same 3.5 kWp PV system. Electricity demand profile and the PV generation profiles (time resolution of 30-min) were taken from a week in winter when the electricity demand will be high compared to the annual average. For the electricity pricing, a dynamic tariff introduced by Octopus Energy in the UK where the user gets access to half-hourly energy prices tied to wholesale prices and updated daily [32] was used. We have previously demonstrated that benefits are best achieved when a dynamic tariff is used [33]. Fig. 1 shows the variations in the price of this dynamic tariff during a week in winter in 2019.

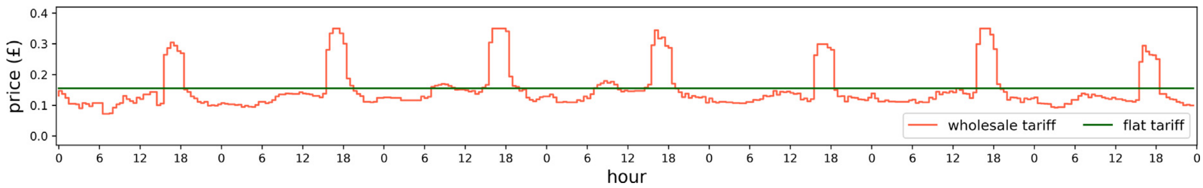

Fig. 1. Agile tariff price compared with a fixed price tariff for one week in winter.

Table 1. Example data used in this work.

Unique ID	Travel day of the week	Start hour	Start min	End hour	End min	Journey number	Trip from	Trip to	Trip distance in miles
2002000001	6	12	18	12	32	1	Home	Escort	3.0
2002000001	6	12	35	12	41	2	Escort	Work	0.5
2002000001	6	17	30	17	56	3	Work	Home	3.0
2002000001	6	20	20	20	23	4	Home	Entertain	0.3
2002000001	6	21	10	21	15	5	Entertain	Home	0.3

Table 2. Vehicle usage categories.

Vehicle usage category	Number of trips per week
Very Low	$0 < \text{trips} \leq 5$
Low	$5 < \text{trips} \leq 10$
Medium	$10 < \text{trips} \leq 15$
High	$15 < \text{trips} \leq 20$
Very High	$20 < \text{trips}$

2.1. Data pre-processing

The NTS dataset provides data on personal travel patterns such as how, why, when and where people travel in the UK. The NTS dataset was collected between 2002 and 2017 containing 4,449,163 records in total with people reporting different modes of transport. For this study, we used a subset of the NTS data with records from people that reported as drivers using their private car as their main mode of transport. This reduced the dataset to a total of 2,103,234 records. An example of the data extracted from the main dataset for this work is shown in Table 1. As there is no information on whether the vehicle is an EV or not, we assume that similar driving behaviour will apply to both EVs and internal combustion engine (ICE) vehicle drivers. As we are interested in V2H services, we assume that the vehicle will be available for V2H services, i.e. the parameter $available = 1$, whenever the vehicle is at home and the vehicle is not available, i.e. $available = 0$, whenever is not at home.

The dataset extracted from the NTS survey was split in two different datasets. The first dataset from 2002 to 2016 train and test the machine learning model with a total of 2,003,013 and 1,965,299 after cleaning. The second dataset from 2017 to identify unique drivers that fit within the five different levels of vehicle usage and as new data instances to predict whether the EV is located at home or not with a total of 100,221 and 55,236 after cleaning. In order to compare different vehicle usages and their capacity to engage in V2H services, we categorised the unique IDs from the second dataset considering the number of trips per week into five different categories, as shown in Table 2, and chose 100 unique IDs from each category at random for later analysis.

2.2. Machine learning algorithm

The machine learning tasks for this work are divided into three steps. The first, a classification problem, predicts the EV's start location, the second, a classification problem, its end location and the third, a regression problem, the total distance covered during a trip.

PyCaret [34], an open-source low-code machine learning library was used to prepare the data for the machine learning algorithm and to test different machine learning algorithms. Finally, Light Gradient Boosted Machine (LightGBM) [35] was the framework used for the three machine learning tasks.

2.3. Optimisation

Once the vehicle availability has been predicted, the charging strategy for the EV was optimised. To achieve the optimisation, we matched 100 availability profiles selected for each usage category to 100 households and a PV profile. For instance, household 1 was used with availability profile 1 of each category and the PV profile, household 2 was used with availability profile 2 of each category and the PV profile and so on. In each case, a house with power derived from the grid and a domestic PV system was modelled such that the EV, when it is not being used for transport, can be charged or used to power the house. In order to reduce the consumers' electricity bill to a minimum, the model determines the optimal charging–discharging schedule of the EV when it is plugged in at the house. The optimisation model firstly proposed by Barbour and Gonzalez [36] and used in previous work [33] is used here. It evaluates the electricity cost at each period, as shown in Eq. (1), where the net electrical load, NL_t, can be represented with D_t, which is the user's demand input/output profile, SG_t is the solar generation and ES_t is the charge or discharge action of the EV. Pr_t is the electricity price at time t. These are defined such that positive demand values represent energy drawn from the grid to charge the battery and negative demand values represents the EV providing electricity to the house or surplus PV generation. In this case, consumption from travelling when the EV is not available is also represented as negative values in this profile, i.e. a power output but which in this case does not contribute to meeting the household electricity demand, instead providing transportation.

$$cost_t = (D_t - SG_t + ES_t)Pr_t \qquad \forall t \tag{1}$$

As it is assumed that there is no payment if excess solar energy is exported to the grid, the following conditions apply as shown in Eq. (2) apply, where Pr_t^b is the buy price of electricity at time t and Pr_t^s is the sell price of electricity at time t, for this study is 0.

$$cost_t = \begin{cases} NL_t^+ Pr_t^b, & \text{if } D_t + ES_t \geq SG_t \qquad \forall t \\ NL_t^- Pr_t^s, & \text{if } D_t + ES_t < SG_t \qquad \forall t \end{cases} \tag{2}$$

The objective function shown in Eq. (3) represents the consumer's total electricity cost over the studied period.

$$min \sum_t (Pr_t^b NL_t^+ + Pr_t^s NL_t^-) \tag{3}$$

The minimisation is constrained by the physical limits of the EV's State of Charge (SOC), given by Eq. (4) with a SOC^{min} of 15% and a SOC^{max} of 85%.

SOC_t^+ and SOC_t^- are described in Eqs. (5) and (6) respectively, where E describes the energy in or out and η the efficiency rate of the EV assuming that charge and discharge efficiency are the same. SOC_t of the system is described in Eq. (7). The charge and discharge rate of the EV process are constrained by Eqs. (8), (9) and (10). The energy produced by solar generation is constrained by Eqs. (11) and (12).

$$SOC^{min} \leq SOC_t \leq SOC^{max} \qquad \forall t \tag{4}$$

$$S\hat{O}C_t^+ = (E_t^{GridIn} + E_t^{SGIn})\eta^{ch} \qquad \forall t \tag{5}$$

$$S\hat{O}C_t^- = (E_t^{LocalOut} + E_t^{SGOut})\eta^{dis} \qquad \forall t \tag{6}$$

$$SOC_t = \begin{cases} S\hat{O}C_t^+ + S\hat{O}C_t^-, & \forall t = 0 \\ SOC_{t-1} + S\hat{O}C_t^+ + S\hat{O}C_t^-, & \forall t > 0 \end{cases} \tag{7}$$

$$P^{min} \leq P_t \leq P^{max} \qquad \forall t \tag{8}$$

$$P_t^{ch} \geq E_t^{GridIn} + E_t^{SGIn} \qquad \forall t \tag{9}$$

$$P_t^{dis} \leq E_t^{LocalOut} + E_t^{SGOut} \qquad \forall t \tag{10}$$

$$E_t^{SGIn} \leq -NL_t^- \qquad \forall t \tag{11}$$

$$E_t^{SGOut} \geq -NL_t^+ \qquad \forall t \tag{12}$$

As we only aim to use energy from the EV to power the vehicle and to provide energy to the household, constraints need to be used to prevent the EV actively participating in market arbitrage. Eq. (13) prevents the EV output exceeding the net consumer demand required at time t, or that every time that the consumer is exporting solar generation at time t, the EV can only charge.

$$ES_t \geq \begin{cases} SG_t - D_t, & \text{if } SG_t \leq D_t \qquad \forall t \\ 0, & \text{if } SG_t > D_t \qquad \forall t \end{cases} \tag{13}$$

Also, to ensure the EV can only charge or discharge to give power to the house whenever it is plugged in at the house, i.e. $A_t = 1$, therefore we introduce additional constraints described in Eq. (14) and Eqs. (15), (16) where M is a very large number.

$$\begin{cases} NL_t^- \geq D_t - SG_t, & \text{if } A_t = 0 \\ & \text{and } SG_t > D_t, \qquad \forall t \\ NL_t^- \leq 0, & \text{otherwise}, \qquad \forall t \end{cases} \tag{14}$$

$$0 \leq S\hat{O}C_t^+ \leq M \cdot A_t \qquad \forall t \tag{15}$$

$$0 \leq NL_t^+ \leq M \cdot A_t \qquad \forall t \tag{16}$$

3. Results

The ability of each of the three parts of the machine learning task to accurately predict the correct outcome and therefore collectively determine the availability of an EV in each vehicle usage category was assessed.

3.1. Model analysis

The first dataset containing data from 2002 to 2016 was used to train and test the model in each of the three learning tasks described previously. Fig. 2 shows the confusion matrix for the first part, where the *where is it coming from* part was predicted, showing an overall accuracy of 86.00% in the test set.

For the first learning task, the model showed a slightly higher percentage of misclassification when the EV is available (true label = 1) returning that the EV is not available (predicted label = 0), compared to the percentage when the EV is not available (true label = 0) returning that the EV is available (predicted label = 1).

Fig. 3 shows the confusion matrix for the second learning task, where the *where is it going to* part was predicted, showing an overall accuracy of 85.88% in the test set.

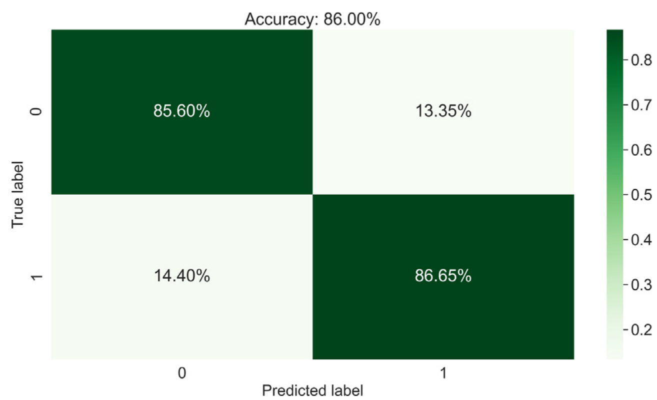

Fig. 2. Confusion matrix for the first *where is it coming from* part of the learning task. The labels indicate predicted location of the EV.

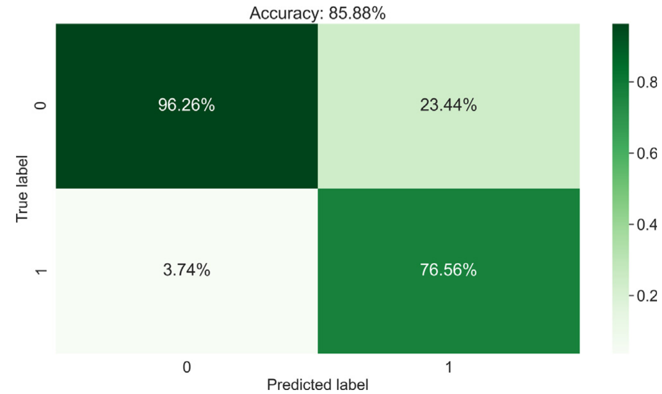

Fig. 3. Confusion matrix for the second *where is it going to* part of the learning task. The labels indicate predicted location of the EV.

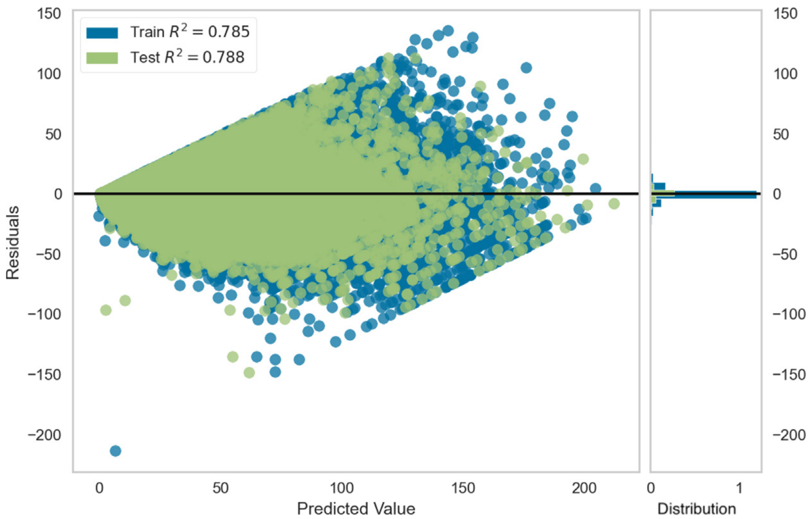

Fig. 4. Residual vs predicted values for the third part of the learning task.

For the second learning task, the model shows a bigger deviation when predicting the destination of the EV. The model seems to struggle to classify when the EV is not available (true label = 0) returning that the EV is available (predicted label = 1),), on the other hand, the model seems to have no trouble classifying when the EV is available (true label = 1) returning only a small number of misclassifications (predicted label = 0)

Fig. 4 shows a plot of the residuals (the difference between the predicted and actual journey length) against predicted values from the third learning task, where the distance travelled was predicted, showing that the results are symmetrically distributed and closer to 0, with an $R^2 = 0.785$ in the training set and a very slightly better $R^2 = 0.788$ in the test set.

3.2. Optimisation analysis

Fig. 5 shows the plot of a successfully optimised profile during one week. Table 3 shows the results of the optimisation of the EV charging schedule to reduce the electricity bill in each vehicle usage category, showing the number of successful profiles out of 100 profiles per category, that were capable of performing V2H during the week and the mean electricity cost for a week with and without V2H. Also shown is the data for the minimum, mean and maximum percentage of time available during the week for each category and the mean electricity cost for a week with and without V2H.

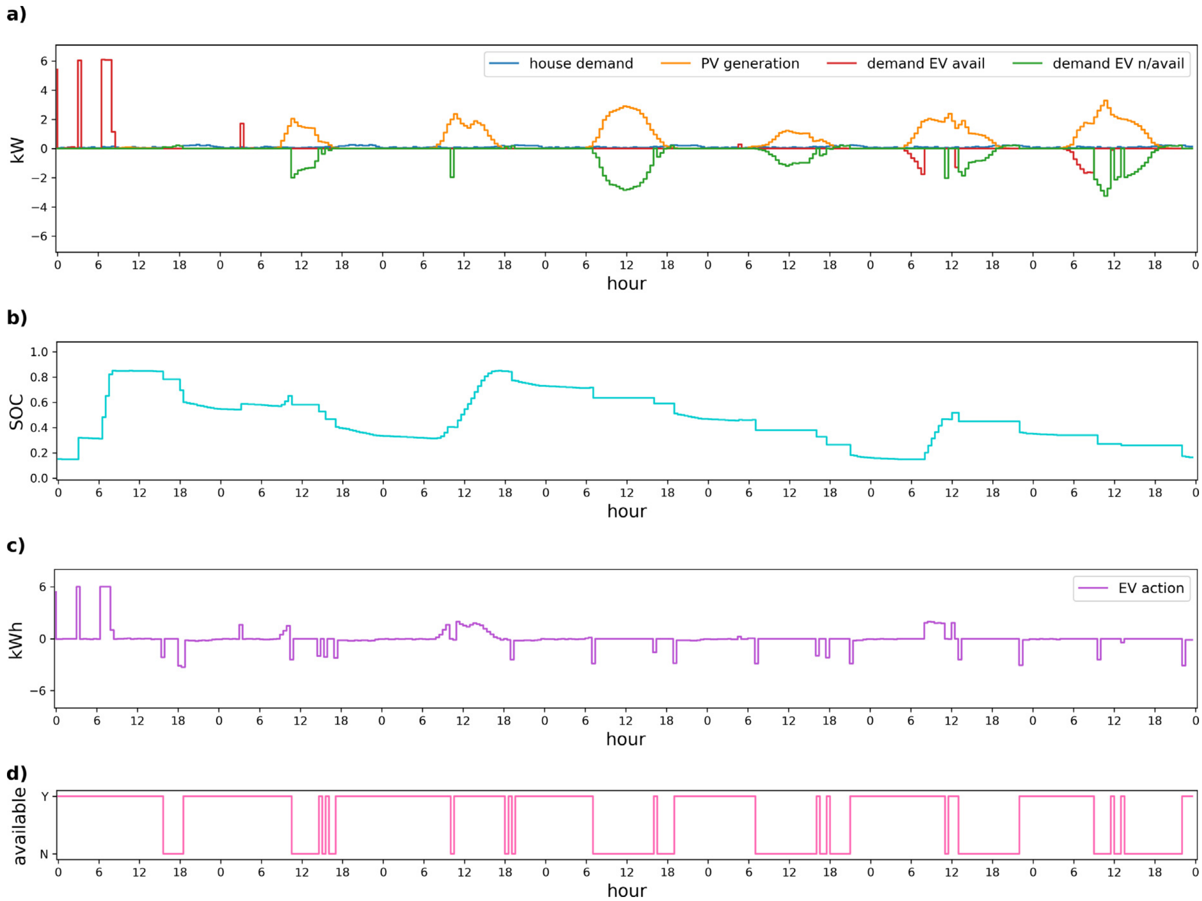

Fig. 5. An example of a very high vehicle usage category profile for a week. **(a)** Demand profile. **(b)** SOC of the EV. **(c)** Input/output profile of the EV. **(d)** Availability profile.

Table 3. Results from the optimisation algorithm for each of the different vehicle usage categories including the number of profiles where the solver found an optimal solution per category, the minimum, average and maximum percentages of time available, the average electricity cost with and without V2H per week and the mean saving achieved by incorporating V2H.

Vehicle usage category	No. of successful profiles	Min. availability rate (%)	Mean availability rate (%)	Max. availability rate (%)	Mean cost with V2H (£)	Mean cost without V2H (£)	Mean saving (£)	% saving
Very Low	98	15.5	77.4	99.7	3.44	6.78	3.34	49
Low	91	22.0	80.8	97.9	4.17	9.27	5.10	55
Medium	83	23.8	76.1	96.4	5.53	11.69	6.61	56
High	72	36.9	70.3	92.0	6.73	13.24	6.51	49
Very High	71	44.3	67.0	85.4	7.18	13.15	6.05	46

For each category, the minimum available rate represents the minimum amount of time during the week that the EV was predicted to be at home and therefore able to engage in V2H and minimise the consumer's total electricity bill. For example, in the case of the very high vehicle usage category, the EV was predicted to be available at least of 44.3% of the time during the week and therefore able to perform V2H services.

The minimum predicted time available was significantly increased as the vehicle usage increased. This may be due the vehicle being more likely to be predicted to return to the residence sooner when the frequency of journeys is higher

The mean availability does not fall below 67%, even for the very high vehicle usage category. The mean saving achieved is greatest for the medium vehicle usage category. This is presumably due to a trade-off between high availability (at low vehicle usage) and greater potential savings (at high vehicle usage) when the total electricity cost is higher. In general a reduction of approximately half the total electricity cost is achieved in all vehicle usage categories when using V2H services compared when it is not used.

4. Discussion

The machine learning approach in this work managed to predict the origin and destination locations of an EV to provide V2H with an accuracy over 85.00% for the classification problems and achieve an R^2 over 0.78 for the regression problem used to predict the journey distance. It should be noted that by dividing the learning approach in three parts, there is the risk of carrying the errors from a previous step through into the next step, which may explain why the second part of the leaning approach had problems classifying accurately when the EV is not available ($availability = 0$). The ideal approach would be to try and predict the three desired parameters independently. Moreover, with the approach taken, there is also the theoretical risk of having *round trips* that start from Home and end at Home, effectively keeping the availability untouched. The final datasets were checked and fortunately, we did not find any journeys like this in our final datasets. This may be because in the training dataset there are no *round trips* i.e. coming from Home ($availability = 1$) and going to Home ($availability = 1$).

The mean availability remains high for all the high vehicle usage categories reducing slightly to smallest mean availability of 67% for the most frequently vehicle usage category. When V2H is deployed there are significant electricity savings made for all categories. This is attributed of the ability to take advantage of the low electricity prices and PV generation whenever the sun is out or the combination of both to charge the EV and therefore avoiding buying electricity when prices are high.

In terms of the average cost of the electricity, unsurprisingly, it is seen to increase when the EV usage is higher due the increase power needed to charge the EV, regardless of whether V2H is deployed or not. When V2H services are used, the average electricity cost per week is significantly lower. There is a general trend whereby the mean electricity cost is reduced by around half with V2H compared with the electricity cost when V2H services are not deployed.

5. Conclusion

In this work, a machine learning model was trained and used to predict the availability of an EV to perform V2H services and an optimisation model formulated using the Pyomo framework and solved with the Gurobi optimisation solver was then able to minimise the consumer's electricity bill for a range of vehicle usage categories. A comparison between five different vehicle usage profiles (very low usage, low usage, medium usage, high usage and very high usage) in order to assess their availability to engage in V2H services and the cost savings that can be achieved. The machine learning task was divided into three parts, two classification problems and one regression model. The machine learning model was trained and tested using the NTS dataset from 2002 to 2016 and data from 2017 was used to identify the profiles for each different vehicle usage category and as new data instances to predict whether the EV is at home or not. The machine learning model performed satisfactorily showing an accuracy over 85.00% for the classification problems which predicted the original and final location of the EV and an R^2 over 0.78 for the regression problem to predict the journey length. Each predicted availability profile was then matched with a different household and a PV generation profile. The data was subdivided into five different vehicle usage categories: very low, low, medium, high and very high usage. An optimisation model was applied for every profile in order to minimise the consumer's electricity bill. With this information, more than 70 profiles per category were successfully optimised and their feasibility to provide V2H services determined.

We concluded that the fewer trip an EV is used for, the higher its availability to engage in V2H services. Also, all categories of EV usage benefit from reduced power bills when deploying V2H. The high and very high EV user categories, unsurprisingly had the highest electricity bills, however they were found to save the most in absolute terms by deploying V2H because they had the largest bills to start with. In general, even the very low vehicle usage category saved significantly. It is estimated that having a V2H capable EV should reduce electricity costs by 46% regardless of the level of vehicle usage because for even very high usage categories the vehicle was available for V2H services for 67% of the time on average.

However, many factors need to be considered that can impact the benefits of providing V2H services such as the electricity demand from the house, the number of trips per day, the time of the day when a trip takes place and the amount of time between each trip which will be explored in future work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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