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Exploring the possibility to provide black start services by using vehicle-to-grid

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Abstract

Black start is one of the most important ancillary services that should be required by National Grid in the UK which traditionally has been provided by large power stations. However, the current shift towards greener technologies have opened the door to non-traditional technologies. In this study, we explored electric vehicles (EVs) and the minimum state of charge (SOC) that can be held by a fleet of EVs during a week that could potentially be used to help provide this service while providing Vehicle-to-home (V2H) services to minimise the consumers' electricity bill. We also explored the impact of different photovoltaic (PV) penetration rates and different electricity tariffs through four different weeks of the year. In this study, we use a machine learning model classifier to predict the *start* and *end* locations of real-world EV travel data in England. These predictions are then used in an optimisation model to generate the SOC percentage and the consumers' total electricity cost for the different scenarios. The machine learning model classifier model had an overall accuracy of over 85.80%. Final results showed that PV penetration rates and different electricity tariffs have an impact on the amount of SOC percentage that can be held during a week for all EVs that could potentially be used in the case of a shutdown and the consumers' final weekly electricity cost. We found that using a dynamic tariff that follows the wholesale electricity market, the SOC percentages to provide black start services can be kept above 40% during the week and at the same time returning a total electricity cost under £30.00 per week.

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

1. Introduction

Black start is one of the most important ancillary services that an electrical grid should requires in order *to keep the lights on*. This service is required to start the grid after a partial or total shutdown of the nations electrical grid [1]. Traditionally, the provision of black start has been provided by large power stations, however, over the last couple of years, the energy sector has shifted towards a greener future [2]. This transition has lead to exploring

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different non-traditional technologies that could be able to support the provision of black start [3]. Considering the increasing number of distributed energy resources [4,5], non-traditional technologies such as electric vehicle (EVs) have been explored by the National Grid ESO [3] as an option to provide black start. This report found that one if the biggest challenges to consider for EVs to participate in the provision of Black Start is the uncertainty surrounding the EVs' availability and state of charge (SOC) during a given time.

Therefore, in this study we explored the minimum SOC that can be held by EVs during a certain period of time, in this case a week, and that would permit them to be potentially used for Black Start in the case of a partial or total shutdown while providing V2G services. In order to achieve this, we proposed a machine learning model to predict the *start* and *end* locations of real-world EV trip data in England and therefore their availability to provide V2G services, which in this case was focused on the provision of vehicle to home (V2H) [6] where we aim to minimise the consumers' electricity bill by optimising their charge/discharge cycles when they are at *Home* by designing an optimisation model using the Pyomo framework [7] and Gurobi optimisation solver [8]. Furthermore, we also explored the impact that photovoltaic (PV) penetration and different tariffs during four weeks of the year can have on both minimising the consumers' electricity bill and the amount of SOC that can be held at all times by the EVs during this period time and then potentially be used for Black Start in the case of a shutdown.

2. Methods

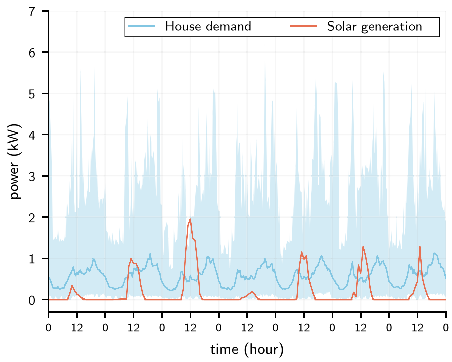
A multi-class machine learning classifier was developed to predict the availability of an EV which is based on the machine learning model reported in previous work by Aguilar-Dominguez et al. [9]. The model was used to determine the location of the EVs and therefore their availability to engage in V2H services. An optimisation model was formulated and solved using the Pyomo 6.3.0 framework [7]. The model was solved using Gurobi 9.5.0 optimisation solver [8]. Transport data taken from the UK's National Travel Survey (NTS) [10] from 2002 to 2019 was used to train the machine learning model and predict the location of the EVs. For this work we used the Nissan Leaf 2018 parameters, with a battery capacity of 37 kWh [11]. A 7.4 kW V2H enabled charger was considered for the EV simulations [12]. For street charging, rapid charge up to 50 kW [13] was used to avoid infeasibility during the optimisation process.

2.1. Case study

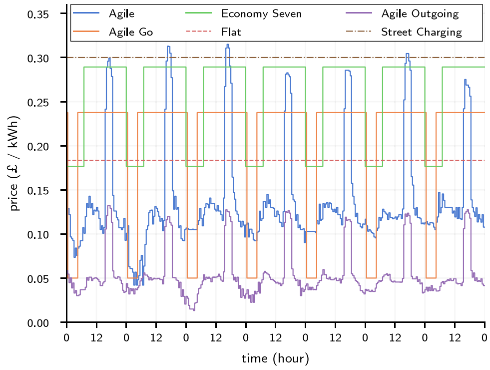
For this work, we used electricity consumption data [14] containing energy consumption readings for 5567 London Households and PV generation data that was collected by UK Power Networks [15] over 480 days between 2013 and 2014 in the Greater London area. The final sample of households is then taken as a stratified sample by total energy consumption through the year of profiles where the total consumption is between 3000 and 5000 kWh per year. This range is according to the average household electricity consumption in the UK is 3731 kWh per year [16,17]. Each household modelled had the same 3.5 kWp PV system. Electricity consumption profiles and the PV generation profile were interpolated from a 30-min resolution into a 1-min time resolution for one week for each of the four seasons of the year. Fig. 1(a) shows the electricity demand of all profiles used and PV generation during a week in winter. We also used data collected by EA Technology [18] containing real residential EV users' travel data in England. Again, the final sample of EVs is considered as a stratified sample by total number of trips per annum.

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 [19] was used. This data has also been reported in previous work by Aguilar-Dominguez et al. [9,20]. Data containing electricity prices for a flat tariff [21], an economy seven tariff [21] and a recently introduced tariff from Octopus Energy called agile go [22]. The price of these tariffs are for the *WC1E 6BT* London area. Finally, street charging electricity price [13] and surplus generation selling prices for London [23] were used. Fig. 1(b) shows a summary of the electricity pricing data used for a week in winter.

Moreover, we explored how PV penetration through the four seasons of the year and different tariffs can impact the minimum SOC that can be sustained at all times by all the EVs when engaging in V2H and are used for their main purpose of travel. For this, we consider PV penetration rates of 0%, 10%, 25%, 50%, 75%, 90% and 100% using the four different tariffs previously described. Moreover, four different weeks representative of the four season of the year were studied which are January 12 to January 19 for winter, April 13 to April 20 for spring, July 20 to July 27 for summer and October 6 to October 13 for autumn. This gives a total of 112 different scenarios.



(a)



(b)

Fig. 1. Data for a week in winter from Monday to Sunday. a. Household electricity consumption mean, min and max aggregated values and PV generation. b. Electricity tariff prices.

2.2. Data pre-processing

As reported by Aguilar-Dominguez et al. [9], the NTS dataset provides data on personal travel patterns such as how, why, when and where people travel in the UK. For this work, we used data collected between 2002 and 2019. We filtered the data to users that were reported as the main driver of a private vehicle.

2.3. Machine learning algorithm

The machine learning tasks for this work are divided into two steps. Both are classification models, where the first task predicts the EV's *start* location and the second task, predicts its *end* location. The predicted locations are: *Home*, *Work* and *Other*. For each task, a total of 1,060,029 rows of data were used which then later was split into training and test set with a split of 70% and 30% of data, respectively.

After preparing the data for each task, we used a Light Gradient Boosted Machine framework [24] for both tasks. Finally, the resulting models were used to predict the location of the EA technology dataset [18].

2.4. Optimisation

After the vehicles' location has been predicted, the resulting data was used in the optimisation model. The final stratified data included 50 profiles which was then used consistently for all scenarios described above. The optimisation model used was originally adapted from Barbour and González [25] and later used in Aguilar-Dominguez et al. [9,20].

The model is constrained by the physical limits of the EV's SOC, given by Eq. (1). For this work we consider $E^{SOC_{min}} = 0.05$ and $E^{SOC_{max}} = 0.95$

$$E^{SOC_{min}} \leq E^{SOC}_{v,t} \leq E^{SOC_{max}} \tag{1}$$

Eqs. (2)–(4) describe the energy stored inside the battery for each vehicle including the initial and final values where η refers to the efficiency of the charger. $E^{SOC}_{v,t}$ refers to the state of charge of the electric vehicle at time t. SOC^{init} and SOC^{final} are the initial and final state of charge values for each electric vehicle, 50% of the original battery capacity in both cases. $E^{charge}_{v,t}$ refers to the energy charged to the EV at time t when at *Home*. $E^{discharge}_{v,t}$ refers to the energy discharged to the house at time t. $E^{charge_{street}}_{v,t}$ refers to the energy charged to the EV at time t when at *Other*. $E^{vehicle}_{v,t}$ refers to the energy required for each trip at time t.

$$E^{SOC}_{v,init} = SOC^{init} * E^{SOC} \tag{2}$$

$$E^{SOC}_{v,final} \geq SOC^{final} * E^{SOC} \tag{3}$$

$$E_{v,t}^{SOC} = E_{v,t-1}^{SOC} + \left[\left(E_{v,t}^{charge} + E_{v,t}^{charge_{street}} \right) * \eta \right] - \left[E_{v,t}^{discharge} * (1/\eta) \right] - E_{v,t}^{vehicle}, \quad t > 0 \tag{4}$$

Eq. (5) imposes the minimum SOC percentage that could potentially be used for black start if required, where $E^{threshold}$ refers to the coefficient that will determine the minimum SOC that can be held during at all times for all EVs.

$$E_{v,t}^{SOC} \geq E_{v,t}^{SOC} * \left(E^{threshold}/100 \right) \tag{5}$$

Eqs. (6) and (7) describe the power balance and the power net coming from each household, respectively, where $E_{v,t}^{import}$ and $E_{v,t}^{export}$ are the energy imported and exported from and to the grid at time t. $E_{v,t}^{solar}$ refers to the solar generation at time t. E^{house} is the energy required from the house at time t. $E_{v,t}^{net}$ is the net load for each household at time t.

$$E_{v,t}^{solar} + E_{v,t}^{import} + E_{v,t}^{discharge} = E_{v,t}^{house} + E_{v,t}^{export} + E_{v,t}^{charge} \tag{6}$$

$$E_{v,t}^{net} = E_{v,t}^{import} - E_{v,t}^{export} \tag{7}$$

Eqs. (8) and (9) prevent energy import when energy is exported from the house. $B_{v,t}^{export}$ is a boolean variable. Eqs. (10) and (11) control the charge/discharge cycles of the EVs. Eq. (12) manages street charging. Eq. (13) restricts charge and discharge at the same time when the EV is available at home. Where $B_{v,t}^{charge}$ and $B_{v,t}^{discharge}$ are booleans variables. $\alpha_{v,t}^{home}$ describes the availability at home of each electric vehicle to charge or discharge at time t. $\alpha_{v,t}^{street}$ describes the availability to be charged using a street charger at time t. In both cases, 1 means available and 0 not available.

$$E_{v,t}^{import} \leq \left(1 - B_{v,t}^{export} \right) * 10^3 \tag{8}$$

$$E_{v,t}^{export} \leq B_{v,t}^{export} * 10^3 \tag{9}$$

$$E_{v,t}^{charge} \leq B_{v,t}^{charge} * 10^3 \tag{10}$$

$$E_{v,t}^{discharge} \leq B_{v,t}^{discharge} * 10^3 \tag{11}$$

$$E_{v,t}^{charge_{street}} \leq \alpha_{v,t}^{street} * 10^3 \tag{12}$$

$$B_{v,t}^{charge} + B_{v,t}^{discharge} \leq \alpha_{v,t}^{home} \tag{13}$$

Eq. (14) prevents the EV participating in arbitrage and providing energy to the house when solar energy is not enough. Eq. (15) constraint the power imported to be equal or less than the energy required from the house or the charger's maximum power as required.

$$\begin{cases} E_{v,t}^{discharge} \leq \left| E_{v,t}^{solar} - E_{v,t}^{house} \right|, & \text{if } E_{v,t}^{solar} - E_{v,t}^{house} \leq 0 \\ E_{v,t}^{discharge} \leq 0, & \text{otherwise} \end{cases} \tag{14}$$

$$\begin{cases} E_{v,t}^{import} \leq E_{v,t}^{house}, & \text{if } E_{v,t}^{house} \geq P^{max} \\ E_{v,t}^{import} \leq P^{max}, & \text{otherwise} \end{cases} \tag{15}$$

In order to minimise the users' electricity bill while maximising the SOC percentage that is held at all times for all electric vehicles and potentially used for black start, the following equation is minimised:

$$min \left\{ \sum_v \left[\sum_t \left(Price_t^{buy} * E_{v,t}^{import} \right) + \sum_t \left(Price_t^{sell_{street}} * E_{v,t}^{charge_{street}} \right) - \sum_t \left(Price_t^{sell} * E_{v,t}^{export} \right) \right] - E^{threshold} \right\} \tag{16}$$

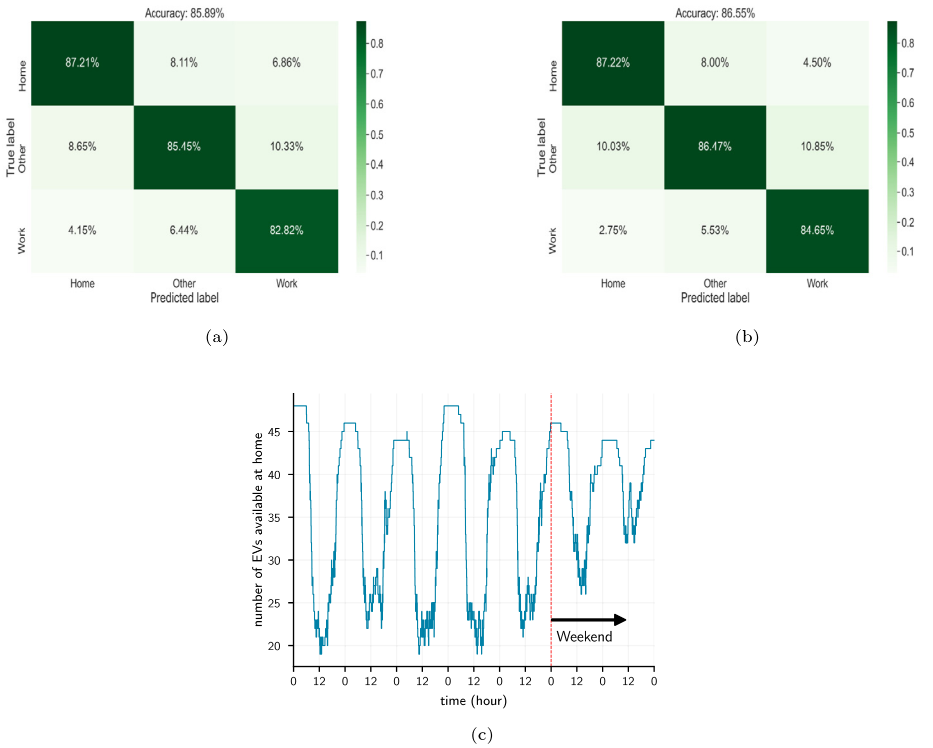


Fig. 2. Metrics of the machine learning classification models and resulting predictions. a. First task, confusion matrix where the *start* location was predicted. b. Second task, confusion matrix where the *end* location was predicted. c. Total number of EVs available at *Home* during one week in winter from Monday to Sunday.

3. Results

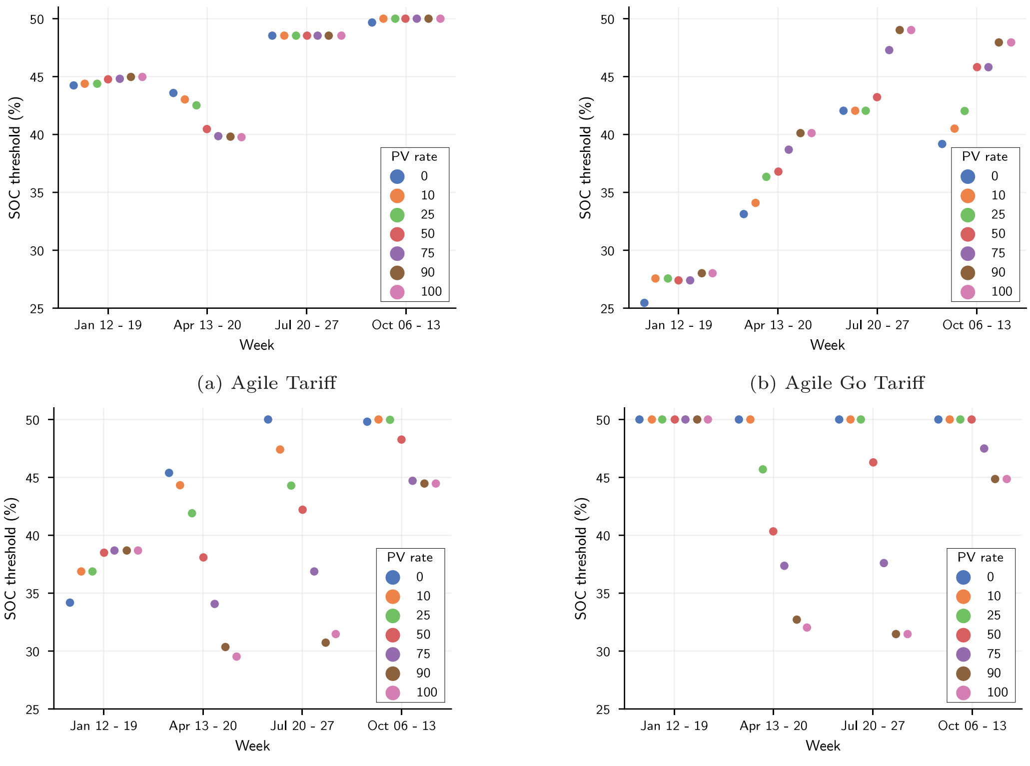
3.1. Machine learning analysis

NTS data containing travel patterns in the UK from 2002 to 2019 was examined. Figs. 2(a) and 2(b) show the resulting confusion matrix for both parts of the machine learning model, which predicts the *start* and *end* locations, respectively. For the first part, where the *start* location was predicted, showing a positive ratio over 82.00% for all labels and overall accuracy of 86.00% was achieved in the test set. For the second part, where the *end* location was predicted, a true positive ratio over 84.00% and overall accuracy of 85.88% was achieved in the test set. Fig. 2(c) shows the total number of electric vehicles predicted to be at *Home* during a week in winter. A trend can be seen where the majority of EVs are at *Home* after around 19:00 h and they are away between 08:00 and 18:00. It also shows that during the weekdays fewer EVs can be expected to be at *Home* when compared to the weekend.

3.2. Optimisation analysis

An optimisation model was used to reduce the electricity bill in each vehicle and get the maximum SOC that can be held at all times for all EVs that could potentially be used for black start by scheduling their charge/discharge cycles.

Fig. 3 shows the minimum SOC that can be held during a week for all EVs through the four weeks of the year, the four tariffs and the different PV penetration rates. Fig. 3(a) shows the Agile tariff where the SOC percentages vary between 40% and 50%. For this tariff different PV penetration rates tend to increase the SOC percentage slowly the higher the PV penetration rate is for most weeks, with only the week during spring shows a decrease of SOC percentage the higher the PV penetration rate is. Fig. 3(b) shows the Agile Go tariff with SOC percentages as



(a) Agile Tariff

(b) Agile Go Tariff

(c) Economy Seven Tariff

(d) Flat Tariff

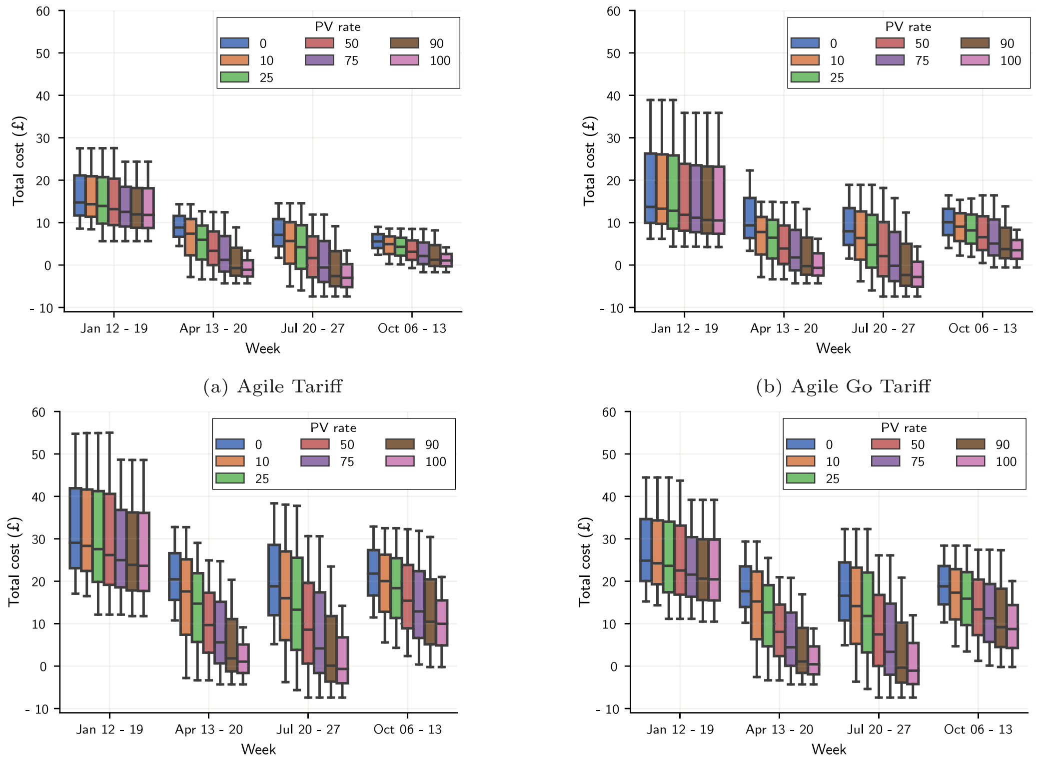
Fig. 3. Minimum SOC that can be hold at during a week for all EVs through the four weeks of the year, four different tariffs and different PV penetration rates that could potentially be used for Black Start in the case of a total or partial shutdown.

low as 25% and as high as around 50%. PV penetration rates seem to have an impact through all weeks. The higher the PV penetration rate, the higher SOC percentage can be sustained. Fig. 3(c) shows the Economy Seven tariff with SOC percentages are between around 30% and can go up to around 50%. PV penetration rates here seems to have the opposite impact as the previous tariff where the higher the PV rate is, the lower the SOC percentage is for most weeks. Fig. 3(d) shows the Flat tariff where the SOC percentages achieve a 50% in most weeks and most PV penetration rates. In this tariff, the lower the PV penetration rate, the higher the SOC percentage is and decreasing the higher the PV penetration rate is in all seasons except for winter, which shows a steady 50% regardless of the PV penetration rate.

Fig. 4 shows the total electricity costs for all the parameters tested in this work. In general, the total cost follows a trend where the prices are low for all tariffs and weeks as long as the PV penetration rates go up. This is because depending to the tariff and time of the day, it might be more beneficial to sell any solar generation surplus to the grid rather than use it to charge the EV, which might also affect the SOC percentages that can be held at all times as there is no incentive to use that surplus energy to charge the EV and increase the SOC of the EV. Moreover, the higher the PV rate is present, the lower the price will be across the four weeks of the year tested in this work. Total electricity cost can range between around -£10.00 and around £60.00, where negative values indicate that the household will be payed (i.e. from selling solar surplus).

4. Conclusion and further work

In this work, a machine learning model was trained to categorise the *start* and *end* locations of a vehicle into three different locations, *Home*, *Work* and *Other*. The model was used to predict the location of real-world EV users' travel data in England. The machine learning task was split into predicting the *start* and *end* locations of an EV. For this task, NTS data from 2002 to 2019 was used to train both classification models. The machine learning model was able to achieve a true positive ratio over 82% for both tasks.



(a) Agile Tariff (b) Agile Go Tariff

(c) Economy Seven Tariff (d) Flat Tariff

Fig. 4. Total electricity cost for each household per week with different tariffs and PV penetration rates.

The resulting predictions were fed into an optimisation model formulated that was designed using the Pyomo framework and solved with the Gurobi optimisation solver. Household electricity consumption data and PV generation data collected between 2013 and 2014 from the Greater London Area was used. Four weeks representative of the four seasons of the year, different electricity tariffs and PV penetration rates were explored in order to know the impact on the amount of SOC that can be held at all times by all EVs that could be used for Black Start in the case of a total or partial shutdown while also providing V2H services to minimise the consumers' electricity bill.

We concluded that different tariffs and different PV penetration rates have an impact on the amount of SOC percentage that can be hold during a week for all EVs that could potentially be used in the case of a shutdown and the consumers' final weekly electricity cost. For the Agile and Agile Go tariffs, PV penetration rates mostly have a positive impact across most of the four weeks tested showing an increase on the SOC percentage consistent to higher PV penetration rates. Opposite to this, Economy Seven and Flat tariffs show a decrease on the amount of SOC percentage whenever the PV rates are high. Surprisingly, the Flat tariff returns the most consistent highest SOC percentages in most weeks with 50% regardless of the PV penetration rate, however, this is at the expense to the customer because the Flat tariff is the one of the most expensive. With Agile tariff the SOC percentage is between around 40% and 50%. The remaining two tariffs, Economy Seven and Agile Go, return SOC percentages between 25% and 50% where lower PV rate for the Economy Seven showed an increase on the SOC percentage and for the Agile Go higher PV penetration rates increased SOC percentages.

Different factors should be considered when providing V2H services, such as the amount of energy required for each different household, EV owners travel behaviour and the location of such household that might impact the solar generation. In general, PV penetration does help to reduce the total electricity costs. Overall, to be available with as much charge as possible for black start at all times, whilst maintaining a low cost for the customer is best for the consumer to be on the Agile Tariff with as much PV as affordable. Using this tariff, the SOC can be kept above 40% during the week and the total electricity cost less than £30.00 per week.

In this work we did not consider any incentive for holding a certain SOC percentage at all times during the week, which by doing so might change the SOC percentage during different weeks of the year, PV penetration rates and tariffs used. Also, we did not simulated a black start event. Both of these will be consider 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.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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References

[1] National Grid ESO. National grid. 2021, URL https://www.nationalgrideso.com/balancing-services/system-security-services/black-start.
[2] Ofgem. Implications of the transition to electric vehicles. Technical report, OFGEM; 2018, URL https://www.ofgem.gov.uk/ofgem-publications/136142.
[3] National Grid ESO. Black start from non-traditional generation technologies. 2019, p. 1–20, URL https://www.nationalgrideso.com/document/148201/download.
[4] Knezović Katarina, Marinelli Mattia, Zecchino Antonio, Andersen Peter Bach, Traeholt Chresten. Supporting involvement of electric vehicles in distribution grids: Lowering the barriers for a proactive integration. Energy 2017;134:458–68. http://dx.doi.org/10.1016/j.energy.2017.06.075.
[5] Thomas Dimitrios, Deblecker Olivier, Ioakimidis Christos S. Optimal operation of an energy management system for a grid-connected smart building considering photovoltaics' uncertainty and stochastic electric vehicles' driving schedule. Appl Energy 2018;210:1188–206. http://dx.doi.org/10.1016/j.apenergy.2017.07.035.
[6] Nissan. "Leaf to home" electricity supply system | NISSAN | technological development activities. 2016, URL http://www.nissan-global.com/EN/TECHNOLOGY/OVERVIEW/leaf_to_home.html.
[7] Hart William E, Laird Carl D, Watson Jean-Paul, Woodruff David L, Hackebeil Gabriel A, Nicholson Bethany L, Siirola. John D. Pyomo – Optimization modeling in Python. second ed. Springer; 2017.
[8] Gurobi. Gurobi - The fastest solver. 2018, URL https://www.gurobi.com/.
[9] Aguilar-Dominguez Donovan, Ejeh Jude, Dunbar Alan DF, Brown Solomon F. Machine learning approach for electric vehicle availability forecast to provide vehicle-to-home services. Energy Rep 2021;7:71–80. http://dx.doi.org/10.1016/j.egyr.2021.02.053.
[10] UK Government. National Travel Survey: 2017 - GOV.UK. 2017, URL https://www.gov.uk/government/statistics/national-travel-survey-2017.
[11] Electric Vehicle Database. Nissan Leaf price and specifications - EV Database, URL https://ev-database.uk/car/1106/Nissan-Leaf.
[12] Quasar. 07/01/2020 Wallbox quasar | the first bidirectional charger for your home. 2020, URL https://wallbox.com/en_uk/quasar-dc-charger.
[13] Zap-Map. How Much Does it Cost to Charge an Electric Car? | Vivint Solar, URL https://www.zap-map.com/tools/public-charging-calculator/.
[14] UK Power Networks. Smart meter energy consumption data in London households - London datastore. 2015, URL https://data.london.gov.uk/dataset/smartmeter-energy-use-data-in-london-households.
[15] UK Power Networks. Photovoltaic solar panel energy generation data - London datastore. 2017, URL https://data.london.gov.uk/dataset/photovoltaic--pv--solar-panel-energy-generation-data.
[16] UK Government. Energy consumption in the UK 2020 - GOV.UK. 2020, URL https://www.gov.uk/government/statistics/energy-consumption-in-the-uk-2020.
[17] Topping C. Average electricity usage in the UK: How many kwh does your home use? | OVO energy. In: OVO Energy. 2021, URL https://www.ovoenergy.com/guides/energy-guides/how-much-electricity-does-a-home-use.
[18] EA Technology. My electric avenue summary report. 2015, URL https://www.eatechnology.com/projects/my-electric-avenue/.
[19] Octopus Energy. Agile octopus | octopus energy. 2019, URL https://octopus.energy/agile/.
[20] Aguilar-Dominguez Donovan, Dunbar Alan, Brown Solomon. The electricity demand of an EV providing power via vehicle-to-home and its potential impact on the grid with different electricity price tariffs. In: Energy reports. vol. 6, Elsevier Ltd; 2020, p. 132–41. http://dx.doi.org/10.1016/j.egyr.2020.03.007.
[21] Octopus Energy. All our tariffs | octopus energy. 2021, URL https://octopus.energy/tariffs/.
[22] Octopus Energy. Introducing octopus go. 2021, URL https://octopus.energy/go/.

[23] Octopus Energy. Outgoing octopus | octopus energy. 2021c, https://octopus.energy/outgoing/, https://octopus.energy/outgoing/?gclid=CjwKCAiAkJKCBhAyEiwAKQBCkrC2So2hxynTlgID2x2-x3nL3LWQvpHyjrLRtS1AgVQD7jpBWZXWjhoC0JwQAvD_BwE.

[24] Ke Guolin, Meng Qi, Finley Thomas, Wang Taifeng, Chen Wei, Ma Weidong, Ye Qiwei, Liu Tie Yan. LightGBM: A highly efficient gradient boosting decision tree. Adv Neural Inf Process Syst 2017;2017-Decem(Nips):3147–55.

[25] Barbour Edward, González Marta C. Projecting battery adoption in the prosumer era. Appl Energy 2018;215(August 2017):356–70. http://dx.doi.org/10.1016/j.apenergy.2018.01.056.