Estimating Plug-in Electric Vehicle Demand Flexibility through an Agent-Based Simulation Model

Gonzalo Bustos-Turu, Koen H. van Dam, Salvador Acha, and Nilay Shah
Department of Chemical Engineering
Imperial College London
London, UK
{gonzalo.bustos-turu12, k.van-dam, salvador.acha, n.shah}@imperial.ac.uk

Abstract—In the future context of smart grids, plug-in electric vehicles (PEVs) can be seen not only as a new spatial and temporal distributed load, but also as an electricity storage system. In this sense, the storage capacity can be aggregated and made an active participant in the power market to provide ancillary services. The estimation of this capacity over time and space is challenging as it depends on many factors such as vehicle owner driving profiles, charging behavior, and charging infrastructure features, etc. In this paper the demand flexibility potential of a PEV fleet is estimated using an agent-based modelling approach in which different scenarios of participation in flexible charging mechanisms are evaluated. The case study depicted in this work is based on current technology and demographic data from an urban area in London (UK).

Index Terms—Agent-based modelling and simulation, demand flexibility, aggregator, plug-in electric vehicles.

I. INTRODUCTION

Plug-in electric vehicles (PEVs) can be seen as a distributed source of energy storage which could provide ancillary services to the system operator, supporting the integration of renewable energies, and improving the reliability of the network. An aggregator could manage the charging of the PEVs taking advantage of any demand flexibility. In order to estimate this charging flexibility, the spatial and temporal characterisation of the PEV energy requirements is crucial, taking into account the heterogeneity of the elements involved in the analysis.

In systems with a high level of renewables, the use of PEVs in demand side management (DSM) schemes could help support grid stability and better match demand with generation. This support can be further exacerbated by studies that show that cars are parked 95% of the time [1]. If many PEVs are aggregated, not only the size of the load is greater, but also the demand becomes more diverse, creating opportunities for a more reliable and robust DSM scheme [2]. However, in order to estimate the level of flexibility the PEV fleet could provide, the proportion of time in which the PEVs are plugged into the grid, and not only the parking time, should be considered. This flexibility will depend not only in technical factors, but also in the driving and charging behaviour of the drivers as well as the charging infrastructure. Previous studies related with the analysis of PEV demand flexibility ([3], [4]) create scenarios assuming driving and charging behaviour with no spatial representation. This is primarily due to the lack of real data, but results from recent demonstration projects have shown substantive deviations from these assumptions [5]. As an attempt to overcome these challenges, this paper presents an agent-based model (ABM) to simulate the charging requirements of a PEV fleet in an urban environment. With this approach, the analysis of interventions targeted at specific areas or population groups becomes more natural considering the bottom-up approach of generating the trips in a simulation environment where the response to certain policies and scenarios can be evaluated.

In recent years, a rich amount of research has arisen using the ABM approach to gain new insights on PEVs integration. A review of this literature has shown the suitability of this approach [6]. Although some (e.g. [7], [8]) analyse the capacity of PEVs to provide demand flexibility to the grid, in [7] the mobility behaviour is determined using driving probabilities, and the driving and charging behaviour is not considered explicitly. In [8] the charging infrastructure in not included explicitly in the analysis, assuming all the vehicles will have access to a charging point. In this paper, the model developed in [9] is enhanced, including explicitly the interaction between driving and charging behaviour, and access to charging infrastructure. The temporal and spatial electricity demand resulting from this interaction is then used to estimate the charging flexibility potential which drivers can offer to the system operator. This flexibility is estimated based on the plugged-in and charging duration, and on the capacity of the PEV batteries to be charged.

The outline of the paper is the following. Next section presents the modelling and simulation framework and the case study is defined in Section III. Results are analysed in Section IV and finally, the conclusions are presented in Section V.

II. MODELLING AND SIMULATION APPROACH

As the literature review [6] shows, there is a gap in the characterisation of the driving and charging patterns that
influence the final energy requirements of PEVs. This work focuses on the generation of these patterns through an agent-based simulation model, in which each agent represents an electric vehicle owner with its own characteristics leading to travel and charging decisions. The main characteristic of the modelling approach in this work is the explicit representation of the interaction between a set of heterogeneous individuals (drivers) and transport and power networks (charging infrastructure), spread in space and time. This socio-technical system model can also be modified in order to analyse different scenarios, presenting a high level of flexibility for decision makers concerned with the future of transport and electricity sectors in urban areas. The aim is to estimate the energy demand flexibility of PEVs, with a clear representation of the differences that may occur in various locations throughout the city, among different types of PEV owners, and in different time periods. To achieve this, the developed model takes into account the heterogeneity in the social and technical aspects of the agents in terms of their attributes and behaviour. In particular, the charging behaviour is represented as a derived demand; derived from the need for energy to refill the PEV’s batteries to meet the travel demand which in turn is also derived from the need to pursue activities distributed in space. This chain of derived demand is important to develop a model with various agents with different activities that result in different travel demands, energy consumptions and charging requirements.

A. Agent model of PEV owners

Using the agent definition of [10], in this work, the PEV owners are modelled as agents who take their travel and charging decisions (performance) based on their perceptions and memories (activities, state of charge, charging prices, charging points location, etc.), but are also capable to adapt their behaviour given a particular situation (policy) such as a reduction in the charging tariff.

In this model the activity profile \( AP_i \) for each group \( i \) of PEV owners is defined with a list of 4-tuples:

\[
AP_i = [(ACT_j, MDT_j, SD_j, PD_j)]
\]

Where \( ACT_j \) represents the activity \( j \), \( MDT_j \) the mean departure time, \( SD_j \) the standard deviation, and \( PD_j \) the probability of departure for the activity \( j \). The departure time is modelled as a stochastic variable following a normal distribution with a mean value representing the peak hour of that period, considering a standard deviation to account for variability among agents. Also, a departure probability is included in the model, to simulate the fact that only a portion of the activities are undertaken by an agent during the day. Furthermore, the agent has behavioural rules that allow it to decide when to charge or change the route if the SOC requires immediate access to a charging point (See Section E).

B. Agent model of PEV aggregator

As the power and energy capacity of individual vehicle batteries is small compared to the power delivered by the grid, therefore the introduction of an agent who aggregates a high number of vehicles is necessary to reach a considerable level of demand flexibility that can be used in the ancillary markets [11]. In this paper the aggregator is introduced as a new agent, who aggregates the charging requirements and sends price signals to influence the PEV owner’s decisions in the charging process. The aggregation of each vehicle is done using a hierarchical structure, first at a building level, and then at the 11kV network level; this structure is shown in Figure 1.

![Aggregator hierarchical structure.](Figure 1)

From the perspective of the aggregator the PEV fleet can be seen as a distributed load able to shift their energy demand. The optimal charging of this fleet will depend on the requirements coming from the distribution network operator according to the electricity and grid service markets, an aspect that is outside the scope of this paper. However, the capability of the aggregator to offer ancillary services will be determined by the charging requirements of the PEV fleet and their willingness to participate in flexible charging schemes. In this paper, the charging requirements are estimated through the ABM simulation, while the willingness to participate in this market are portrayed in different scenarios.

III. Case Study

Using the previous modelling approach, a case study is presented using a real area in London, UK. In this section, the main parameters and assumptions are presented.

A. City Layout

In this work, geo-referenced maps are used to generate the city layout over which the agents pursue their activities. In this case, the Old Oak Common (OOC) area in North West London is used for the case study. The maps are extracted from [12], and edited in open source GIS software [13]. To account for trips made to other parts of the city, a simplified external area is also included (located in central London) to represent a destination for any trips made outside the neighbourhood studied. This area includes all the services as the OOC are and thus all agent activities can take place either in or outside the OOC area. In Figure 2 the city layout with the different type of buildings is shown.

B. Charging infrastructure

In this case study Slow and Fast charging units are considered, with a power rate of 3.6 and 7.2 [kW] respectively. It is assumed that slow charging units can be installed everywhere, whereas fast charging units are deployed only in public areas such as commercial or leisure areas. The spatial distribution of the charging network is generated randomly, assuming known levels of deployment. Based on
[14], it is assumed that in residential areas 76% of the PEV owners will have access to a garage or other off-street parking facility, and therefore capable to have a home charging unit. According to [15], 25,000 charging points across London are expected to be installed by 2015, with the majority of these (22,500) installed in workplace car parks, including a network of fast charging sites, and 100,000 EVs circulating in London. Furthermore, 2,000 charging points in publicly accessible car parks and 500 points on-street are planned [16].

Using these figures, it is assumed that 22.5% of PEV owners will work in a destination with access to a charging unit. This proportion includes the case when the agent works in the external area. In addition, this model considers 2,500 fast charging points for every 100,000 cars (2.5%) to be in public areas such as shopping and leisure areas. Table I shows the summary of the charging infrastructure design.

Finally, Table II shows the simplified 11kV distribution network allocated within the city layout to represent different zones among the area.

C. Agent’s activity profile

Only two types of PEV owners are considered, namely “Worker” and “Non-Worker”. The proportion of Worker agents is 61.8% [17]. The activity profile for each type of agent is shown in Table III using the notation presented in equation (1).

The previous parameters are set in order to have a general travel distribution similar to the results shown in [17]. However, a more rigorous calibration of these parameters should be done if data related with travel behaviour of electric vehicle owners is available.

D. Plug-in electric vehicle fleet

As the scope of this work is in the interaction between the transport and the electricity sector, only PEVs are considered in the simulation. The definition of the PEV fleet is based on the types of vehicles eligible for the Plug-In Car Grant in UK [18]. The information for each model was extracted from the brochures and then classified according to [19]. The main parameters for each type of PEV are presented in Table IV. In this case two thousand PEVs are simulated and the distribution follows the market share presented in the last column of Table IV. This distribution is estimated based on the data presented in [20] for new car registration for the segments Mini, Small and Medium. An average speed of 40 [km/h] is assumed as constant, as differences between small and main roads or traffic conditions are not yet considered, but to prepare for extension data on the road network is included in the spatial model description.

E. Flexible charging scenarios

With the previous parameters set, different scenarios in terms of percentage of PEVs participating in the flexible charging mechanism are defined. In the first scenario (FOS), drivers will charge their vehicles as soon as they arrive to a place with a charging point available and the charging process lasts until the battery is fully charged or until the next activity starts, when the vehicle is unplugged from the grid. In the case the state of charge (SOC) is lower than a threshold (in this case 30%), the driver goes to the nearest charging station in
considered in the analysis, as it is assumed that in those cases the driver will not remain plugged-in once the charging is over. The plugged-in duration is the elapsed time between the moment when the driver arrives at a destination with a charging point available and the time when the driver has to go to the next activity.

Charging events are characterised through the probability that a particular charging event lasts less or equal to a certain amount of time, i.e. the Cumulative Distribution. On the other hand, the plugged-in events will be characterised by the probability that a particular plugged-in event lasts more than a certain amount of time, i.e. the Exceedance Distribution (Also called Complementary Cumulative Distribution). The results are plotted in the same graph to compare both indicators.

In Figure 4 it can be seen that most of the time (89.9%), the drivers spend less than 1 hour charging their vehicles. On the other hand, usually (96.9%) the plugged-in duration lasts more than 1 hour. The results show that on average a charging event takes 0.64 h. In contrast, plugged-in events take 8.5 h on average. Further analysis is needed in order to calibrate and validate these results, if real data is available. However, these results seem optimistic if they are compared with the results of a demonstration project [23], where the average charge duration for private vehicle drivers was 2.98 hours. The differences can be explained by the fact that the simulation results only take into account charging events in charging points available in daily activity locations (in-schedule). The duration of off-scheduled charging events tends to be higher as the vehicles go there when SOC is too low. As the charging power in those places tends to be higher (public fast chargers) the duration can be counteracted. The average time spent in off-schedule charging events in public charging points is 1.1 h, 71% higher than the case of in-scheduled charging events (0.64 h). Another source of difference can be the high level of access to the charging infrastructure assumed in this work. With more charging points available, average SOC tends to be higher and therefore the time of charging would be lower.

The simulation shows that on average drivers spend 56% of the time plugged-in. This result is important because most of the time PEVs could be available to provide services to the grid.
B. Scenario analysis

For the scenario analysis, the model was run starting at 5:00, for a weekday with a 3 minutes time step. In Figure 5 the aggregated demand for the F0S scenario is shown in a stacked area chart, differentiating between the different nodes of the distribution network.

![Figure 5](image)

Figure 5  Load power for the F0S scenario, for each 11kV node.

In the previous figure it can be seen that the energy demand varies temporal and spatially according to the node. These nodes represent different areas in the city layout. Node 4 is located in the external area with most of the workers pugging their PEVs in that node in the morning. In the evening the peak demand is more distributed among the different nodes. The results can also be shown according to the working status of the drivers; see Figure 6.

![Figure 6](image)

Figure 6  Load power for the F0S scenario, for each type of agent.

The previous results are compared with the rest of the scenarios in Figure 7 which shows how the charging load is shifted from day to night time and how this feature becomes more important with higher participation of drivers in flexible charging schemes. It also shows some charging processes between 7:00 and 11:00 due to the delay introduced in the Economy 7 flexible tariff. In the NChS scenario, there is a small load between 15:00 and 23:00 due to drivers going to charging stations with low SOC. The peaks shown in the F0S and F100S scenario could create an impact in the 11kV network, but a complete analysis should include the static demand profiles, network constraints, etc. This analysis is part of the current work of the authors but outside the scope of this paper.

![Figure 7](image)

Figure 7  Load power for the flexible charging scenarios.

In Figure 8 the energy flexibility to charge the vehicle for all the scenarios is shown.

![Figure 8](image)

Figure 8  Energy flexibility for the flexible charging scenarios.

The previous results show that with higher levels of participation the flexibility of the PEV fleet increases. When drivers postpone their charging demand their SOC starts to decrease over time. As the energy flexibility is defined as the complement of the SOC, this parameter reaches its maximum value before the Economy 7 period starts. In theory, this period would represent a good opportunity to manage the charging demand, maximising the provision of ancillary services during that period. Table V shows the indicators used to compare the different scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>SOC average (*) [%]</th>
<th>Off-schedule charging events (**) [#]</th>
<th>Average energy flexibility (**) [MWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>F0S</td>
<td>90.7</td>
<td>19</td>
<td>0.11</td>
</tr>
<tr>
<td>F50S</td>
<td>89.4</td>
<td>40</td>
<td>0.88</td>
</tr>
<tr>
<td>F100S</td>
<td>88.1</td>
<td>58</td>
<td>1.71</td>
</tr>
<tr>
<td>NChS</td>
<td>66.1</td>
<td>63</td>
<td>2.46</td>
</tr>
</tbody>
</table>

(*) Value calculated from the 1 week simulation.

(**) Value calculated from the 1 day (weekday) simulation.
Table V shows that the average SOC for the fleet slightly decreases with more participation in the flexible charging schemes, with possible effects on EV owners who can see in these a source of range anxiety. Additionally, with higher level of participation, the number of off-schedule charging events increases due to vehicles with low SOC going to a public charging station. Finally, the average energy flexibility increases considerably when drivers postpone their charging.

V. DISCUSSION AND FURTHER WORK

The new interdependencies between technologies and stakeholders that are emerging in current transport and power sectors are forcing designers and planners to make decisions about an increasingly complex system. In the case of PEV integration these new interactions can be analyzed by new computer-based analytical tools such as the one presented in this work. The ABM framework used allows a flexible implementation of a decision-maker simulation tool, in which the inputs and parameters can be easily edited. City layout, charging infrastructure and agent profiles can be set for every simulation, making the analysis of different scenarios easier.

The results of the case study show the estimation of the demand flexibility for a PEV fleet in an urban area of London, UK. This level of flexibility increases when drivers postpone the charging process to a more convenient time of the day; with a lower SOC, the availability for flexible charging is higher. The implementation of these smart charging schemes could represent an opportunity for PEV owner to perceive new revenues associated with the grid services provision. However, further analyses are needed to fully evaluate the impact of this service provision on driving behaviour; including range anxiety, off-schedule trips, battery degradation, etc.

Possibilities of future work of this modelling framework include the design of different charging strategies to improve the capability of PEVs to provide ancillary services to the grid. Planners and decision makers can benefit from this simulation model, testing different charging infrastructure types, including charging points and distribution network upgrades and considering larger city layouts. Finally, new services can be included in the model such as vehicle-to-grid services and smart charging under multiple criteria. For all of these research areas, improvements in the EV owner model are needed as well, including its willingness to participate in new charging mechanisms.

REFERENCES


