EVALUATING THE FINANCIAL ATTRACTIVENESS OF SMART-CHARGING SCHEMES FOR ELECTRIC VEHICLES DRIVERS AND AGGREGATORS

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ABSTRACT

Uncontrolled charging of a large fleet of electric vehicles (EVs) represents a challenge for the electricity network. However, a suitable controlled strategy could not only ease the process but also provide grid services by increasing or decreasing the charging load. So far research lacks understanding how individual behaviours may impact the availability of EVs for grid services. This paper presents a simulation model of a fleet of electric vehicles and an EV aggregator to assess availability in offering demand response services. A case study using London neighbourhoods was developed to analyse the charging demand and the potential for grid services to compare attractiveness to customers and profitability for the aggregator

The model leads to two main outputs: the aggregated availability of cars and owners' bills and savings. Therefore it helps understand the attractiveness of these schemes for both actors. Additionally agent-based modelling allows analysing the influence of each agent on the system, which leads to valuable insights for grid operators who can better understand the local impact of individual behaviours on EV charging and grid services, and subsequently on their network. It was notably demonstrated that the tested Smart-charging schemes should be offered to drivers who own a domestic charger.

INTRODUCTION

Uncontrolled charging of electric vehicles (EVs) with a large and uncertain mobile load may represent a threat for electricity networks [1]. This could be eased through a controlled charging strategy and could be implemented across a region to provide grid services by increasing or decreasing the charging load depending on (local) grid conditions. This would benefit a wide range of actors from grid operators and energy suppliers up to end-users; however, the willingness of EV drivers to participate in such schemes is still unclear as the risks and benefits to them are uncertain. Similarly, the availability of EVs and therefore the profitability of this kind of schemes need to be addressed.

In this work it was considered that an aggregator would serve as a third party, aggregating a fleet of EVs and using them to provide grid services. Although not necessary, the emergence of a third party seems the likeliest scenario [2][3]. Here EV drivers interact with an aggregator to optimize their charging processes, based on their individual requirements and external electricity prices. The aggregator minimizes EV customer bills by offering the lowest fare available via three dynamic time-of-use (TOU) pricing schemes. In return the aggregator is free to delay or postpone the charging process when the network is congested, and to start it again when the demand is low. More specifically it was considered that the aggregator was participating in *Demand Side Frequency Regulation.*

This paper describes the agent-based model used to calculate the aggregated availability of cars and the drivers' bills, therefore their savings. These two outputs lead to insightful information regarding the attractiveness of the three pricing schemes, both for owners and for the aggregator. In a first part the agent-based vehicle model is presented then the scenario to simulate are detailed. Subsequently results are analyzed in term of cars availability and of savings for customers before concluding.

AGENT-BASED VEHICLE MODEL

An agent-based model (ABM) is an analytical tool for simulating the actions and interactions of autonomous agents. Agent based models are used as an attempt to re-create and predict agents' effects on the system as a whole and therefore they can generate complex phenomena from simple behavior rules [4].

In this work an ABM was implemented in *Repast Simphony* based on Malleson's RepastCity model [5], which was adapted to EV modelling [6]. The model is based on a set of behavioral rules. The behavior of agents is implemented as algorithms in Java. Agents use the road network to travel to different locations according to their activity schedules (e.g. go to work in the morning and to leisure center in the evening) and while doing so their cars get discharged. When charging they interact with the

aggregator. The model keeps track of the state of charge of all vehicles, of their availability to provide grid services and on the bills paid by each agent. This leads to spatial and temporal information on the availability to offer grid services. Additionally, each agent has a specific access to charging infrastructure; some of them own a charger or can charge at work, other have to charge in shopping center for instance. Therefore the influence of the charging infrastructure of vehicle availability can be analyzed.

A simple schematic description of the charging process controlled by the aggregator is described in Figure 1. Individual schedules leads to journeys that define the charging demand. However market prices add-up to this basic construction. When vehicle owners plug their car they inform the aggregator of their departure time and the minimum state-of-charge they will need when leaving; this is their charging demand. Knowing these requirements and the external prices, the aggregator is then able to optimize the owner's bill. If an agent plugs his car for a few hours when prices are high and if he already has enough battery in his car (i.e. more than the required state-of-charge), then the aggregator may not charge the car. This illustrates how the market has an influence on the charging demand.

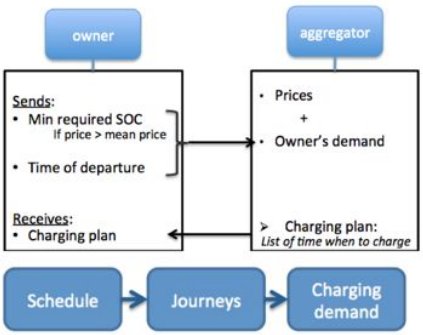


Figure 1: Simple schematic description of the model process

CASE STUDY AND SCENARIOS DEFINITION

An illustrative case study has been performed, using an area within Greater London. A district of London was chosen as a case study and all data and properties of roads, buildings and electricity network were stored using Geographic Information System (GIS) files, representative of this area, from which the model was initialized. Similarly, surveys from Transport for London were analyzed in order to simulate driver profiles based on real travel patterns [7]. Finally features such as the battery capacity and the energy consumption of electric vehicles on the market were included.

As shown in Figure 2, a small number of buildings were modeled in Central London to account for journeys outside of the area. Accounting for the density of population in London and the government's target for the spread of EVs in the city, a fleet of 500 cars, participating to Smart-charging, was modeled. Cars were modeled along three categories: small, mini and medium. These three sizes were defined after a market analysis of the electric vehicle segment that led to summarizing the whole market into three main categories, whose characteristics are summarized in Table 1.

Figure 2: City layout used in the case study

Table1: Average annual savings with and without domestic infrastructure [8]

Categories	*Battery capacity*	*Energy consumption*	*Market share*
Mini	26 kWh	39 Wh/km	5%
Small	23 kWh	150 Wh/km	47%
Medium	14 kWh	169 Wh/km	48%

Charging infrastructure was modeled along the City's target: 75% of the homes and 25% of the offices were equipped with a charger, 30% of which were fast (7kW), and the rest were normal (3.5kW). Additionally 2% of public places (shopping or leisure center) possess a fast charger.

Three different Time-of-Use (TOU) tariffs were modeled and compared to a basecase (BC) scenario in which customers are offered a flat price. The TOU were chosen after Dütschke's work [9]. They are dynamically varying according to the spot market. Two typical winter days are represented on Figure 3; from a Friday morning to a Saturday night. It can be added that, with the TOU3, electricity may be free. Analysis of spot market data shows that this can happen at night, mainly in summer.

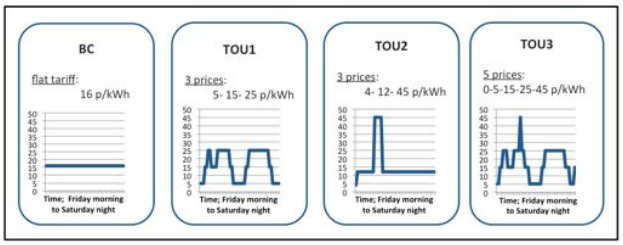


Figure 3: Scenarios definition – example of available prices with the various tariffs

It was considered that the aggregator was optimizing bills while providing *Demand Side Frequency Response* with the aggregated cars. This service is paid through two mechanisms. First, units are paid a relatively low price for being available; it is the *Availability price*. The aggregator has to give windows of availability, indicating when a certain load will be available. He will be paid according to the level of the available load, and to the duration of the window. Then the PEVSA is paid for the actual utilization of the service a price depending on the energy curtailed from the load or added to the load. Projections done by National Grid show a price of £20/MW-hours for availability and a price of £150/MWh of utilization, with an average utilization of 100 hours per annum [10], and these numbers were used in this case.

The model was used to calculate cars' availability to provide these services. A car is considered available for load increase if it is not charging and if its battery could be charged for 30 minutes (required duration of the service). Similarly a car is considered available for load decrease if it is charging and if the minimum state-of-charge required would be reached by the time the agent requires his car, even if the charging process is stopped to provide load decrease. These availabilities are calculated by the ABM and used to estimate the potential revenue that could be yield by the aggregator. However, the actual participation to grid services was not modeled. Although it is to be noted that such aggregated loads are used during a very short percentage of the year, modeling the participating to grid services would be a natural pursuit of this work.

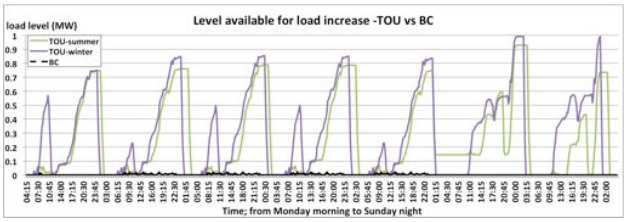
The ABM is executed to simulate a week in London. To account for seasonal prices variations two weeks were modelled, one in summer and one in winter. Results were then extrapolated to a year in term of bill savings and of vehicle availability for grid services.

RESULTS

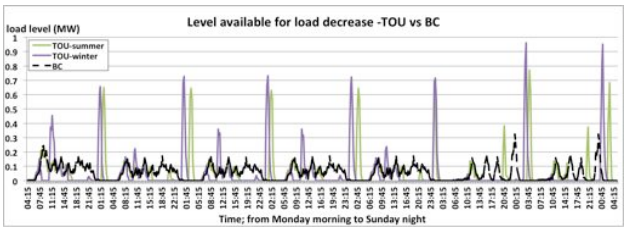
For each of these scenarios, the EV owner's savings and the aggregator's revenues were calculated based on vehicle load flexibility to ramp up or ramp down demand (Figure 4) while the aggregator uses EV loads to provide demand-side-management.

Availability for grid services

First, results can be analysed in term of availability for providing grid services. Figure 4 shows the load available for load increase (Figure 4.a) and decrease (4.b) in the base-case and with the TOU3. When using a TOU tariff, these curves vary from winter to summer because the charging process is influenced by prices. When no TOU is applied, cars start charging as soon as they are plugged and the charging process ends either when they are fully charged or when they unplug due to activity schedule constraint. Therefore there is no load available for load increase. On the contrary, when using a TOU, owners plug their car and wait for a better tariff (as indicated in the charging plan prepared by the aggregator), meaning that from evening to midnight most of cars are plugged but not charging. Figure 4.a shows how the load increases during the evening, as the number of plugged car increases, and drops quite abruptly in the middle of the night when the price drops. It can be noted that the load remains high longer on Tuesday and Thursday night in summer. This is due to the availability of free electricity during these two nights. This occurs later than the usual decrease of price. It must be noted that prices are not generally speaking lower on Tuesday and Thursday. This is solely linked to the modelled week.



a. load increase



b. load decrease

Figure 4: Comparing availability between the base-case and the scenario tested, and seasons

Regarding the load decrease the comparison is more delicate. In the BC scenario a low load is very often available because cars arrive at different time and start charging immediately. This means that the supplier-aggregator can offer long but low-capacity availability windows. These windows are basis on which the aggregator is paid. When using the TOU, cars are all charging when the price is low, meaning that most of the time few cars are charging, if any. This results in very short high-price availability-windows, which may be an issue as the PEVSA is taking more risk when planning the windows. Indeed, small behavioural changes could drive drastic reduction of the window. However when cars start charging the available load is significant, approximately four times higher than the BC one.

Customers' savings

The use of the Agent Based model allows a detailed analysis of customers' savings, enabling a more

comprehensive understanding of the different factors that influence these savings.

Based on the simulation results, domestic infrastructure is a crucial factor for both the owner, who will be able to charge at night when prices are low, and for the aggregator who will have a long and secure window of availability. Figure 5 shows the savings made by customers owning a charger (left) and the ones who do not (right). Savings are calculated by comparing the price paid and the price owners would have paid in the basecase scenario. It is to be noted that savings may be negative (hence losses) for owners who can only charge during peak-time. Even if some agents are able to make savings without domestic infrastructure, it is clear that they save less money and in some cases they can even lose money from TOUs. Results show that in average owners save respectively, with the three TOUs, £26, £39 and £8 without charger at home, compared to £83, £78 and £86 when they own one. These figures are summarized in Table 2.

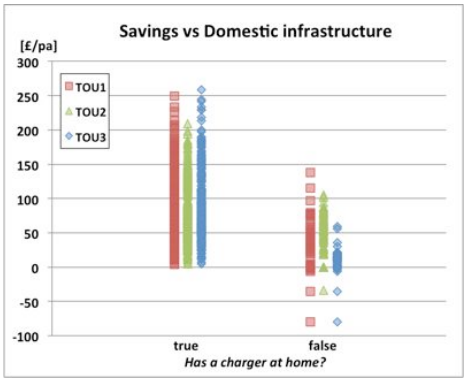


Figure 5: Savings made with and without domestic charger with the three TOUs

Table 2: Average annual savings with and without domestic infrastructure

Savings (£/year)	*TOU1*	*TOU2*	*TOU3*
With domestic infrastructure	26	39	8
Without domestic infrastructure	83	78	86

Additional factors were further analyzed to gain a finer understanding of the scheme: agents were sorted according to their status (workers vs. unemployed) and according to the size of their car (mini, small or medium). These two analyses show that, neither the owner's status nor the size of his car impacts on its availability to provide services and therefore to save money. This can be explained partly by the case study chosen in which owners are driving daily short distances (around 6 km). Therefore the capacity of their car battery was never fully used.

Finally the impact of the distance driven on the results was studied, showing how longer journeys lead to higher availability. Indeed, cars need to charge during longer periods, meaning that their availability to provide load decrease improves. To emphasize this phenomenon the layout was modified: all distances were tripled in order to increases the distances driven daily. Figure 6 compares this *new* scenario with the first one (*old*). It is clear that this layout in which travel costs are higher means that more people are able to save a higher percentage of their bill, with 50% of them saving at least £220 per year, while only 1% of them were saving more than that in the first scenario.

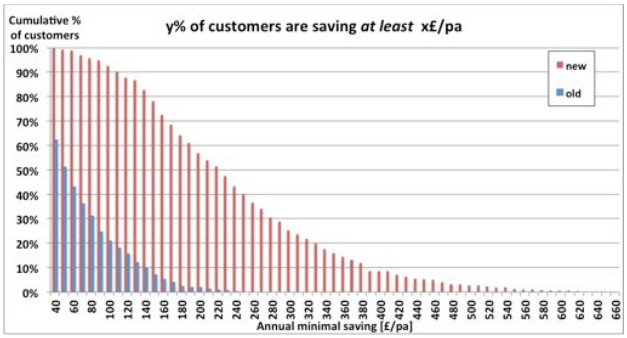


Figure 6: Comparison of cumulative savings made when distances are tripled (new) vs. in the first scenario

CONCLUSION

The results of this work represent a contribution in understanding the attractiveness of Smart-charging to EV owners, under dynamic pricing. In particular this work identifies the factors that impact the availability of cars in order to have a better understanding of this scheme and of the tariffs tested. The use of an ABM allows analysis of the influence of each agent in the system, which leads to valuable insights for network managers who can better understand the local impact of individual behavior on EV availability and therefore on their network.

Regarding modeling, the main contributions of this work are the following:

- The addition of a behavior model for the charging process of agents.
- The implementation of Smart-charging and more precisely of the creation of charging plans by the aggregator.
- Scenario analysis of the impact of the pricing scenario on the charging behavior.

With these additions the model represents a useful computational tool for the decision makers and all the different stakeholders involved.

The specific following findings emerge from this work are:

- In the scenario considered, demand response has more potential when EV owners can charge at

home. It increases the availability for grid services and allows customers to benefit from the best tariffs. Without a home charger owners save on average less than £25/pa, compared to £80 for those with a home charger. Owners may be incentivized (e.g. by the grid operator or government) to buy one in order to offer flexibility to the grid.

- This scheme appears to be more interesting in less dense urban areas where people drive longer distances, offering more flexibility to charge. By participating in grid services it allows customers to save relatively more money on their bills as they buy more electricity.

The aggregator could thus help distribution-network operators (DNO) by reducing network congestion; avoiding or deferring new investments and this could be analyzed in further work. The spot market could be integrated in the model in order to send more accurate signals to the aggregator and to be able to assess the peak shifting. This could also account for a possible payment mechanism from DNOs rewarding electricity network congestion management.

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