INTEGRATED MODELLING OF AGENT-BASED ELECTRIC VEHICLES INTO OPTIMAL POWER FLOW STUDIES

Salvador ACHA
Imperial College
London, UK
salvador.acha@imperial.ac.uk

Koen H. VAN DAM
Delft University of Technology
the Netherlands
k.h.vandam@tudelft.nl

James KEIRSTEAD
Imperial College
London, UK
j.keirstead@imperial.ac.uk

Nilay SHAH
Imperial College
London, UK
n.shah@imperial.ac.uk

ABSTRACT

So far research on modelling the travelling patterns of electric vehicles (EVs) lacks technical depth since the variability of individual travel behaviour lack spatial and temporal disaggregated details - this data is needed by operators (DNOs) to assess EV impact at a low voltage level. Thus, it is essential to integrate issues concerning the mobility of EVs with the operational issues facing DNOs.
This paper discusses how a bottom-up agent-based modelling (ABM) approach, addressing the mobility of EVs, can be combined with power flow studies at different levels of abstraction. From the DNO's perspective the fact that EVs can move around means loads disappear and may re-appear at a different location, which has consequences on the power flows. Hence the data collected from the EV driving patterns are quantified to monitor the state of charge of the batteries. Subsequently, the output collected from the ABM simulations are applied to power system studies by incorporating its data into a time coordinated optimal power flow (TCOPF) program.
An example proof-of-concept case study is showcased to demonstrate the relevance of the ABM paradigm and the effectiveness of the TCOPF solver when they are merged for a small network; in this fashion proving interoperability between the models. Preliminary results illustrate the valuable operational information utilities can obtain regarding optimal EV charging strategies when considering an ABM approach to represent EVs in power flow studies.

INTRODUCTION

The impacts EVs have on electrical distribution networks will be closely related to the driving styles of these agents. This is because the amount of petrol displaced by the electrical power from the grid is influenced by various factors, such as energy consumed per recharge (i.e. battery capacity) and the total driving distance between recharges (i.e. driving profiles). Both environmental and energy efficiency benefits can come with the introduction of EVs, however if not properly rolled out the technology will be undermined [1]. Furthermore, some effects DNOs might face with EVs in the networks include [2]:

- Modifying electric load profiles;
- Altering electricity delivery costs and losses;
- Shortening the life of substations;
- Closer monitoring of operating data (e.g. voltage).

Therefore, in order to gain the most from the deployment of EVs, it is imperative that power system engineers address the challenges these vehicles bring to utilities, the main challenge being: *the mobility of units*; hence understanding the driving profiles of users is fundamental. This is because EV deployment will create a "new" type of load for utilities, while also possibly offering power back to the grid when necessary. So far simulations employ limited data from travel surveys which are then aggregated [3]. For example, data reveals half of the daily driving distance of light duty vehicles is less than 65 *km* in the USA and less than 40 *km* in the UK [4] and [5].

Electric utilities are designed with the premise to satisfy the instantaneous consumer demand that varies over time. Initial practical studies suggest GPS technology can aid DNOs in tracking and registering the movements of EV units so they easily cope with this "new" type of customer [6]. Nevertheless, on-field data is hard to come by for research purposes and robust modelling tools need to be explored through agent-based models in order to properly portray travel profiles in power system studies. Hence, this work presents an encouraging approach to represent mobile EV agents in optimal power flow studies through a holistic framework. By keeping track of the energy consumption these units have at each time interval, as well as their location in the network, it is possible to quantify "*when*" and "*where*" EVs will be able to charge; hence providing valuable temporal and spatial data to utilities which need to supply this type of load. The mobility data provided by the ABM model will be employed by the TCOPF program which functions as intermediary entity which making it possible to assess the optimal charging profiles EVs can have in local distribution networks.

OPTIMAL POWER FLOW MODEL

The TCOPF model introduced in [7] strictly focuses on operational issues; covering topics that deal with optimal power delivery at a distribution level and the dispatch of energy conversion and storage technologies. Hence, the goal of the TCOPF tool is to optimally coordinate the dispatch of EV units so they can have a seamless and advantageous integration into the grid. The TCOPF algorithm focuses on minimising a nonlinear objective function over multiple intervals that are restrained by a set of nonlinear constraints. By analysing the state of energy service networks for example for daily load profiles it allows the solver to devise the best moments to dispatch its control variables.

Based on these characteristics, the TCOPF problem formulation can be categorised as a typical multi-period nonlinear constrained optimisation problem that possesses continuous and mixed-integer properties. As a consequence, the TCOPF model can send operating signals based on the grid condition and the state of plugged EVs; effectively functioning as a body that enables demand response strategies.

Demand response refers to "deliberate load control during times of system need, such as periods of peak demand or high market prices; creating in this manner a balance between supply and demand" [8]. Overall, these types of services are very valuable because of the load flexibility they offer to utilities. Therefore, the TCOPF tool functions as an intelligent coordinator that commands EV charging according to the conditions of the DNO, the power market, and the needs of the customers. Nevertheless, an assumption made so far in the TCOPF model did not address the issues regarding the mobility of EVs throughout the network. This critical issue needs to be tackled, since static representation of EVs limit the scope of analysis when calculating optimal charging of these agents.

AGENT-BASED VEHICLE MODEL

Since the mobility of EVs needs to be properly portrayed in power flow problems, agent-based modelling has been chosen as the ideal compliment to this complex problem. Agents, software entities which are autonomous, reactive, pro-active and capable of social interaction [9] can be used to simulate complex systems where the actions of individual "actors" lead to the emergence of overall behaviour or when the domain is too complex to be modelled in another way [10]. Hence, in this work when considering the individual owners of EVs as agents, each with their own profile and individual pattern of journeys, a bottom-up model allows experimenting with different scenarios and activities they must or might fulfil. The modelling results are estimated electricity demand to charge vehicles over time, and when using a geographical representation of the city, also unit distribution over space.

In order to simulate EVs in an urban environment, an ABM of a virtual city was adopted from Malleson's [11] RepastCity model and implemented in Repast Simphony. Driver profiles and location-specific activities have been considered based on travel habits. Likewise, characteristics such as battery capacity and energy use of electric vehicles available on the market have been included [12]. In addition, an 11 kV network was added to the city, with substations representing nodes to supply the urban area. All locational data and properties of roads, buildings and agents are stored using GIS (Geographic Information System) files from which the agent-based model is initialised and then the agents behaviour is implemented as algorithms in Java.

During a simulation run, the drivers go about their day and choose activities based on the time (e.g. go to work in the morning, visit friends in the evening, etc) and their profile (e.g. pick up kids from school when the driver is a parent, if active go to work in the early morning). Through these activities, the batteries of electric vehicles are partly discharged. The model tracks the state of charge of individual batteries and stores the aggregated data at each substation (per time interval) when an EV unit is plugged to the network when idle and linking it to the nearest node.

Existing micro-simulation traffic models and other agent-based models of driver behaviour may be more advanced and provide more realistic traffic simulation (e.g. including congestion or traffic light control), instead here we chose to start with a relatively simple model that focuses on the temporal and spatial distribution of demand for electricity based on the activities of the drivers.

Once the resulting travelling profiles of the agents have been calculated through the ABM model, this data needs to be interpreted and adopted by the TCOPF program.

LINKING THE MODELS

The energy demands generated by the agent-based simulation form one of the inputs for the power flow optimisation formulation. The relevant output of the ABM model consists of a matrix detailing the aggregated state of charge of batteries for each node at 30 minute intervals. Aside from the cumulative state of charge of all plugged vehicles in the direct vicinity of substations, the model gives the nodal maximum state of charge (i.e. the total capacity of all batteries together). Furthermore, for each vehicle in the city, the distance travelled during the day and the state of charge at the end of a day is registered. Now, it is important to clarify that the travel profiles from the ABM model serve as a forecasting tool that allows the TCOPF to estimate how much energy will be supplied per for EV charging. As such, the TCOPF solver then decides the duration and amount of power to supply the required energy for particular nodes. This type of problem is innovative in itself; henceforth the examples that can be carried out turn out to be as complex as the user desires. It is the purpose of this work to simply illustrate the main features of the ABM-TCOPF tool.

CASE STUDY AND RESULTS

An illustrative case study has been performed, as a proof-of-concept exercise, to show how the interaction between the two steady-state models function; hence demonstrating the synergy of linking spatial and temporal energy use data from ABM modelling with optimal power flow algorithms for novel power system studies. As a consequence, this example demonstrates the type of valuable data that can be obtained once utilities have a forecast of EVs embedded in their networks and dispatches (charge) them accordingly.

A simple city layout is assumed, consisting of a road network next to a set of houses, offices, schools, shops and leisure centres. There are four 11 kV network nodes in the city serving the local surroundings, please see Figure 1.

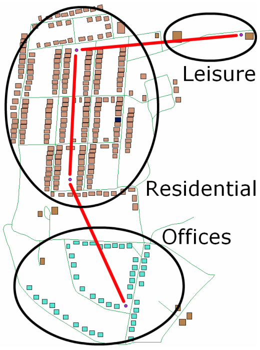

Figure 1 – City layout used in the case study, the transport and electrical network are overlapped.

The city is populated by 14 electric vehicle owners, even though this number can easily be changed, a small number units was chosen to clearly depict the level of granularity the ABM simulation can achieve. The EV unit used in this case study employ the technical characteristics advertised by the Nissan Leaf [13], having a battery capacity of 24 kWh and an available range of 100 miles, which only 35% is used here as travel surveys suggest. To compliment the technical features of the EV, each driver has a particular profile to guarantee diversity in their daily activities; including job status and number of children, being assigned a house as its home and an office as its workplace. Finally, the problem is set-up so all agents have their batteries fully charged by 6 a.m., the time they leave home for their daily commute. Commonplace electricity demand of households, offices and shops which are *not* related to electric vehicles are not generated by the ABM, but used as separate input data for the TCOPF based on typical urban load profiles. Finally, a key assumption made in this study is that all EVs that are not driving are plugged into the electricity network and the substation nearest to them supplies their load.

The ABM is executed to simulate a period of 24 hours on a typical week day in an UK urban area. Figure 2 shows the state of charge at 30 minute intervals for each of the four nodes, as output of the ABM model. Similar graphs can be created for the maximum charge at each node, and these bounds give the load flexibility at each substation as it determines how much electricity can be supplied at each node over time for EV customers, but it also shows how much energy is potentially available to feed back to the grid if required. Meanwhile, Figure 3 shows these bounds for one of the substations. As said before, the EVs do not charge based on decisions of the agents, instead the TCOPF solver functioning as a coordinator acknowledges the status of the networks and energy costs to make an informed decision which is given to the plugged EVs and DNOs.

Figure 4 and 5 illustrate the ideal charging profiles of the EVs under two different objective function formulations.

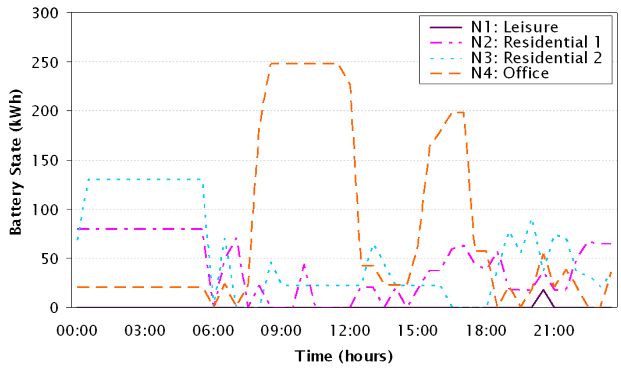

Figure 2 – State of charge of all plugged in vehicles over the day for each of the 4 substations.

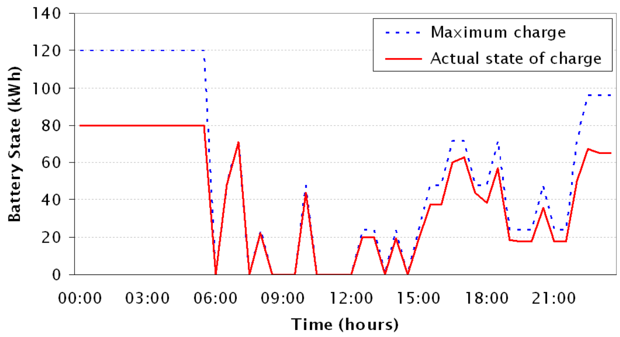

Figure 3 – Maximum charge and actual state of charge in one of the residential substations (e.g. node 2).

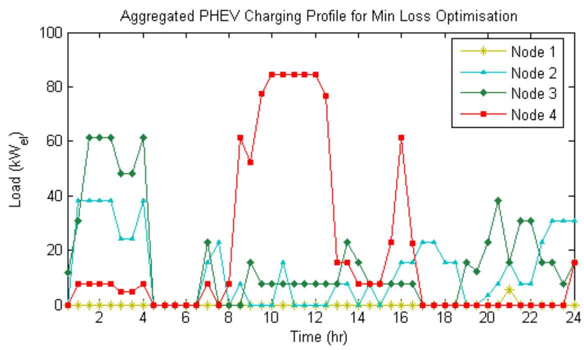

Figure 4 – Optimal nodal charging of EVs for loss minimisation in the distribution networks.

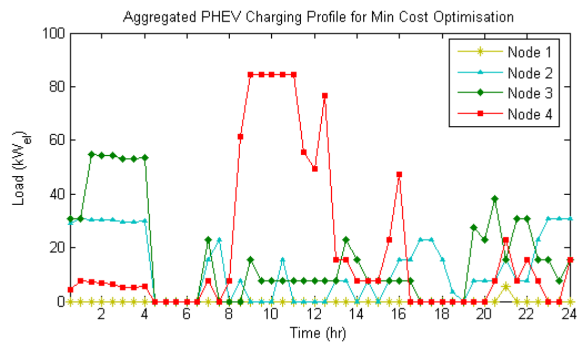

Figure 5 – Optimal nodal charging of EVs for cost minimisation in the distribution networks.

The two optimisations performed by the TCOPF program are minimum energy loss reduction (Figure 5) and minimum energy cost reduction (Figure 6); details on how the TCOPF problem is defined and established can be found in [14]. Now, although the simulation only considers 14 EVs present in the urban network, the optimisation does provide distinctive recommended charging profiles for the units based on the priority of the stakeholders. It is evident the at residential nodes EVs charge mainly during the night time, while in the office nodes EVs draw power during working hours. Special node deserves the scarce charging taking place at the leisure node since few EVs perform this activity during a working weekday, it can be expected this particular profile will be drastically different if a weekend day was simulated. Finally, it is important to clarify that although the profiles vary from each optimisation case, the power drawn by each node is the same in both formulations; thus the impartial TCOPF solver dispatches the EVs differently.

CONCLUSIONS

An example proof-of-concept case study is showcased to demonstrate the relevance of the ABM paradigm and the effectiveness of the TCOPF solver when they are merged for a small network; in this fashion proving interoperability between the models. Based on the TCOPF formulations proposed, the preliminary results illustrate the valuable operational information utilities and EV users can obtain regarding likely optimal charging strategies future networks may grow familiar with. An ABM approach is employed to represent and forecast the travel profiles EVs may take, serving as valuable input for power system engineers to perform power flow studies. Results confirm the ABM simulations correspond to typical behaviour of drivers and it is possible to translate their actions into energy demands which the utilities will have to provide in a cost-effective manner. Furthermore, results show the powerful level of granularity the simulations offer.

Further work on this stimulating subject will consider fine-tuning the ABM and TCOPF models. Then, additional experiments can be performed for a larger case study, for example by using a longer time-frame to include weekends or adapting the urban areas to different city layouts. Also modelling different sets and numbers of electric vehicles can provide meaningful data. Such experiments will not require any major changes to the models, but merely involve setting the right parameters and adding features as necessary. Furthermore, the ABM can be greatly expanded by just focusing on developing additional driver profiles (e.g. people working different shifts, taxi fleets of EVs), traffic to and from out of town, etc. An attempt will be made to create a link with the SynCity framework [15] which includes a unit on travel behaviour and other activities that could generate realistic and valuable EV forecasting for power flow optimisation simulations.

This particular power system problem is an expanding research field of paramount interest for academics and industry, with direct consequences on operative, planning, and sustainability issues. We believe merging transport and energy models from different perspectives is the way forward to studying this complex energy systems issue.

Acknowledgments

The authors would like to thank Nick Malleson for his open-source Repast City model and Claire Encely for her work on adapting it to include electric vehicles.

REFERENCES

[1] The Royal Academy of Engineering, "Electric Vehicles: charged with potential". [Online]. Available: *www.raeng.org.uk/news/publications/list/reports/**Electric_Vehicles.pdf*** [Accessed: 25th of August 2010].

[2] S. Acha, T. Green, and N. Shah, "Impacts of plug-in hybrid vehicles and combined heat and power technologies on electric and gas distribution network losses", *Conference on Sustainable Alternative Energy, 2009. PES-IAS. IEEE*, pp.1-7, 28-30 September 2009.

[3] A. J. Tomic and W. Kempton, "Using fleets of electric-drive vehicles for grid support", *Journal of Power Sources*, Volume 168, Issue 2, June 2007, Pages 459-468.

[4] Bureau of Transportation Statistics, "Highlights of the 2001 national household travel survey (NHTS)", U.S. Department of Transportation, 2001.

[5] Element Energy, "Strategies for the uptake of electric vehicles and associated infrastructure implications", The Comitte on Climate Change, 2009.

[6] National Renewable Energy Laboratory (NREL), "Using GPS travel data to assess the real world driving energy use of plug-in hybrid electric vehicles", [Online]. Available: www.nrel.gov/docs/fy07osti/41410.pdf [Accessed: May 31, 2009

[7] S. Acha, T. Green, and N. Shah, "Effects of Optimised Plug-in Hybrid Vehicle Charging Strategies on Electric Distribution Network Losses", *Transmission and Distribution Conference and Exposition, 2010 IEEE PES* , pp.1-6, 19-22 April 2010.

[8] Brooks, E. Lu, D. Reicher, C. Spirakis, and B. Weihl, "Demand Dispatch", *Power and Energy Magazine, IEEE* , vol.8, no.3, pp.20-29, May-June 2010.

[9] Jennings, N. R. (2000). "On agent based software engineering", *Artificial Intelligence* 117(2): 277–296.

[10] Luck, M., McBurney, P., Shehory, O. & Willmott, S. (2005). *Agent Technology: Computing as Interaction (A Roadmap for Agent Based Computing)*, AgentLink, ISBN 9780854328451

[11] Malleson, N. (2008) "RepastCity – A demo virtual city" http://portal.ncess.ac.uk/wiki/site/mass/repastcity.html (accessed 13 January 2011).

[12] Encely, C.E. (2010) "Plug-in Hybrid Electric Vehicles Agent-Based Modelling", MSc thesis, Imperial College London, UK.

[13] Nissan Vehicles. Leaf electric car model. [Online]. Available: http://www.nissanusa.com [Accessed: 25th of October 2010].

[14] S. Acha, T. Green, and N. Shah, "Techno-economical Tradeoffs from Embedded Technologies with Storage Capabilities on Electric and Gas Distribution Networks", *General Meeting, 2010 IEEE PES* , pp.1-8, 25-29 July 2010.

[15] Keirstead, J., Samsatli, N. & Shah, N. (2009). "SynCity: an integrated tool kit for urban energy systems modelling", *Proceedings of the 5th Urban Research Symposium*, Pages: 21-42, Marseille, 28-30 June