PROBABILISTIC IMPACT ASSESSMENT OF ELECTRIC VEHICLE CHARGING ON RESIDENTIAL UK LV NETWORKS

Jairo QUIRÓS-TORTÓS
The University of Manchester – UK
jairoquirostortos@ieee.org

Luis F. OCHOA
The University of Manchester – UK
luis_ochoa@ieee.org

Alejandro NAVARRO-ESPINOSA
The University of Manchester – UK
alejandro.navarroespinosa@manchester.ac.uk

Mary GILLIE
EA Technology Limited – UK
mary.gillie@eatechnology.com

Richard HARTSHORN
Scottish and Southern Energy Power Distribution – UK
richard.hartshorn@sse.com

ABSTRACT

The electricity demand from high penetrations of electric vehicles (EVs) in the UK may result in significant asset capacity issues (transformers and cables) and/or voltage drops in residential low voltage (LV) networks. This paper presents a probabilistic impact assessment of realistic EV charging on nine UK LV networks that are part of the 'My Electric Avenue' project. A deterministic impact assessment is initially compared against the stochastic to highlight the benefits of the latter. Monte Carlo simulations (considering 1-min resolution data) are undertaken to cater for domestic and EV load profile uncertainties. Results show that simplified (deterministic) analyses cannot truly quantify the impacts of EVs in LV networks. More importantly, the probabilistic assessment highlights that technical problems in these LV networks may occur for EV penetrations larger than 30%, and that 20 and 50% of the feeders and transformers, respectively, may exceed their capacity limits for high penetrations. Guidelines to adapt the probabilistic approach to help a network planner are finally discussed.

INTRODUCTION

The number of domestic electric vehicles (EVs) in the UK may soon increase given their potential contribution to reduce greenhouse gases and dependency on fossil fuels [1]. However, high penetrations of EVs may lead to technical impacts on the very infrastructure they will be connected to: the residential low voltage (LV) networks. Indeed, part of the demand from EVs is likely to be coincident with the peak demand of households, resulting in significant stress (excess of transformers and cables capacities, i.e., asset congestions, and/or voltage drops) on the LV networks [2, 3].

Different recent works have quantified the impacts of uncontrolled EV charging, e.g., [2-9]. Simplified analyses (e.g., deterministic and/or snapshot) that do not consider the random nature of the demand from households and EVs and/or the time-series behaviour of loads have been presented [2-4]. Some other works [4-6] have focused on assessing the aggregated impacts of EVs on medium voltage (MV) circuits, without quantifying the effects on LV networks – which are likely to be the first bottleneck as EVs tend to be connected at home. However, to truly quantify the EV impacts on the LV networks, the adoption of real ones is critical given that generic models (e.g., [7]) may not reveal their particularities [10, 11].

In addition, some of these studies, e.g., [6-8], have used travel surveys that consider the use of conventional cars to model the EV demand – they assume that the start charging time corresponds to the home arrival time, that the initial state of charge (SOC) can be calculated from the travel distance and that the final SOC is in most of the cases 100%. However, the (charging) behaviour of car users is likely to change as a result of the new technology uptake and the ability to charge EVs at home (instead of going to the petrol station). Hence, real EV charging behaviour is needed to correctly model the EV demand if adequate impact analyses are to be undertaken.

This paper presents a probabilistic impact assessment of realistic uncontrolled EV charging on nine residential UK LV networks that are involved in the 'My Electric Avenue' project [12]. To cater for the uncertainties associated with household demand as well as EV demand and location, the analyses are carried out using the Monte Carlo methodology presented in [9, 10]. The impacts of uncontrolled EV charging are quantified in terms of asset utilization (transformer and cables) and voltage drops at customer nodes (according to the British Standard EN50160 [13]). The corresponding time-series domestic demand profiles consider 1-min resolution data for a typical weekday during winter in the UK (worst case scenario, i.e., maximum demand). EV load profiles (1-min resolution) are created using real data obtained from actual EV users also part of the 'My Electric Avenue' project. Three-phase four-wire power flow studies are adopted using OpenDSS [14] to cater for voltage unbalance due to single-phase connections.

LV NETWORKS AND LOAD PROFILES

This section describes the residential LV networks and the domestic and EV load profiles used in this work.

LV Networks

Nine residential UK LV networks are used in this paper to quantify the technical impacts of different EV

Table I. Summary of LV Feeders

Characteristic (Main Cable Length)	*No. Feeders*	*No. Customers*
Small (1 – 200 m)	2	29
Medium (200 – 500 m)	14	803
Large (> 500 m)	15	1261

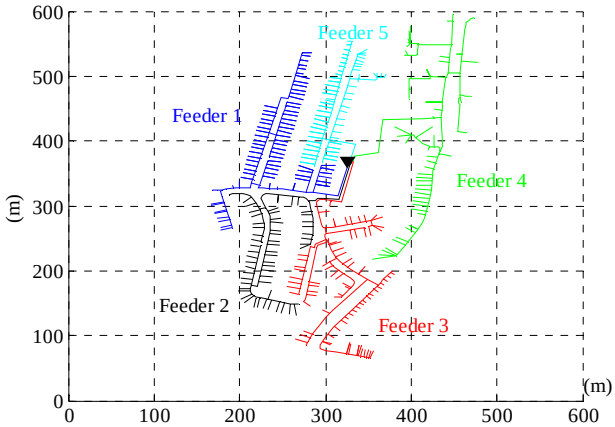

Fig. 1. Example LV network

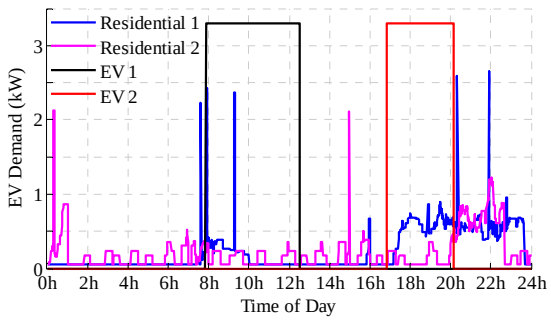

Fig. 2. Individual profiles

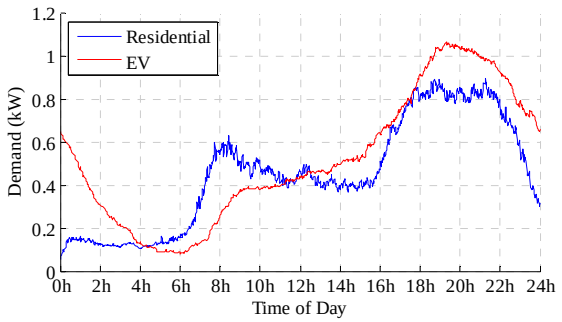

Fig. 3. Diversified profile for 1000 loads

penetration levels. This corresponds to a total of 31 LV feeders, 30% of which are monitored as part of the 'My Electric Avenue' project [12]. Table I summarises the number of small, medium and large feeders, as well as the total number of customers. Each LV network (i.e., topology, power transformer, and type of conductor) is fully modelled using OpenDSS [14]. Fig. 1 shows, as an example, the topology of a LV network from the North East of England that consists of five feeders, a 750 kVA distribution transformer (black triangle), and 428 customers (modelled as Profile Class 1 and 2 [15]), based on data obtained from the Distribution Network Operators (DNOs) involved in the 'My Electric Avenue' project. The busbar voltage is considered to be 424V (line-to-line), aligned with DNO practice.

Domestic Load Profiles

The domestic load profiles used in this paper correspond to a typical weekday during winter (e.g., January). This is done to study the charging of EVs for the worst case scenario, i.e., maximum demand in the UK. The time-series behaviour of the domestic loads is created using the CREST tool [16] – a tool that considers the domestic behaviour of British costumers, the number of people at home, the type of day, the month, and the use of the appliances. This tool is used to generate a pool of 1000 profiles that are randomly allocated at customer nodes to model their demand at each Monte Carlo simulation. These profiles consider the proportion of houses with one, two, three and four or more people: 29, 35, 16 and 20%, respectively, based on UK National Statistics [17]. As an example, Fig. 2 shows two individual residential profiles and Fig. 3 presents the diversified profile for the 1000 residential profiles.

EV Load Profiles

The charging behaviour of EVs is modelled using real data obtained from the trials undertaken as part of the 'My Electric Avenue' project [12]. The start charging time, the initial SOC and the final SOC over a year trial have been collected, and they are used to create a pool of 1000 realistic EV profiles [18]. Fig. 2 and Fig. 3 also show individual EV profiles and the diversified profile for 1000 EV profiles, respectively. Note that the diversified peak demand of EVs, which is similar to the peak found in the real data collected during the trials, is higher than that of the residential one.

To cater for the uncertainties associated with the EV demand and location, the EV load profiles are randomly allocated at customer nodes in each simulation. This allocation is done according to the EV penetration level – a penetration level indicates the percentage of houses with an EV. In this work, the EV battery charging process is continuous, i.e., once it starts, it will not stop until the battery stops withdrawing power (e.g., the EV is disconnected or the battery is fully charge). It is also assumed that EVs are connected only once per day (real data suggest that this is true in 70% of the cases). The EVs considered in this paper are similar to the commercially available Nissan Leaf, i.e., the battery capacity is 24kWh [19], and they are charged at home, i.e., a constant charging rate of 3.3 kW at 230 V is used.

EV IMPACTS ON LV NETWORKS

This section quantifies the technical impacts of the uncontrolled charging of EVs on the LV networks. The

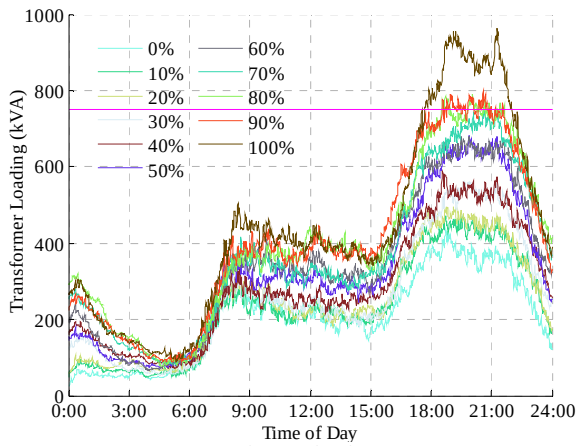

Fig. 4. Diversified profile for 1000 loads

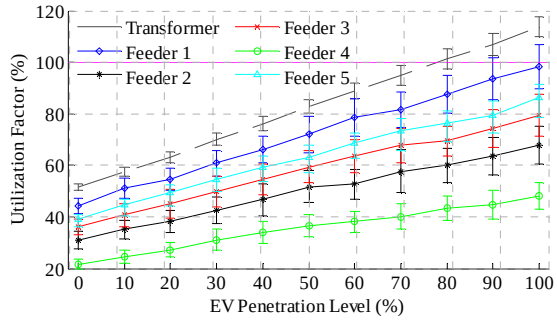

Fig. 5. Utilization factor of the assets

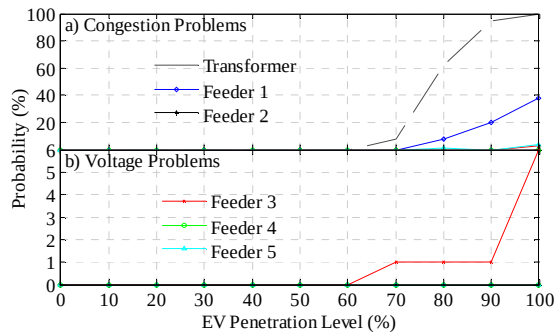

Fig. 6. Probability of: a) Congestion b) Voltage problems

Table II. Percentage of customers with voltage issues in Feeder 3

EV Penetration (%)									
60		70		80		90		100	
Avg.	Std.	Avg.	Std.	Avg.	Std.	Avg.	Std.	Avg.	Std.
0.0	0.0	0.062	0.614	0.072	0.972	0.085	0.946	0.383	1.529

example LV network is initially used to highlight the benefits of carrying out probabilistic analyses (i.e., hundreds of simulations) that cater for the uncertainties instead of deterministic ones (i.e., one single simulation) that may fail to quantify some of these impacts. When the benefits of probabilistic assessments are shown, these are then extended to the other LV networks to truly quantify the EV impacts and to determine their probabilities.

In the analyses, the EV penetration is increased from 0 (base case) until 100% in steps of 10%. The probabilistic analysis for each penetration is based on a Monte Carlo approach with 100 simulations [9, 10]. For each one, a time-series three-phase power flow is solved using OpenDSS. After each solution, the utilization factor of the assets (i.e., maximum power through the asset divided by its capacity) and the number of customers with voltage problems (according to the British Standard EN50160 [13] – considering a daily analysis instead of a weekly one) are quantified to assess the technical impacts.

Deterministic vs Probabilistic

Deterministic Assessment: The technical problems in the LV network shown in Fig. 1 are initially quantified using a deterministic approach, i.e., one single simulation with random allocation of load profiles according to the penetration level. Fig. 4 shows that transformer congestions (i.e., above 750 kVA) may occur for penetrations higher than 70%. For this particular LV network, no problems have been found at the feeder level (i.e., feeder congestions and/or significant voltage drops) at any penetration level.

Probabilistic Assessment: The Monte Carlo methodology (with 100 simulations) detailed in [9, 10] is now implemented on the same LV network. Fig. 5 and Table II show the magnitude of each technical problem (congestion and voltage) and Fig. 6 presents their associated probability. Unlike the deterministic approach, the probabilistic assessment highlights that transformer congestions may actually occur for EV penetrations higher than 60% (i.e., a penetration earlier than the deterministic). More importantly, the probabilistic assessment highlights that feeder congestions may happen in feeders 1, 3 and 5 for EV penetrations higher than 70% and that significant voltage drops may be experienced at some customer nodes in feeder 3 for EV penetrations higher than 60%. It is important to mention that transformer congestions occur first in most of the studied cases (97%). Finally, although the magnitude and probability of feeder congestion and voltage issues may not be so significant in this LV network, the probabilistic assessment highlights that deterministic analyses may fail to quantify some of the EV impacts in LV networks given that the residential demand and EV charging behaviour (i.e., demand and location) are stochastic in nature.

Remarks: Deterministic approaches may not be able to show the frequency of the technical problems and the consequences that they may have. Indeed, simplified approaches may under or overestimate the true impacts that different EV penetrations may have in LV networks. Therefore, probabilistic (i.e., Monte Carlos-based) analyses must be carried out to cater for the large number of uncertainties associated with the demand of households as well as the demand and location of EVs.

In addition, it is important to understand which technical problem occurs first, as this information is crucial for

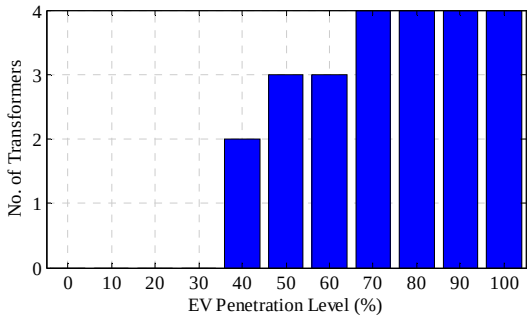

Fig. 7. Number of transformer with congestion problems

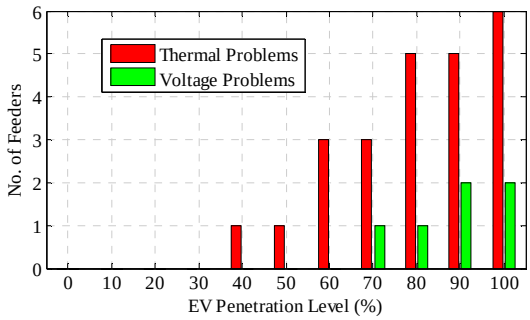

Fig. 8. Number of feeders with technical problems

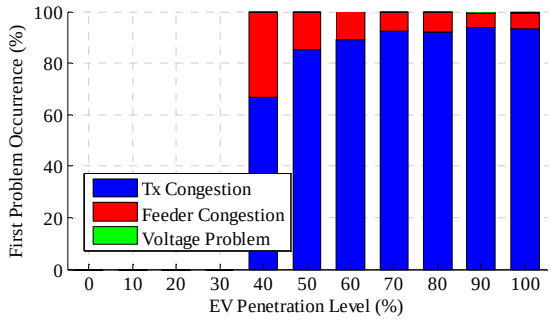

Fig. 9. Probability of occurrence of the first problem

DNOs to design potential Smart Grid schemes to cope with high EV penetrations. In this particular LV network, it was found that transformer congestions occur first. However, this may not be the case in other LV networks with different number of customers and topology.

Finally, it is important to highlight that DNOs may be more interested for network planning purposes on the EV impact on a particular LV feeder (e.g., a highly loaded feeder with a new housing development at the remote end of it). Thus, the probabilistic assessment presented here can be adapted to use information available for a particular feeder. For instance, the probabilistic assessment can be tailored so all the charging points are located at the end of the feeder or to consider that every house has only one or two residents (i.e., 1 bedroom flats). With this information and the layout of the feeder, the probabilistic approach can then be used to determine the EV penetration that is possible without breaching voltage or thermal limits.

Multi-Network Assessment

The impact assessment presented above is useful to understand the behaviour of one particular LV network under different EV penetrations. However, the lessons learnt from one network cannot be necessarily extrapolated to a different one [9]. Two networks can present different problems at different EV penetrations.

Since a probabilistic assessment provides a better understanding of the technical issues experienced in LV networks, the Monte Carlo methodology is now implemented on the other LV networks to truly quantify the technical impacts of different EV penetrations.

Fig. 7 shows for a penetration as low as 40% that two transformers may present congestion problems (i.e., the probability of congestions is higher than zero at 40% EV penetration for at least two transformers). More importantly, it shows that up to four transformers may be congested for high EV penetrations.

In terms of problems at the feeder level, Fig. 8 shows that at least one feeder will present congestion problems for a 40% penetration. It also highlights that 20% of the total number of LV feeders will face thermal issues for the highest penetration level. As for voltage issues, Fig. 8 also shows that up to two feeders may experience significant voltage drops for the two highest penetrations.

In terms of the occurrence of the first problem, which is important to know for the future design of control strategies, Fig. 9 shows that 65% of the problems that may occur for a 40% EV penetration are due to thermal issues at the transformer level and the remaining 35% are feeder congestions. This stresses the necessity for designing control strategies to cope with both problems at the feeder and transformer level (see for example [11]).

Finally, it is important to mention that although Fig. 9 highlights that these LV networks may face voltage problems before any other technical issue in less than 1% of the cases, this may not be the case of other LV networks where voltage issues may become a more serious problem.

CONCLUSIONS

This paper has presented a probabilistic impact assessment of realistic EV charging on nine UK LV networks that are part of the 'My Electric Avenue' project. This probabilistic impact assessment has also been compared against a (simplified) deterministic approach to highlight the benefits of carrying out the former, particularly when the variables involved (i.e., load and EV demand and location) are stochastic in nature.

The impacts have been quantified in terms of asset utilization and percentage of customers with voltage problems. Time-series simulations have been adopted considering 1-min resolution data for a typical weekday during winter in the UK (worst case scenario, i.e., maximum demand). The time-series behaviour of EVs has been created using real data from actual EV users. The probabilistic impacts of uncontrolled EV charging have been quantified using a Monte Carlo methodology to cater for the uncertainties.

It was shown that simplified approaches may not truly quantify the impacts of uncontrolled EV charging, as they may not be able to show the frequency of the technical problems and the consequences that they may have.

Using the probabilistic assessment, it was found that congestions may occur in at least two transformers for a penetration as low as 40%. In addition, at least one feeder may present congestions for a 40% penetration. More importantly, it was highlighted that 20% of the total number of feeders (31) and half of the total number of transformers (9) may present congestions problems for the highest EV penetration. For high penetrations, the latter occurs first for most of the studied LV networks.

The probabilistic assessment is flexible in that can be adapted to cater for specific conditions of EV locations and specific type of customers. Therefore, it can be used to guide network planners to determine the capacity available on feeders under particular scenarios of interest.

Finally, further research should investigate the cost-effectiveness of Smart Grid strategies to mitigate these technical impacts as opposed to traditional network reinforcements.

ACKNOWLEDGMENTS

This work has partly been funded by EA Technology, UK, through Ofgem's Low Carbon Networks Fund Tier 2 Project "My Electric Avenue", 2013-2015. In addition, the authors would like to thank Northern Powergrid and Scottish and Southern Energy Power Distribution for providing the LV network data.

REFERENCES

[1] Committee on Climate Change, "Reducing the UK's carbon footprint and managing competitiveness risks," http://www.theccc.org.uk/wp-content/uploads/2013/04/CF-C-Summary-Rep-web1.pdf, Apr. 2013.

[2] L. Pieltain Fernández, T. G. S. Román, R. Cossent, C. M. Domingo, and P. Frías, "Assessment of the Impact of Plug-in Electric Vehicles on Distribution Networks," *IEEE Trans. Power Systems*, vol. 26, pp. 206-213, Feb. 2011.

[3] P. Richardson, M. Moran, A. Maitra, J. Taylor, and A. Keane, "Impact of electric vehicle charging on residential distribution networks: An Irish demonstration initiative," in *CIRED*, Stockholm, 2013.

[4] K. Clement-Nyns, E. Haesen, and J. Driesen, "The Impact of Charging Plug-In Hybrid Electric Vehicles on a Residential Distribution Grid," *IEEE Trans. Pow. Syst.*, vol. 25, pp. 371-380, 2010.

[5] R.-C. Leou, C.-L. Su, and C.-N. Lu, "Stochastic Analyses of Electric Vehicle Charging Impacts on Distribution Network," *IEEE Trans. Power Systems*, vol. in press, pp. 1-9, May 2013.

[6] Z. Darabi and M. Ferdowsi, "Aggregated Impact of Plug-in Hybrid Electric Vehicles on Electricity Demand Profile," *IEEE Trans. Sustainable Energy*, vol. 2, pp. 501-508, Oct. 2011.

[7] M. S. ElNozahy and M. M. A. Salama, "A Comprehensive Study of the Impacts of PHEVs on Residential Distribution Networks," *IEEE Trans. Sustainable Energy*, vol. 5, pp. 332-342, 2014.

[8] N. Leemput, F. Geth, J. Van Roy, A. Delnooz, J. Buscher, and J. Driesen, "Impact of Electric Vehicle On-Board Single-Phase Charging Strategies on a Flemish Residential Grid," *IEEE Trans. Smart Grid*, vol. 5, pp. 1815-1822, Jul. 2014.

[9] A. Navarro and L. F. Ochoa, "Report for Deliverable 3.6 "What-if Scenario Impact Studies based on real LV networks"," The University of Manchester, "Low Voltage Network Solutions" Project, www.enwl.co.uk/lvns, Apr. 2014.

[10] A. Navarro, L. F. Ochoa, and D. Randles, "Monte Carlo-based assessment of PV Impacts on real UK low voltage networks," in *IEEE PES General Meeting*, 2013, pp. 1-5.

[11] K. Petrou, J. Quirós-Tortós, and L. F. Ochoa, "Controlling electric vehicle charging points for congestion management of UK LV networks," in *IEEE PES ISGT*, Washington, USA, 2015, pp. 1-5.

[12] My Electric Avenue. Available: http://myelectricavenue.info/

[13] British Standards Institution, "BS EN 50160: Voltage characteristics of electricity supplied by public distribution systems,," ed, 2000.

[14] EPRI. *Open Distribution System Simulator, 2012*.

[15] ELEXON, "Load Profiles and their use in Electricity Settlement," Nov. 2013.

[16] I. Richardson, M. Thomson, D. Infield, and C. Clifford, "Domestic electricity use: A high-resolution energy demand model," *Energy and Buildings*, vol. 42, pp. 1878–1887, Oct. 2010.

[17] Office of National Statistics, "Families and Households, 2013," Statistical Bulletin, Oct. 2013.

[18] J. Quirós-Tortós, L. F. Ochoa, and B. Lees, "A Statistical Analysis of EV Charging Behavior in the UK," *IEEE PES Letters*, submitted, Jan. 2015.

[19] Nissan LEAF. Available: http://www.nissan.co.uk/