Available online at www.sciencedirect.com

ScienceDirect

Energy Procedia 158 (2019) 6458–6465

Energy Procedia

www.elsevier.com/locate/procedia

10th International Conference on Applied Energy (ICAE2018), 22-25 August 2018, Hong Kong, China

The Prediction of Electric Vehicles Load Profiles Considering Stochastic Charging and Discharging Behavior and Their Impact Assessment on a Real UK Distribution Network

Qian Hu[a], Haiyu Li[b], Siqi Bu[a,*]

[a]*The Hong Kong Polytechnic University, Hong Kong, China*
[b]*The University Of Manchester, Manchester, UK*

Abstract

Electric vehicle (EV) as one of the most promising solutions to reduce the greenhouse emission is developing faster than ever. With the increasing number of EVs, the additional load will cause technical issues on the existing distribution network. To cope with possible challenges, the reasonable prediction of EV load profile is fundamental to the evaluation of how the distribution network responds to the potential increasing EV penetration. This paper investigates the critical issues that EVs bring into the network at various penetration levels considering the uncertainties due to stochastic charging and discharging behaviour. To deal with these uncertainties, a Monte Carlo based simulation method is utilised to create EV charging and discharging profiles. Three scenarios are proposed and their impacts on a real UK distribution network are analysed by the simulation in OpenDSS and MATLAB. The simulation results imply that EV charging process has the negative effect in regard to thermal stress, voltage drop, system efficiency and power factor of the network. Conclusions are drawn to provide the guidance for the upgrading and reinforcement of the existing network assets.

Keywords: Electric Vehicles (EVs), Monte Carlo simulation, Distribution network, Impact assessment

1. Introduction

Personal vehicles are blamed for the emissions that cause air pollution in the urban areas. The transport sector is facing a serious challenge on its sustainable development path than ever. In the past few years, interests in electric vehicle (EV) has been motivated by the carbon emissions savings. The increasing number of EVs connected to the grid would bring both negative and positive impact on the existing energy systems. The rising power demand due to

* Corresponding author. Tel.: +852 27666163; fax: +852 23301544.
E-mail address: siqi.bu@polyu.edu.hk

10.1016/j.egypro.2019.01.134

the large penetration of EV could provide an effective approach to consume the electricity generated by the renewable energy sources (RESs) which will stimulate the large integration of renewable energy. Nevertheless, the localised distributed network will be more vulnerable in the front of large number of EVs as they are mainly connected to the local residential areas where the networks are sometimes heavily loaded.

To cope with possible challenges and realise the optimal planning of distribution network with large penetration of EV, understanding their charging and discharging behaviour is the primary task. From the distribution planning perspective, EV can be characterized as a flexible and stochastic load that changes spatially and temporally across the power grid [1]. As the deployment of the EV is still in the early development stage, it is hard to obtain comprehensive historical data of electric vehicles, such as daily travel distance and the charging duration. Besides, EV charging demand is highly dependent on the owners' habits and influenced by several random factors. Uncertainties should be dealt with carefully when establish the EV charging model.

In this paper, a comprehensive probabilistic model considering the EV random impact factors is created. Three charging scenarios which cover the most typical scenarios, including peak charging, off-peak charging and V2G charging are proposed to predict the charging and discharging profiles. Then the case studies on a real UK distribution network will be carried out to assess the impact on the distribution network. Results can be used to provide the guidance for the future EV integration planning and optimisation. It should be noted although EV profiles in the paper are established on the basis of several assumptions, the method implemented and the analysis carried out below are applicable to other cases.

2. Determination of Critical Impact Factors

For simplicity, all-electric vehicle， which is capable to complete a significant percentage of trips electrically and can be easily accepted by the market, is chosen as the electric vehicle type in this paper. EV is referred to all-electric EV hereinafter. For owner's convenience, home charging will be the most common charging venue in the future. Therefore, it is assumed that EV charging solely occurs in EV owner's residence. Only single-phase EV connection is considered in the paper. EV power factor is set to 0.98 inductive.

2.1. EV battery type and capacity

Lithium-ion is selected as it has a much longer lifetime and is capable of more charging cycles, which has been mainly applied to EV battery currently [2]. Since the behavior of the all-electric vehicle is studied and it is assumed that charging solely occur in the user's home above, three representative all-electric vehicle models of city cars that are currently on sale in the market are chosen for the typical EV load profile creation. They are Peugeot ION (16.5kWh), Volkswagen GOLF (26.5kWh) and Nissan LEAF (25kWh). As it is hard to predict the market share of each model, the battery capacity is randomly selected within three values in each iteration of the simulation.

2.2. EV charging rate and energy efficiency

IEC 61581-1 standard defines three types of AC charging modes according to the rated charging voltage and current level. Slow charging mode is adopted in both domestic and public charging infrastructures, while both fast charging and rapid charging are only found in the public charging points which can provide much higher charging current [3]. Considering the real scenarios, it is more likely that the first users of EVs would be those who can charge at home or during the work with relatively longer charging time. Hence, slow charging mode is chosen to establish EV profiles. The average power demand of 3.5 kW, which is assigned to a typical EV power level in slow charging mode, is donated to the following model creation. Around 80% of the energy stored in the EV battery can be used to drive the wheels [4], which is the set value for charging efficiency in the following calculation.

2.3. Daily driving distance

To create a probabilistic model that reflects the most likely behaviour of the EV load profile, the general pattern related to the mobility behaviour of the normal vehicles which is extracted from long-term traffic habits is relatively more convincible [5]. A probability density function of daily driving distance generated from travel survey data in [6] is selected to use, as shown in equation (1), where μ=3.7, σ = 0.92. Figure 1 plots its probability distribution curve.

$$f_d = (1/d\sigma\sqrt{2\pi})\exp[-(\ln d-\mu)^2/2\sigma^2] \quad (1)$$

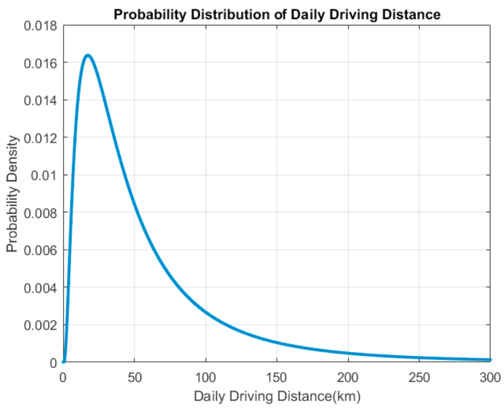

Fig. 1. probability distribution of daily driving distance

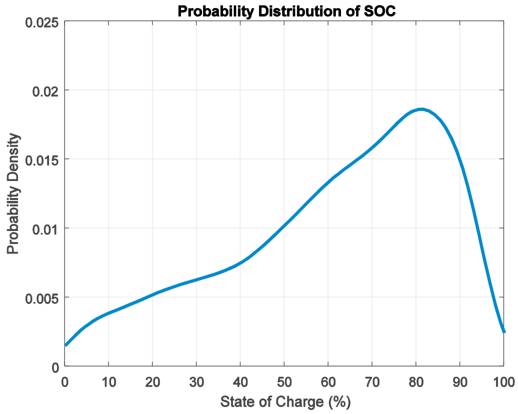

Fig. 2. probability distribution of state of charge

2.4. State of charge (SoC) and required charge/discharge duration

Initial and final SoC are important variables to describe the percentage of charge remaining in the EV battery before it is recharged and discharged respectively [7]. The linear relationship between SoC and travel distance is shown in equation (2), where *d* is the daily driving distance and *R* is the maximum driving duration when an EV is fully charged. To simplify the following analysis, *R* is assumed as 100km so that $d \leqq 80$km based on 80% EV battery efficiency mentioned before. From equation (1) and (2), probability density function of SoC is derived as equation (3). Accordingly, probability distribution of SOC can be plotted which is shown in figure 2. Following it, SoC can be randomly sampled and then allocated to every single charging behaviour through Monte Carlo method.

$$SoC = 1 - d/R \quad (2)$$

$$fsoc = (1/R(1-SoC)\sqrt{2\pi})\exp[-(\ln(R(1-SoC))-\mu)^2/2\sigma^2] \quad (3)$$

Required charging energy for an EV is determined by initial *SoC* and battery capacity *C* (kWh). Considering the energy conversion efficiency 80% proposed previously, required charging duration T_{charge} to refill the battery to the full capacity can be calculated by equation (4), where *P* is the charging power level.

$$T_{charge} = E_{charge}/P = C(1-SoC)/(0.8\cdot P) \quad (4)$$

Similarly, required charging duration $T_{discharge}$ is calculated by

$$T_{discharge} = E_{discharge}/(-P) = C\cdot SoC/(-0.8\cdot P) \quad (5)$$

3. Simulation Methodology

Based on the content above, the flow chart of EV profile establishment approach via MATLAB is illustrated in figure 3. A pool with 1000 EV load profiles can be created by 1000 times iterations. OpenDSS is introduced to assess the EV impact on the distribution network. A flow chart mapping out the working interaction between OpenDSS and MATLAB is shown in figure 4. The procedure to carry out the impact assessment of the EV load profile consists following steps, where EV penetration level and the total number of customers are *P%* and *N* respectively, *M=P*N* is the number of customers who own an EV in the network:

- *M* of EV profiles are randomly selected from the pool consisting 1000 EV load profiles in MATLAB.
- Selected EV load profiles are added and randomly allocated to *M* customers in LOAD file in OpenDSS.
- Driven by MATLAB, the time-series power flow with 1-min resolution is executed in OpenDSS.
- The electrical quantities revealed in power flow results, including voltage, power consumption, power losses,

power factor and system efficiency are obtained in MATLAB for the impact assessment.

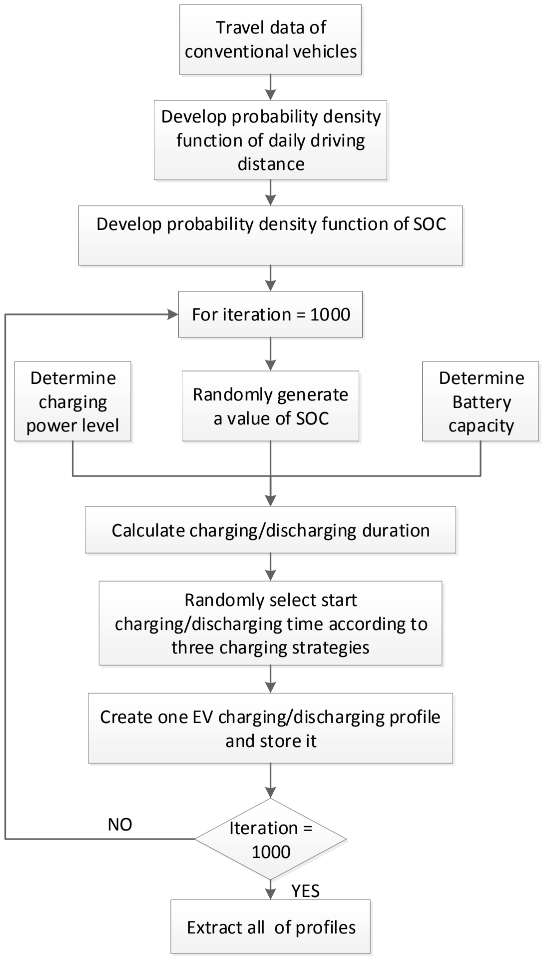

Fig. 3. Flow chart of EV profile creation in MATLAB

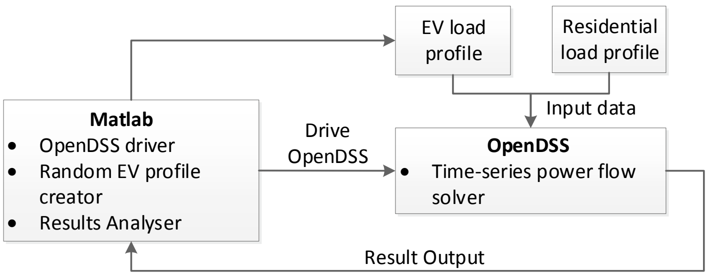

Fig. 4. Workflow of OpenDSS and MATLAB

In the following, three charging scenarios will be proposed. The starting charging time within a day has a notable effect on the resulting load demand profile. To simplify the analysis and meanwhile to cope with the uncertainties, the start charging time is randomly selected within a certain time scope in the simulation for each proposed scenario. The average profiles of 100 electric vehicles under three charging scenarios are illustrated in figure 5(a)-(c).

Uncontrolled Charging: It is assumed the charging starts as soon as the drivers arrive home from work without consideration of the electricity tariff. Start charging time is regarded as vehicle arrival time (4 pm to 8 pm.)

extracted from travel survey in [8]. This scenario represents the worst case where no incentive to motivate the EV owner to charge their cars in the off-peak time.

Economy 7 Charging: Electricity price is one of the factors that determine when customers would charge their cars. Economy 7 is a differential electricity tariff scheme offering cheaper off-peak electricity for 7 hours during the night in the UK [9]. Therefore, a desirable charging strategy which could be encouraged by lower off-peak electricity prices is proposed based on this tariff. From the perspective of EV owner, the objective of off-peak charging is to minimize the charging cost. In the simulation, it is assumed that the charging starts at a certain time between 11 pm and 2 am and can be lasted for the whole night. Such charging strategy could favour an effective utilization of electricity as EVs can be charged during the night off-peak periods.

V2G Discharging & Charging: With the development of V2G technology, it is possible that EV could flexibly play the role of energy storage source. Therefore, V2G discharging strategy is proposed to simulate an ideal case that under large EV penetration, the excess electrical energy in the EV battery can be resent to the grid to support the peak demand. Specifically, it is assumed that EV users could discharge their EVs to the grid during the evening peak between 5 pm to 8 pm so that the load peak can be clipped. As the main incentive, they can earn the payback from the electricity they sell. However, the battery degradation is a concern that must be considered in the real life.

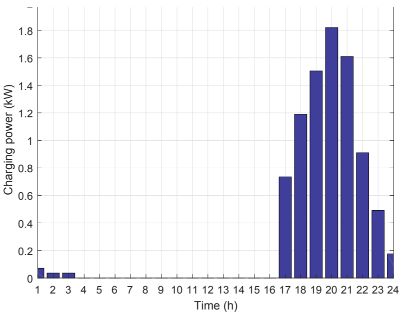

Fig. 5(a). EV load profile under uncontrolled charging

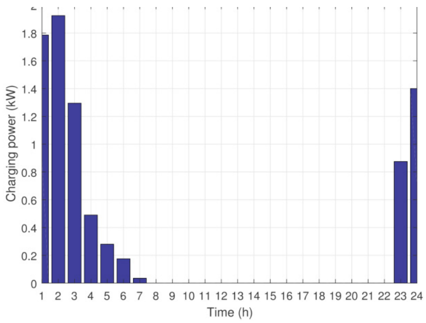

Fig. 5(b). EV load profile under E7 charging

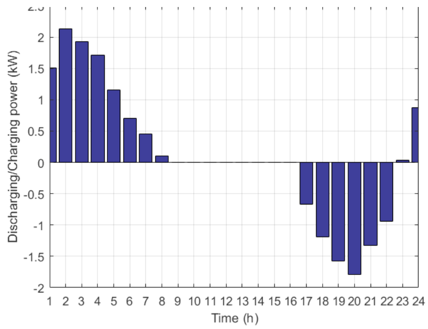

Fig. 5(c). EV load profile under V2G

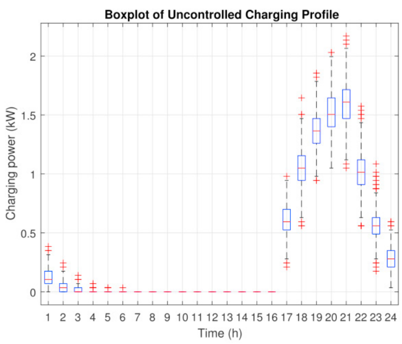

Fig. 6(a). Boxplot of EV load profile under uncontrolled charging

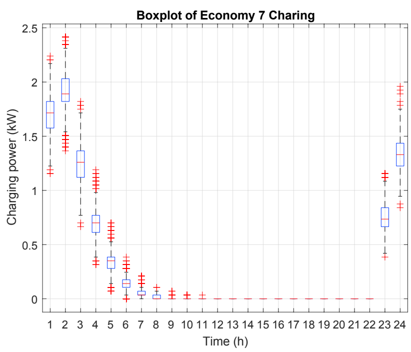

Fig. 6(b). Boxplot of EV load profile under E7 charging

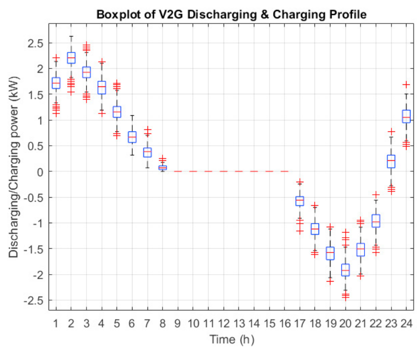

Fig. 6(c). Boxplot of EV load profile under V2G

To truly demonstrate the statistical distribution of EV charging and discharging data from 1000 times of simulations, boxplots are generated by MATLAB, which are shown in figure 6 (a)-(c). Each box represents a cluster of charging data in each hour within a day. Red lines in the boxes represent the median charging power demand in each time slot. Upper and lower whisker of each box reflect the minimum and maximum power in the specific hour. Wrong data in each slot are displayed as +. By comparing the histogram and boxplot under the same strategy, it is noticeable that they have a similar pattern. Therefore, it can verify that most of the data randomly generated by Monte Carlo simulation to create the average profiles fall in the reliable range. However, it should be noted the model created in this paper results relatively higher EV demand as it is assumed that all EV users charge their vehicles simultaneously during the fixed period. However, in the real life EVs do not necessarily being charged every day and some users may charge EV more flexibly instead of strictly following the charging time proposed here. Therefore, the impact assessment conducted in the next session might slightly overestimate.

4. Case Study - Impact Assessment on Real LV Network

A real low voltage network Denton East in England, which is modelled in OpenDSS, is used as the test network to integrate the various penetrations of EV. The network with rated 500 kVA capacity is supplying 296 domestic customers. It is expected the phase connected with EV would experience the most severe voltage drop. Hence, the phase denoting the minimum voltage (i.e., the phase connected with EV) is investigated for the interest. The lower voltage limit is set to 0.94 p.u, which is the minimum UK legal requirement. Results in terms of minimum voltage and peak power demand are recorded in table 1. The values in red represent that the voltage lower limit or power capacity for normal operating is violated. Power consumption profiles are shown in figure 7(a)-(c).

Table 1 Minimum voltage and peak power consumption under three scenarios

	EV Penetration level	**0%**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**
Uncontrolled	**Vmin (pu)**	0.995	0.968	0.956	0.934	0.917	-	-	-	-	-
	Smax (kVA)	313.1	364.6	401.7	461.9	519.6	-	-	-	-	-
Economy 7	**Vmin (pu)**	0.995	0.995	0.985	0.981	0.962	0.949	0.948	0.946	0.945	0.926
	Smax (kVA)	313.1	313.1	313.1	313.1	315.5	362.4	410.6	468	537	590.3
V2G	**Vmin (pu)**	0.995	0.991	0.988	0.986	0.96	0.946	0.937	0.929	0.919	0.903
	Smax(kVA)	313.1	273.6	242	267	307.2	377.8	419.6	489.5	533.2	591

For uncontrolled charging, as there is no incentive to encourage EV owners to charge the cars at the off-peak time, the charging load overlaps with original peak load in the peak time, shown in figure 7(a). Only 20 % of customers can charge their EVs in the peak time simultaneously. For Economy 7 charging, 80% EV penetration level can be achieved. Peak power remains the same as the initial value until EV penetration level reaches to 40%. This is because the peak demand is still dominated by residential load under low EV penetration level. For V2G mode, figure 7(c) tells that power demand of the peak time is cut down due to the reversed power flowing into the network. Noticeably, the power curve is levelled off at 20% penetration so that a flat curve can be seen. The maximum penetration level is 50%.

In addition, power factor and system efficiency of test network are also examined under three scenarios. The results show that power factor is decreased as EV can be regarded as the inductive load with power factor of 0.98 when it's connected to the grid for charging. The system efficiency is poorer with the larger number of EVs.

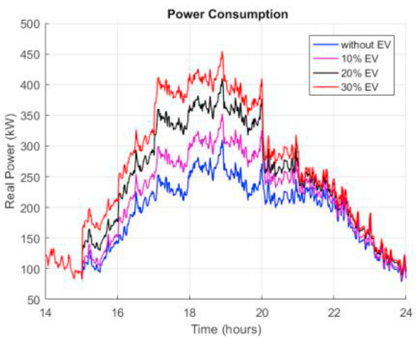

Fig. 7(a). Power consumption under uncontrolled charging

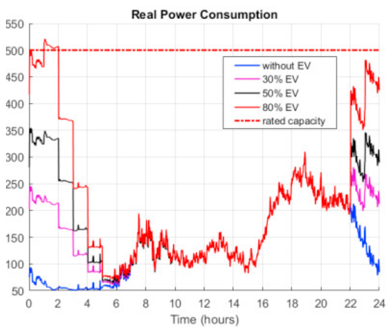

Fig. 7(b). Power consumption under E7 charging

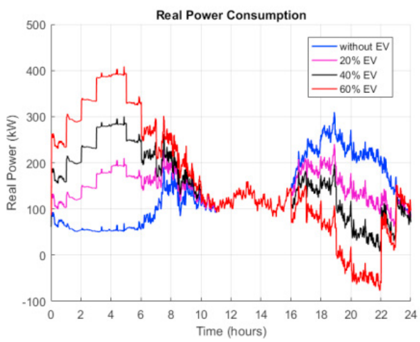

Fig. 7(c). Power consumption under V2G mode

The utilisation level is defined as the ratio of the maximum apparent power through the asset and the rated capacity of the asset [10]. It provides an insight how different penetration level of EV affects the asset loading and the adequacy (capacity to supply the demand) of LV networks, which is shown in figure 8. Under V2G mode, the utilisation level is decreased but only when penetration is less than 20%. It is found the benefit of discharging process in V2G to reduce the congestion is limited comparing with E7 charging. To maximize the lifespan of the asset in the system, the transformer should not be loaded to full capacity for long time. Therefore, the EV penetration level acquired here can be only taken as the reference. In real life, the number of EVs that can be connected to this distribution network will be less.

Generally, real power losses are rising with the growing number of EVs. More power losses are generated under uncontrolled charging scenario at the same penetration level, which is shown in figure 9. If a network has a fixed total daily load, there would be fewer power losses of the network with a flatter the daily load curve [6]. In other words, much more power loss of the network will be produced if there is a larger difference between the peak and the valley power. As EV uncontrolled charging increases the gap between peak and valley, it results in more extra power losses. For V2G mode and E7 charging, the off-peak power valley is filled by EV charging demand so that the losses are reduced. Moreover, under V2G mode, the power curve is levelled off to a flatter curve when the penetration level is less than 30%. Therefore, slightly less power losses can be observed under V2G mode than E7 when penetration is lower that 30%.

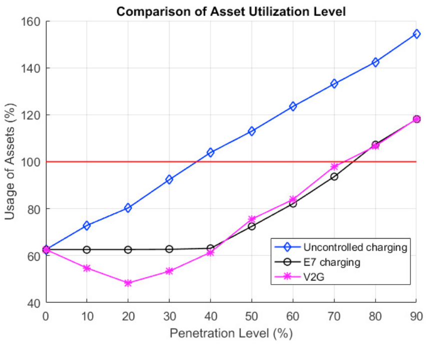

Fig. 8. Comparison of the utilisation level under three scenarios

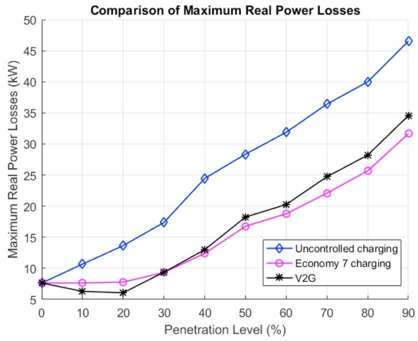

Fig. 9. Comparison of maximum real power losses under three scenarios

Three potential solutions towards distribution network management are discussed according to the acquired results. Additional investments for asset reinforcements can be made by Distribution Network Operators (DNOs) to deal with the increasing penetration of EVs in the future. The straightforward solution is to install enough number of voltage regulators to maintain the voltage within the acceptable range, which is only applicable to the situation that EVs take account for a small proportion of the automotive sector. With the expanding number of EVs in the future, necessary smart actions are obliged to be taken by DNOs. From the simulation results, it has known electricity price could be a critical factor that influences the charging pattern of EV users and could reduce the potential peak stress significantly. Therefore, advanced metering infrastructure (AMI) systems for real-time pricing can be introduced [11]. By setting the real-time electricity structure, the load demand between peak time and off-peak time can be balanced dynamically to release the network congestion. Given that, EV charging loads within the household could be potentially controlled in a coordinated manner. Furthermore, aiming to control and predict the load patterns on the residential distribution networks, active demand side management should be developed. For example, the communication system between DNOs and EV drivers could be established. The individual battery charging process will be monitored and controlled to realize the optimization of the functioning of the distribution system.

5. Conclusion and Future Work

In this paper, the impact factors of EV charging behaviour are discussed comprehensively. By using Monte Carol simulation method, EV load profile for three charging strategies: uncontrolled charging, Economy 7 charging and V2G mode are created considering the uncertainties. Their impacts on a real LV network are analysed with respect to thermal and voltage issues in OpenDSS and MATLAB at various EV penetration levels. The results show EV charging demand is detrimental to voltage deviation, asset congestion, system efficiency and power factor. The test network can accommodate the substantial penetration levels of EVs if the charging is restricted at off-peak time by the incentive tariff scheme. It should be noted that the results acquired in the paper are network-dependent and can be different from the results from other studies. Nevertheless, the conclusions achieved are general and can be applied to different circumstances.

In terms of EV load profile creation, three improvements could be further implemented to create more comprehensive demand scenarios. Firstly, in addition to the city car model used in the paper, more different types of vehicle models with a wider range of battery capacity should be considered, for example, vans and SUVs. Secondly, the behaviour of commercial charging can be potentially combined with the residential charging which is the study focus in this paper. Thirdly, fast charging and rapid charging mode can be discussed considering a more flexible charging demand of different EV users in the future. Besides, more networks with various load patterns and system configuration can be studied.

Acknowledgements

The authors would like to acknowledge the support from Department of Electrical Engineering, The Hong Kong Polytechnic University for the Start-up Fund Research Project (1-ZE68), Hong Kong Research Grant Council for the Research Projects (25203917) and (15200418), and National Natural Science Foundation of China for the Research Project (51807171).

References

[1] ElNozahy M, Salama M. A Comprehensive Study of the Impacts of PHEVs on Residential Distribution Networks. IEEE Transactions on Sustainable Energy. 2014;5(1):332-342.
[2] Boxwell M, Boxwell M. The 2011 electric car guide. Ryton on Dunsmore, Warwickshire, U.K.: Greenstream Pub.; 2011.
[3] Chan C, Chau K. Modern electric vehicle technology. Oxford (England): Oxford University Press; 2001.
[4] Qian K, Zhou C, Allan M, Yuan Y. Modeling of Load Demand Due to EV Battery Charging in Distribution Systems. IEEE Transactions on Power Systems. 2011;26(2):802-810.
[5] Tehrani N, Wang P. Probabilistic estimation of plug-in electric vehicles charging load profile. Electric Power Systems Research. 2015;124:133-143.
[6] Wang H, Song Q, Zhang L, Wen F, Huang J. Load Characteristics of Electric Vehicles in Charging and Discharging States and Impacts on Distribution Systems. Int. Conf. Sustain. Power Gener. Supply (SUPERGEN 2012), 2012; pp. 144–144.
[7] Darabi Z, Ferdowsi M. Aggregated Impact of Plug-in Hybrid Electric Vehicles on Electricity Demand Profile. IEEE Transactions on Sustainable Energy. 2011;2(4):501-508.
[8] ElNozahy M, Salama M. A Comprehensive Study of the Impacts of PHEVs on Residential Distribution Networks. IEEE Transactions on Sustainable Energy. 2014;5(1):332-342.
[9] Economy 7 tariff - A guide to the cost and energy savings [Internet]. uSwitch. 2018. Available from: https://www.uswitch.com/gas-electricity/guides/economy-7/
[10] QUIRÓS-TORTÓS J, F. OCHOA L, NAVARRO-ESPINOSA A. Probabilistic impact assessment of electric vehicle charging on residential UK LV networks. 23rd International Conference on Electricity Distribution. 2015;.
[11] Richardson P, Flynn D, Keane A. Optimal Charging of Electric Vehicles in Low-Voltage Distribution Systems. IEEE Transactions on Power Systems. 2012;27(1):268-279.