Electric Vehicles- Effects on Domestic Low Voltage Networks

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Abstract— Electric Vehicles (EV) charging from a domestic power socket are becoming increasingly popular due to their economic and environmental benefits. The large number of such vehicles presents a significant additional load on existing low voltage (LV) power distribution networks (PDN). Evaluating this impact is essential for distribution network operators (DNO) to ensure normal functioning of the distribution grid. This research uses predictions of EV development and penetration levels to create a stochastic model of aggregate charging demand in a neighbourhood. Combined with historic distribution substations data from the Milton Keynes, UK total loads on the distribution transformers are projected. The results show significant overloading can occur with uncoordinated charging with just 25% of EVs on the road. The traditional way to solve this problem would be upgrading the transformer; however, that could be avoided by implementing coordinated charging to redistribute the load.

Index Terms—Electric vehicle, Load Modeling, Power system planning, Substations

I. INTRODUCTION

Electric vehicles (EV) are becoming increasingly popular and are set to become very common in the near future. Some reasons for their popularity identified by Go Ultra Low campaign [1] are environmental friendliness, comfort (low noise), good performance and low running costs. With the anticipated high penetration ratio in future vehicle market and proposition of majority of them being charged at home, concerns regarding their impact on domestic low voltage (LV) electric distribution networks have been raised. This particular study was initiated by Western Power Distribution (WPD), the electric distribution network operator (DNO) serving 7.8 million customers across UK [2]. WPD have provided real data on distribution network layout, customers and current loads in the area of Milton Keynes, UK (MK) to support the research. Our aim is to use the data and combine them with literature sourced predictions to determine the expected impact of EVs on LV networks in the future. The analysis will serve UK DNOs as an indicator of the required investment in infrastructure to support these additional upcoming loads.

A. Background

In the UK Ultra Low Emission Vehicles (ULEV; vehicles producing 75g or less of CO_2 per kilometre from the tailpipe) already had more than 1% market share in last quarter of 2014 and first quarter of 2015 [3]. One very important factor affecting the sales is governmental activity. UK Government's influence includes investments in industry, subsidizing purchase of ULEVs and other stimulations, for instance lower taxes and levies for such vehicles; currently there is a plug-in grant of up to £5000 for eligible cars and up to £8000 for light commercial vehicles [4]. The driving force behind these activities is the UK Government's commitment to the legally binding obligation to cut greenhouse emissions by 80% by year 2050 in comparison with 1990, introduced in The UK Renewable Energy Strategy in 2011 [5]. Another motivator is the determination to pursue the strategic opportunity of the new technologies and help the UK's automotive industry be at the forefront of ULEV design, development and manufacturing [4].

B. Related Work and the Research Gap

Case study of New York state undertaken by New York Independent System Operator (operates the state's high-voltage transmission network) highlighted that delivery ''to the last mile'' in the local energy system could be a great challenge [6]. To fully exploit EVs' potential positive impact, a third party control over the charging process would be the best option, but even simple time-of-use residential meters coupled with revised retail rate structures would have an enormous positive influence. A low voltage network case study was made for the city of Blackburg, Virginia, US where the typical 25 kVA distribution transformer serves 4-7 homes in a neighbourhood [7]. The drawback of using hourly data is pointed out; domestic load curve is greatly smoothened [7]. Salah, Ilg, Flath, Basse and Dinther [8] made a study of impacts on distribution substations in Switzerland and find that using dynamic pricing is potentially more problematic as the majority of the vehicles would start charging at exactly the same time: the start of the lowest price period, thus creating a pronounced peak. Another study identifies potential issues of high EV penetration: excessive wear on residential

transformers, transformer overloads, transmission bottlenecks, increased line losses and power quality issues, meaning network reinforcements or charging management technologies will be needed to safely integrate large numbers of EVs [8]. These technologies are: stagger charge (charging in steps) and household load control (giving customer the choice to shed non-essential load in exchange for quicker EV recharging) [7].

Plenty of work has been focused on implementing new smart charging technologies, with the aim of smoothening the load curve rather than creating new peaks with EV charging. Schuller, Flath and Gottwald [9] assume a bundle of many EVs being charged together in a coordinated way (EV aggregator) and evaluate their system balancing potential. The study found that EVs have a huge potential for balancing the grid if coordinated properly in case of wind power generation; it was previously indicated that only 1 million EVs in use could provide half of the balancing power for a 30% wind power share in the UK [9]. Acha, Green and Shah [10] go a step further with optimisation and propose time coordinated optional power flow (TCOPF), which includes vehicle to grid (V2G) mode. This enables the EV to act as a power source or load, depending on other loads on the network.

A limitation of the previous studies is the lack of precise input data. There were few studies using real transformer data; and the ones that were used hourly ([7] and [11]) or half-hourly data [10]. The consequence of this is a much smoothened daily consumption curve, which is not representative of normal peaks and fluctuations. Another area that could be improved are the vehicle charging patterns. Often different states of charge of a large number of vehicles and home arrival times were not based on any real historic data. None of the reviewed works had taken the users already using Economy 7 (E7) or similar split tariff scheme into account. That way, a mixed scenario can be created, where the majority of people are ignorant towards charging start time, but a minority using some sort of coordination is present.

II. METHODOLOGY AND MODELLING

After thorough understanding of the subject, gained through the extensive literature review we determined worst case scenarios for EV charging. Next step was to create a model illustrating those scenarios and determine the effects on LV networks (Figure 1). At the end we analyzed possible solutions and indicated the most suitable ways to overcome potential threats.

A. Data Collection

Historic transformer loadings data were provided by WPD from 6 neighbourhoods in MK. Loadings were in the form of 10 minute averages for winter months from November till March, when the consumption is at its highest. From those data, we picked the days with highest the peak load and highest daily average consumption. The latter were considered because of potentially being more problematic for the off peak charging scenarios. Interestingly, only in one out of the 6 cases max. peak and max. daily average transformer loading occurred on the same day. Another surprising fact is that most of these days were Sundays and after closer inspection we realized that consumption was generally greater during the weekends. The reason for such distribution is probably in the fact that all areas are predominantly residential and people spend more time at home during the weekend, increasing the electricity consumption.

Next parameter needed to be determined was number of cars per household. Long-term trends are hard to predict, as they depend on technology advancements, government policies, personal preferences and many other factors [12].

Due to the lack of dependable trends we assume this to remain on the same level as today 1.30 cars per household [14]. For small commercial customers we assume 2 cars and for large commercial customers a 10 car fleet. Having established the number of vehicles present we had to define the share of EVs.
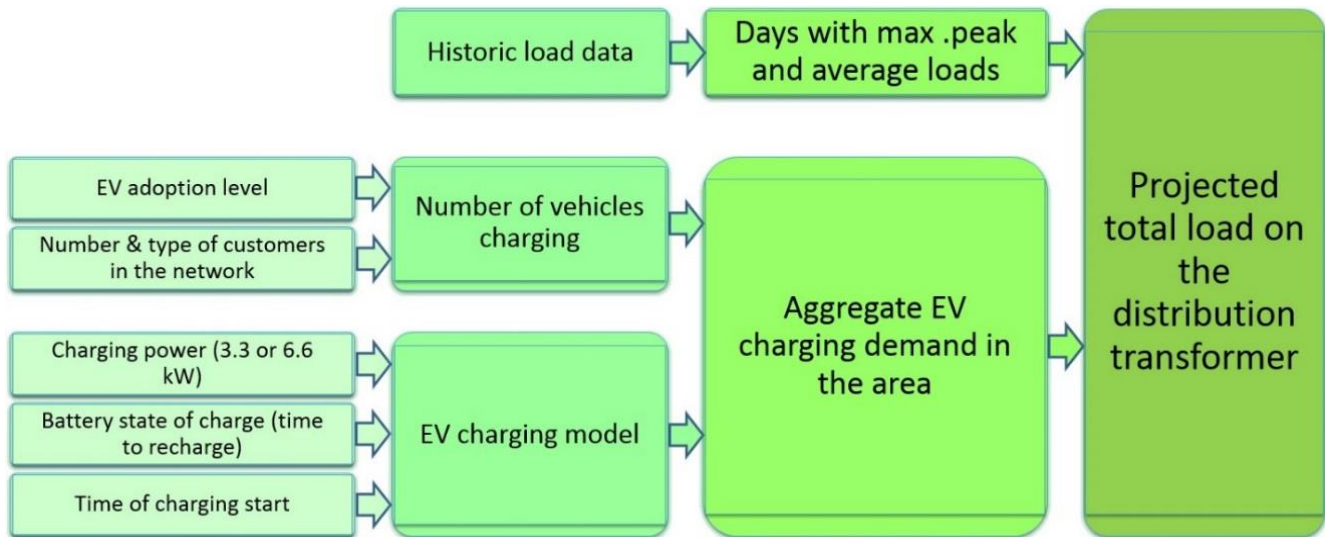

Figure 1. Work flow for Total Load on distribution transformer calculation

There is no agreement between different authors regarding the predicted EV penetration levels. We will assume the prediction already used in Project FALCON by WPD, which matches the medium DECC projection [13]. A strong argument for using the official governmental prediction is their knowledge of the funds planned for EV technology improvement [4]. The share of EVs on the road resembles their market share from 7 years before (the average age of a car on the UK roads) [14].

Charging power of the vehicle depends on the type of charger installed at owner's home or availability of on-board charging. EVs are charging with either 16A or 32A current [15]. Manufacturers usually specify charging power of 3.3 kW ([16]) and 6.6 kW ([17]) for slow and quick domestic charging respectively. We assume that the share of quick chargers will increase with time because of an increased share of Battery Electric Vehicles (BEV) and Range Extended Electric Vehicles (E-REV). These vehicles have larger batteries, requiring more time to recharge. Other factors driving more fast chargers are likely to be their decreasing cost and a need for quicker charging in the case of dynamic tariffs for better economic efficiency.

State of discharge of the battery depends on the distance driven and the vehicle's power consumption. Consumption was determined at 0.35 kWh per mile driven, which is in the middle of figures claimed for ULEVs currently on sale [18]. The distance driven was sourced from National Travel Survey (NTS); the data were for South East England in 2012/13 [19].

B. Modeling

The model was made with MS Excel spreadsheets. Each car had its own charging power, home arrival time and state of charge. The number of cars was determined for each scenario and the aggregate demand from all the cars in an area was summed up. Due to great uncertainty regarding EV market development we considered three scenarios with 25, 50 and 100% EV share on the road and the same increasing share of fast chargers, as shown in Table 1.

TABLE I.   EV DEPLOYMENT SCENARIOS

Scenario name	S25	S50	S100
EV presence on the road [%]	25	50	100
Slow (3.3 kW) : Fast (6.6 kW) chargers ratio	25:75	50:50	0:100
Year of realization according to FALCON	2036	2043	2060

The time needed to recharge was derived from battery state of charge (SOC), which was dependent on the distance driven by the vehicle. We assumed this to be at least twice the distance of an average trip, since we assumed vehicles to be charging at home only. To make it easier to model and introduce an element of randomness we assumed the length of the trip to be a normally distributed random variable with a mean value of 20 miles and standard deviation of 15 miles. With some numbers being negative (simulating cars not in use that day and not charging; these values were ignored) that gave us an average of around 19 miles, slightly more than double the distance of an average trip (8.5 miles for South

East England in 2012/13). That simulated some cars charging after more than 2 trips (multiple destination journeys, e.g. shopping and visiting friends). Depending on the type of charger, which was chosen randomly with pre-determined probability distribution the time needed to recharge was calculated and rounded to 10 minute intervals to match the base load data. The NTS data were also used for the times of trips back home, but a random sample with normal probability distribution was again introduced. The distribution has a mean at 16:40 and a standard deviation of 100 minutes.

Time of charging start is possibly the most important aspect that will define the impact on the network. Three different scenarios with differing structures of charging times were constructed:

- **Uncoordinated charging:** the most basic scenario, very likely in the event of inadequate education and incentives to the EV users. It was assumed that fixed tariff customers will be charging their vehicles directly upon arriving home, on average around 30 minutes after the start of their trip (average time for a car trip + 9 minutes for parking and plugging the car at home) [19]. The users already using the E7 scheme are expected to start charging their vehicles at 00:30 in the morning, at the beginning of the low price period, using some form of simple charging start delaying device. Commercial users' cars charge at random times between 9-5pm during the day.

- **Off peak clustering:** a scenario, where all domestic users that own and EV start using the E7 scheme. This scenario could lead to severe off peak clustering, if all the owners would start charging their cars at the same time. The peak load can be more than four times higher for the same number of cars as before.

- **Smart Charging:** includes some form of load control, which distributes the load evenly. This control could be external or some sort of integrated intelligence in the charger or vehicle. We imitated this logic by assigning the vehicles randomly chosen start times during the night time. The only form of control is internal; depending on SOC the interval is adjusted to make sure all charging is finished by 07:30 in the morning. The peak EV load itself is somewhat greater than in the case of uncoordinated charging, but comes at a much more favourable time, when the overall electricity demand is at its lowest.

C. Model Validation

To validate our model we compared it with similar examples from the literature. A good comparison is seen in the model from [20], which has 20% EV penetration. When compared with our model, (with the same EV penetration level) we see a similar 30% increase in peak load. Tehrani and Wang [21] produced a probabilistic estimation of EV charging load profile; their predicted load distribution is very similar to ours.

III. RESULTS AND DISCUSSION

A. Effects of Increasing EV share

Figure 2 displays how total load on the transformer (Noon Layer Drive West, NLDW) is increasing with rising presence of EVs. The maximum historic load was 150 kVA; that rises to around 200 kVA at 25%, 300 kVA at 50% and slightly past the 500 kVA transformer rating at 100% EV share.
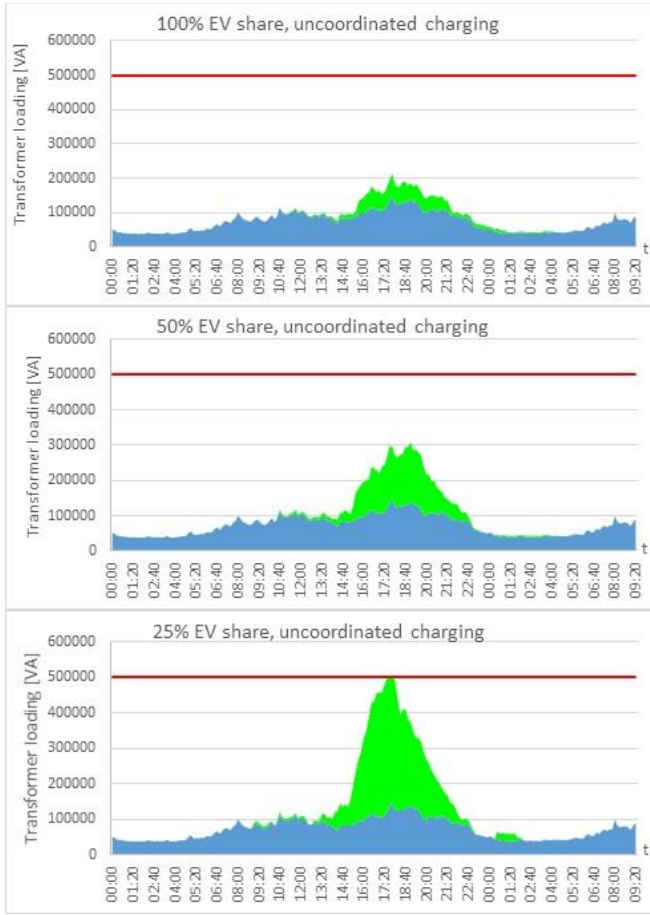

Figure 2. Uncoordinated charging loads for different EV penetration levels

The number of EVs likely to charge is one of the most difficult factors to predict, but we can confidently assume that the number will rise in the years to come. With 100% EV share, their daily electricity consumption in Barnfield Drive West (BDW) neighbourhood is in the range of 2600-2900 kWh, similar to 2850 kWh used on an average winter day there now. EVs could therefore more than double the overall electricity consumption, which is in line with Kelly's estimate [22].

B. Effects of Different Charging Schedules

Loads on Bletchley area A (BAA) transformer for the three possible charging patterns (uncoordinated, off-peak clustered and coordinated) are shown in Figure 3. The historic peak load of 247 kVA rises to 400 kVA with uncoordinated and around 470 kVA in the case of off-peak clustered charging. If distributed in a coordinated way, EV charging does lead to a new peak during the night; however it is lower than the maximum daily peak.
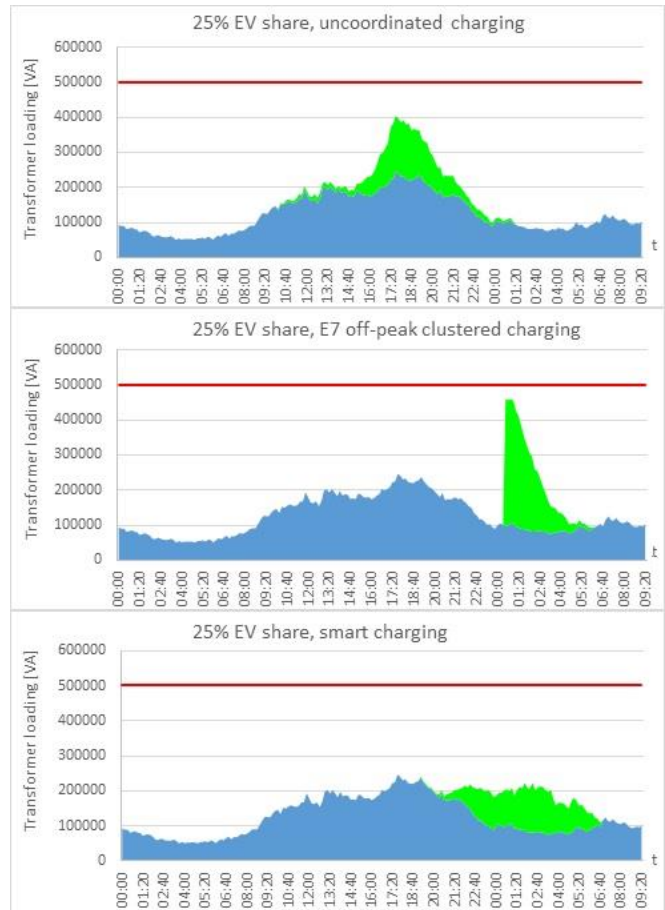

Figure 3. Loads with different charging patterns for a 25% EV share

Many literature sources consider the uncoordinated charging to be the worst case scenario [6], [7]. However, results in Figure 3 show the E7 split tariff regime with only 2 different price periods would likely be even more problematic, because it could lead to significant off-peak clustering. In our study it was assumed that people using this scheme would use simple delay devices to start charging at the desired time. While the low price period lasts for 7 hours during the night, we expect people would want the charging to begin as soon as possible to secure the vehicle would be charged in time for morning use. Interestingly, despite those assumptions seeming sensible, historic data analysis put us in doubt. The difference between daily max and average values is very similar in neighbourhoods with low and high share of E7 users, indicating that in reality currently people tend to not take advantage of the split tariff scheme. This might be due to a lack of awareness of the potential benefits or not having sufficiently intelligent infrastructure and appliances installed.

Another observation is that due to the scale of EV loads the charging start times make the greatest difference at low deployment scenarios. At 25% EV deployment rate in case of E7 clustering the EV load peak alone already greatly exceeds the previous residential only peak load; when this rate is 100%, the peak is at least doubled in all areas with smart charging as well. Therefore the redistribution strategies should aim to avoid creating peaks, rather than shifting them to more convenient times.

C. Significance of the Transformer Rating

The same scenario (25% EV share being charged in a cluster) was compared in two different areas; NLDW and BDW. The former has a 500 kVA rated transformer and had historic peak load of 150 kVA; for the latter those values are 315 and 233 kVA, representative of higher number of customers in BDW. After adding the EV load the total peak load for NLDW didn't even reach half of the limit, while in BDW more than 40% overload occurred. The potential overload issues therefore greatly depend on the rating of the installed transformer. There are large discrepancies; similarly populated neighbourhoods of BDW and Stamford Avenue (SA) have 315 and 800 kVA transformers respectively; NLDW with slightly more than half the population of BDW utilizes 500 kVA transformer. The former will likely need an upgrade soon even without significant EV deployment, while the one in SA could easily accommodate 50% EV deployment in the case of uncoordinated charging.

D. Effects of Difference in the Base Loads

For the case of uncoordinated charging the previous max peak load days are the most problematic. In the case of uncoordinated charging (Perran Avenue Fishermead neighbourhood, PAF, 50% EV share) that was not the case; a new peak was just below transformer rating with a max peak base load, while that limit was exceeded in the case of base load with max average. Considering both base load curves (with max peak and max daily average) was therefore necessary. The max average base load turned out to be worse for smart charging, because the base load at the time of new smart EV charging (night) was higher than on the day with the max peak base load.

E. Research Limitations and Future Work

This work only focuses on transformer overloads in intact network . Large load increases and fluctuations however could have other negative effects, such as increased wear of transformers, line limit violations and especially voltage quality effects. Voltage fluctuations are caused by significant sudden variations in current drawn from the network [23]. Start of EV charging causes sudden current increase, especially in the case of large scale clustering, such as at the beginning of E7 low tariff period.

It is assumed that all vehicles will be charged at home overnight, which is a very pragmatic assumption. Daytime charging workplace, shopping centre or public parking could greatly impact load distribution. The model also made no distinction between different days of the week; our charging scenario only considers an average day in the year. More precise predictions could be made if weekday and weekend cases were differentiated. That could impact the distance driven as well as home arrival times.

Some of the assumptions used for designing the model require further refinement and validation, such as assuming the second half of all the trips made in a day were return home trips. However, in every situation like this we took the pragmatic approach and normally assumed the situation to be worse than it is in reality. Some of the trips in second half of the day will be departing from home and some of the trips returning home will occur in the morning, meaning the distribution of return home trips will be less peaky.

The main uncertainty is associated with the expected EV penetration levels. This has been addressed by modeling three different EV penetration scenarios. Studies have been made to determine when certain scenarios will most likely realize based on economic and technical factors [24]. Battery and charging equipment technology advancements will likely dictate the future EV market potential. In addition, embedding source voltage sensing into EV chargers would help to distribute the load on the distribution network.

Another opportunity for future work is to use an additional model to forecast the development of base load in the future. We assumed it will remain unchanged; however this might be very inaccurate. An important new factor could be large scale of electric heat pumps deployment [20]. That would present a new load similar in power requirements to EVs. Linking of the domestic appliances and assessing the possibilities of household load control (shifting other domestic loads) should be taken into account.

Our research used simplified model of smart charging, as it was only intended to demonstrate the capability of such methods. Models encompassing internal intelligent mechanisms, vehicle to vehicle and vehicle to infrastructure communication and external control should be considered to find the best solution and discover its full potential.

Assessing the impact of new means of energy production, especially renewables and small scale combined heat and power will be important. Renewables are largely unpredictable, but could help balancing the peak load demand; in this context the potential of V2G technologies is being explored. Peterson, Whitacre and Apt [25] question the economics of V2G; they conclude it would not bring the owner adequate profits, especially with battery degradation taken into account. The profit would furthermore decrease with large EV penetration levels, as that would increase the night demand and decrease peak demand, reducing the difference in tariffs. Another aspect to consider is the public acceptance of V2G. Hidrue and Parsons [26] conducted an internet-based survey to predict near-term success of such vehicles on the market. The study predicted little chance of success, with the main reasons being range anxiety, proposition of stringent contract and high battery costs.

Another aspect that has to be considered is the party taking control of charging activities distribution in the case of smart grid. DNOs and other stakeholders might have different preferences.

In addition to assessing the impact on existing networks, research should be done to produce guidelines for designing new networks in residential communities currently being planned or under construction. They should be adequately dimensioned to cope with increased overall loads and changing network dynamics.

IV. Conclusions

As predicted, EVs do indeed present a major load on LV power distribution networks. Results suggest that in the case of uncoordinated charging, some distribution transformers in Milton Keynes could get overloaded with less than 25% of EVs on the road, potentially affecting the resilience of the system.

This research project showed the risk of distribution transformer overloading worsens with increasing EV penetration levels. However, a more innovative result showed even if EV shares remain the same, the off-peak clustering charging scenario would cause more problems of transformer overloading than uncoordinated charging and would likely cause even worse voltage quality issues. This is a scenario we deem is expected to happen.

These problems can be significantly facilitated by implementing smart grid technologies, but even in this case, transformer upgrades would be necessary to support high EV deployment. This consequentially impacts WPD's planning development; transformer upgrades are required if the future projected EV demand will become a reality.

There are many opportunities for our model to be refined for more precise estimations. We recommend a wider range of charging patterns, such as including public and workplace charging during the day. Moreover, the model should assess additional impacts charging has on networks, such as voltage quality. Assessment of EV charging impacts on LV domestic power network would also greatly benefit from a well-rounded assessment of smart grids incorporating technological maturity and public acceptance aspects.

Acknowledgments

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