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ORIGINAL RESEARCH

Impact of electric vehicles on low-voltage residential distribution networks: A probabilistic analysis

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Abstract

The past two decades have seen a rapid increase in electric vehicles (EVs) for several reasons, such as policy directives to reduce carbon emissions in the transport sector and technology advancements in the EV industry. However, this has increased the load demand on the power grid, especially in the low-voltage (LV) network, as most EVs are charged at EV owner premises. This paper investigates the impact of EVs on the LV residential distribution network using a probabilistic modelling framework. Probability distribution functions for EV charging power are derived using the United Kingdom (UK) EV dataset. The study has investigated multiple EV penetration levels, different probability distribution functions for EV charging representation, vehicle-to-grid (V2G), solar photovoltaic (PV) generation, and the volt-var capability of the solar-PV inverter. The results have shown that as EV penetration increases in the distribution network, there is a significant increase in transformer loading and a decrease in the steady-state voltage levels. V2G has positively impacted the distribution network. A case study carried out on a real LV feeder with solar-PV generation has shown how PV generation and volt-var functionality of the PV inverter help reduce the impact of EV charging and V2G.

KEYWORDS

distribution network, electric vehicle, electric vehicle charging, probabilistic analysis, solar power stations, vehicle-to-grid (V2G), volt-varcontrol, voltage control, voltage unbalance

1 | INTRODUCTION

The transport sector is one of the major contributors to air pollution, with vehicular transport at the top of the list. The main component responsible in a vehicle for air pollution is the internal combustible engine (ICE). The ICE vehicle pollution contributes to over 1700 deaths in Australia annually, so an alternative solution is required [1]. Electric vehicles (EVs) can reduce air pollution and greenhouse gas emissions in the transportation sector. Therefore, various countries (e.g. Norway and the United Kingdom (UK)) have implemented policy directives to promote EVs in their transport sector aggressively [2].

These policy directives and concerns about greenhouse gas emissions have led to a significant increase in EV sales. For example, EV sales is expected to reach 145 million by 2030 [2]. Also, in Australia, EV sales increased by 300% in 2021 compared to 2020 [1]. Like refuelling an ICE vehicle's petrol tank, the EV battery should be charged after an EV has been used for travel. To charge the battery of an EV, it is connected to the grid via a home charger or a charging station. Therefore, an increase in EVs will increase the load demand on the grid, resulting in an overloading of network assets, high system peak demand, voltage unbalance and so on [3]. According to forecasts, by 2040, 54% of new car sales around the globe will be EVs [4], which further highlights the need to examine the impacts of EVs on the grid and plan for future potential effects on the power grid.

1.1 | Motivation

Deterministic studies provide the worst-case impact on the power grid without considering the probabilistic nature of EV charging. Such analysis may provide unrealistic predictions on EV charging demand, and hence it is uneconomical to design a network with the data from a deterministic study. Hence, it is imperative to examine the EV impact from a probabilistic perspective. The probabilistic analysis will help realistically characterise the EV impact on the grid. It will provide insight to distribution network service providers (DNSPs) on how EV penetration would affect the distribution network assets, such as transformers and cables. Consequently, it will help DNSPs to make economic planning decisions.

1.2 | Related studies

Power quality is one of the most critical aspects for DNSPs, since they should ensure that power delivered to consumers meet a certain minimum standard. Main power quality issues are over and under voltage, voltage unbalance and harmonics. In addition, from the DNSP's perspective, line losses, transformer loading and thermal limits of assets are essential to maintain the reliability of the distribution network. It is well-known that uncontrolled EV charging may lead to adverse power quality effects [2]. Under uncontrolled charging, the voltage and thermal limits can exceed safe operating limits, which is detrimental to the grid equipment's lifespan and safe operation [5]. Another effect is harmonic distortion, as high-frequency switching happens at semiconductor switches used in EV chargers. Some studies have concluded that as the EV penetration level increases, the total harmonic distortion of current and voltage increases beyond the standard limits, damaging the grid equipment [6].

The lifespan of grid equipment, such as feeders, transformers, transmission lines and so on, will be affected as more EVs are integrated into the grid. The transformer ageing was seen to be accelerated as the EV charging demand increased [7]. The low-voltage (LV) transformers are significantly affected due to probable violations of statutory voltage limits [8]. A study that characterises the effects of EVs on the LV grid has used a novel statistical analysis method and has considered parameters such as the number of cars, daily travel times and daily travel distance to characterise the EV grid impact [9]. That study has shown that an increase in EV penetration level leads to LV transformer overloading.

For a more accurate analysis of the impact of EVs, it is essential to have real-world EV dataset. Ref. [10] provides a list of open EV datasets and models available for studies from various countries worldwide, including countries such as Norway, UK, Sweden, USA, Germany, the Netherlands and Japan. The parameters considered in EV modelling include battery characteristics (e.g. the state of charge and depth of discharge) and travel behaviour. The travel behaviour of vehicle owners is pivotal to simulating real-time scenarios. Moreover, weather parameters need to be considered, which include wind speed, rainfall, sunny hours etc. Economic factors (e.g. tariffs and incentives) should also be considered since tariffs and government incentives on EVs affect the purchase of EVs. Lastly, daily and seasonal patterns should be taken into consideration. This refers to how EVs are simulated in days, weeks and months [10].

The slow and fast charging modes are the different modes of EV charging. Depending on the EV charging mode, it impacts the low-voltage grid differently. Electric vehicle owners can charge their EVs at any time of the day, and hence leading to uncontrollable charging. This leads to obvious problems, such as spontaneous power demand increase, voltage violations and voltage unbalance [11]. A solution for this is creating a differential price for electricity, that is, a low price during the night when the energy consumption is low and a high price during peak hours. This would lead to a reduction in overloading and power losses as well as flattening the load curve [12]. Coordinated EV charging can positively impact the grid, such that improved voltage regulation, power quality and better power management can be achieved [2, 13]. Moreover, orchestrating EV charging with renewable energy sources can further help reduce green-house gasses emissions [2].

The majority of the studies discussed above used deterministic approaches to characterise the impact of EVs on the power grid. The impact of EVs on the LV grid has been examined with the deterministic approach, and a limited number of studies have used a probabilistic approach for EV impact assessment on the grid [14–17].

A probabilistic load-flow technique was used in Ref. [14] to determine the impact of smart charging in an unbalanced LV distribution network. This study has demonstrated the benefits of smart charging and has also shown that concentrated allocation could adversely affect the LV network. A probabilistic study of EV impact was conducted on a typical British distribution network has considered uncertainties associated with the EV charging locations, types, time and duration and has concluded that EV charging could breach the lower voltage limit under high EV penetration, and DGs can assist in flattening the load profile [15]. Another study on the UK LV residential networks has modelled the uncertainties associated with EV's demand and location and highlighted the transformer overloading issues under low EV penetration [16]. A high-performance computing framework is employed in Ref. [17] to conduct a probabilistic EV impact analysis using the Monte Carlo simulation. A probabilistic approach will provide a more realistic analysis of the impact on the LV network from EVs, which helps DNSPs to implement more economically feasible strategies in tackling the challenges associated with high EV penetration.

1.3 | Paper outline and structure

This paper models the charging power of EVs as a probability distribution function (PDF) and uses it as the primary input to the unbalanced load-flow simulation. PDF of EV charging power was derived using a UK EV dataset [18], and 1000 unbalanced simulations were conducted for each scenario using 1000 samples generated from the Monte Carlo method. Since PDF was derived from a real dataset, it encapsulates the nature of the EV charging (e.g. charging power, time effects and charging behaviour) within the PDF itself, and hence additional complexities need not be modelled separately. Both grid-to-vehicle (G2V) (i.e. EV charging) and vehicle-to-grid (V2G) impacts are analysed in this study. Two LV network models, namely a standard LV feeder and a real LV feeder, have been used for simulations. In particular, the real LV feeder with solar-PV generation has been used to analyse the impact of solar PV generation and inverter volt-var functionality.

The remainder of the paper is organised as follows; Section 2 covers the research methodology and the step-by-step process followed to characterise the impact of EVs on the grid. Study results for the standard LV feeder are discussed and analysed in Section 3. A case study based on a real LV feeder model is presented in Section 4. Discussion and Conclusions are presented in Sections 5 and 6, respectively.

2 | PROBABILISTIC ANALYTICAL METHODOLOGY

To analyse the impact of EVs on the grid, a probabilistic analytical framework is developed in this study. This section delineates the probabilistic analysis framework supported by a flowchart shown in Figure 1. The methodology consists of three main stages: data preparation, data fitting and probability density function generation, and DIgSILENT PowerFactory simulation study using LV distribution feeders with EVs. The following subsections delineate each stage of the framework.

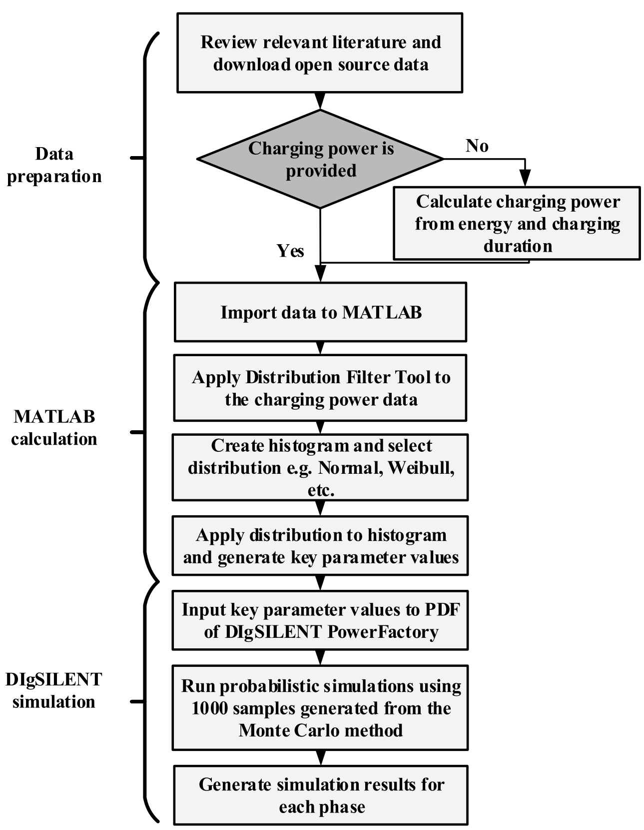


FIGURE 1 Probabilistic electric vehicle grid impact analysis framework.

2.1 | Data preparation

The following factors are considered in data preparation: '*Does it contains a raw dataset of EV charging characteristics?*', '*Does the data contain residential profile information?*', '*Does the data have charging power* versus *time*' and '*Can the data be downloaded and used?*'. The credibility of data is also important as most literature cites different sources available on the Internet [9].

This study has used the domestic UK EV charging dataset from [18] to derive the appropriate probability density function for representing the charging behaviour of EVs. The dataset includes charging data over a one-year period from 1st January, 2017 to 31st December, 2017. These data contain the driving duration and parking duration of EVs, which show an average parking duration of 9.16 h. These data indicate a typical residential EV owner characteristic, and hence it is used in this study to develop appropriate probability distribution functions. The key characteristics of this dataset are illustrated in Figure 2.

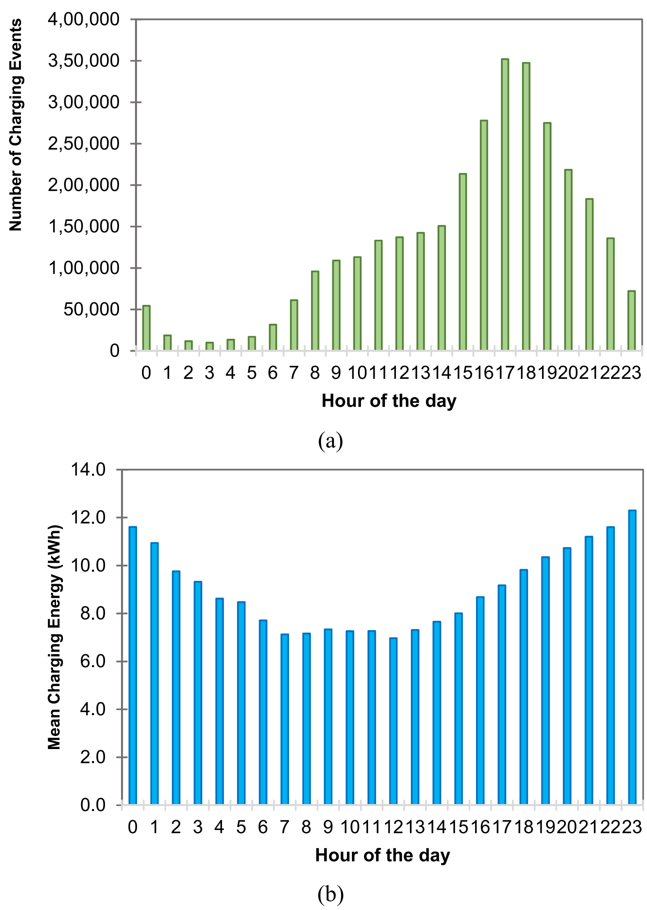


FIGURE 2 United Kingdom electric vehicle charging dataset characteristics, (a) Number of charging events versus an hour of the day, (b) Mean charging energy versus an hour of the day.

According to Figure 2a, most EV charging events happen between 4 and 7 pm. However, according to Figure 2b, charging energy peaks between 9 pm and 1 am, where peak mean charging energy was reported at 11 pm. Since the primary objective is to develop a probability density function (PDF) for charging power, the charging energy corresponding to each charging event is converted to power per-charging event to develop the EV charging PDF.

2.2 | Data modelling

The focus of this study is to analyse the impact on the distribution grid from large-scale EV charging and V2G; therefore, this study explores the impact on parameters such as voltage unbalance, transformer loading and the voltage profiles across the feeder. Characteristics of the EV itself have not been focused on in this study. Since the study has used real data, it is envisaged that characteristics such as EV charger type and EV model are encapsulated within the charging power profile derived from the real EV dataset. For example, if it is a level 2 charger, the power profile will indicate a charging power between 7 and 22 kW. Therefore, the charging power profile is ideal for developing an appropriate PDF to represent EV charging.

A PDF or probability distribution of x is given by function $f(x)$ as follows:

$$P(a \leq x \leq b) = \int_{a}^{b} f(x)dx \tag{1}$$

For all values of x, $f(x) > 0$.

To determine the best probability distribution to represent EV charging, the EV charging characteristics should be compared against the characteristics of the probability distribution function. Although an EV charging event can be considered as a discrete quantity, the charging power can be viewed as a continuous quantity as it varies over time, which can be broken down into finer levels. The two distributions that fit this characteristic are the Weibull distribution and the lognormal distribution.

2.2.1 | Weibull distribution

The Weibull distribution is a continuous probability distribution function, as given as follows:

$$f(x;\ \lambda, k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(x/\lambda\right)^{k}}, x \geq 0 \\ 0, x < 0 \end{cases} \tag{2}$$

where $k > 0$ is the shape parameter and $\lambda > 0$ is the scale parameter of the distribution. The shape parameter shows the main characteristics of the distribution: if $k < 1$, it means the distribution has a failure rate that decreases over time; if $k = 1$, it means the distribution has a failure rate that is constant over time; and if $k > 1$, it means the distribution has a failure rate that increases over time.

2.2.2 | Lognormal distribution

Lognormal is also a continuous probability distribution function. The main characteristic of a lognormal distribution is that it is the logarithm of a normal distribution. One of the disadvantages of the lognormal distribution is it can only fit positive values in a dataset, and this will be discussed later when the V2G scenario is explained. For a random set of variables fitted to a lognormal distribution, the probability density function is given as follows:

$$f_x(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right) \tag{3}$$

where μ and σ are the mean and standard deviation of the dataset.

2.2.3 | MATLAB data fitting

To develop the PDFs to represent EV charging based on the selected dataset, the MATLAB Distribution Fitter App has been used. The raw data file for the domestic UK EV dataset discussed above is used to develop the PDFs. This data contains session start and end times, energy consumed, plugin duration, charging-cycle duration and customer identifier. Using a basic energy conversion formula, the charging power at each time interval can be calculated as follows:

$$\text{Charging Power, P (kW)} = \frac{\text{Energy Consumed, E (kWh)}}{\text{Charging Cycle Duration}, t \text{ (hr)}} \tag{4}$$

The distribution fitter toolbox in MATLAB aids in generating the parameters for each PDF. Figure 3 illustrates the fitting of the charging data into the Weibull and the lognormal distributions. The parameters of the Weibull and the lognormal distributions after fitting into the EV charging dataset are shown in Table 1.

2.3 | Probabilistic electric vehicle simulation

This section presents test networks, load profiles and simulation scenarios analysed in this study.

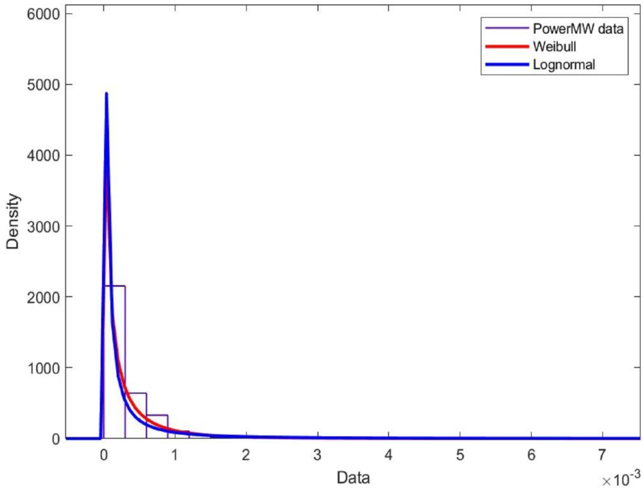


FIGURE 3 Distribution fitter result for the Weibull and the lognormal distributions.

TABLE 1 Parameters of the Weibull and lognormal distributions after fitting into the electric vehicle dataset.

Lognormal	$\mu = -9.48838$
	$\sigma = 1.97991$
Weibull	$\lambda = 0.000196954$
	$k = 0.598432$

2.3.1 | LV network model

Two LV network models, namely a standard LV network model and a real LV residential feeder, are used for simulations. Standard LV distribution network consists of eight terminals per-phase, and each terminal is connected to a residential household (see Figure 4). The MV/LV transformer is rated at 0.3 MVA and has a short-circuit voltage of 4.5%. Transformer has 32 tap positions with a 2.5% voltage change per tap, and the tap position is fixed at 3.

The real residential LV feeder is comprised of 56 customers, and 23 customers have solar-PV systems on their rooftops (see Figure 5) [19]. The rated power of each solar-PV system varies from 1.65 to 6 kW. The total installed solar-PV capacity is 96 kW, and solar-PV systems operate at a unity power factor. The 11/0.415 kV upstream transformer has a short-circuit voltage of 4.5%. Transformer has six tap positions with a 2.5% step voltage change per tap. The tap position was fixed at 1. The hosting capacity of this feeder is constrained by the transformer loading and not by the voltage limits [19]. A case study was developed using this LV feeder to analyse EVs' impact on residential LV networks with solar-PV generation.

2.3.2 | Residential load profile

The residential load of 2.4 kW was considered across each terminal as the base case load in the standard LV network model. Also, the LV network model has used three different load profiles (shown in Figure 11) to assess the EV charging impact under load variations. This enables the simulation of a more realistic scenario for LV feeder with load unbalance.

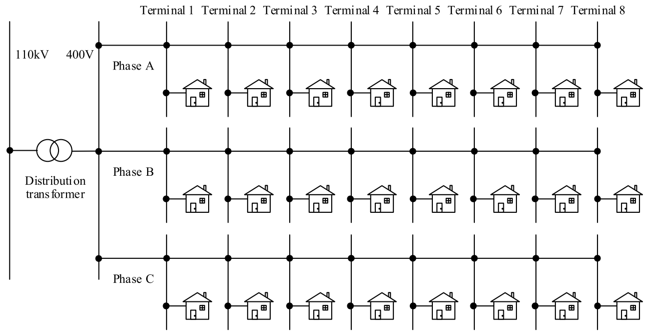


FIGURE 4 A standard three-phase low-voltage residential distribution network model.

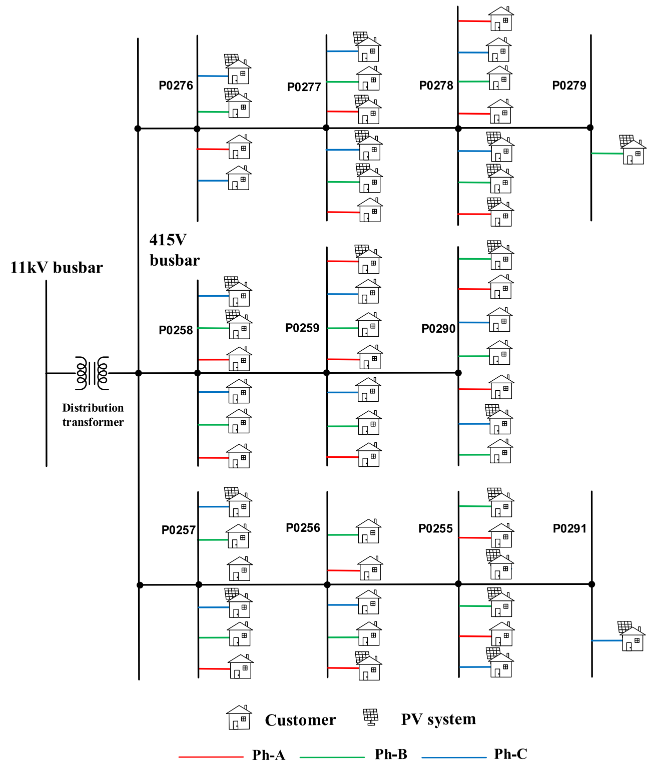


FIGURE 5 A real residential LV feeder with solar-PV generation.

Regarding the real residential LV feeder, three household load conditions (e.g. 1.8 kW, 3.4 kW and 8.4 kW with 0.95 lagging power factor), typically seen in residential LV feeders, are randomly assigned to household loads [20]. Also, it is assumed that each household load is operating at 0.95 lagging power factor. Therefore, the feeder has a total active and reactive power load of 229 kW and 75 kVAr, respectively.

2.3.3 | Electric vehicle penetration

An EV charger has been assigned to each terminal of both LV networks. They have been connected to the same point as the household load. To analyse the impact of EV penetration on the LV feeder, EV chargers connected to each terminal are enabled to achieve different penetration levels (e.g. 25%, 50%, 75% and 100% penetration). For example, only two EV chargers per phase have been enabled in the standard LV network to achieve 25% EV penetration.

2.3.4 | Probabilistic simulations

To initiate a probabilistic simulation in DIgSILENT PowerFactory, the EV charging was represented by the PDFs derived in Section 2.2. Then unbalanced load-flow studies were performed in DIgSILENT PowerFactory with 1000 samples generated from the Monte Carlo method.

3 | STANDARD LV NETWORK: RESULTS AND DISCUSSION

3.1 | Voltage distribution in each node

Figure 6 shows the voltage distribution at each node after running a probabilistic load-flow simulation. It must be noted that the distribution feeder is simulated with the base residential load (2.4 kW) and EV charging load mentioned above. The normal distribution represented the EV charging load.

According to Figure 6, the voltage distribution plot is skewed more when the node is closer to the distribution transformer. In contrast, a much larger voltage distribution can be seen when the node is located far from the distribution transformer. Therefore, the voltage drop along the feeder becomes more prominent when the node is away from the transformer.

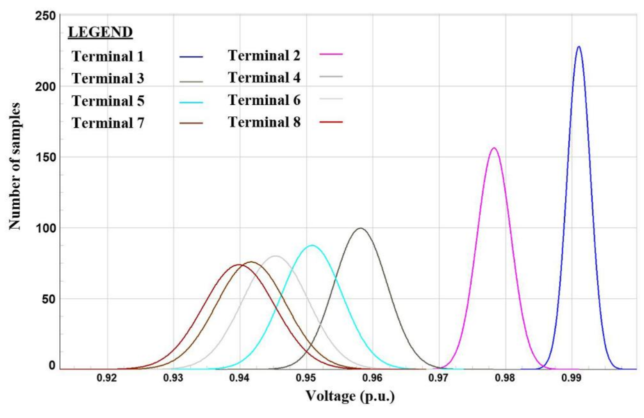


FIGURE 6 Voltage distribution plot for each node after running the probabilistic load-flow simulation.

3.2 | Weibull versus lognormal distribution

A simulation was conducted to analyse the effect of two PDFs (i.e. Weibull and lognormal distributions) derived from the real EV data in Section 2.2. The household loads were set to 2.4 kW. The probabilistic simulation is conducted using 1000 random samples generated through the Monte Carlo method. Simulations have been conducted with 1000 samples for each distribution function (i.e. Weibull and lognormal distributions) to represent the EV charging. Weibull and lognormal distributions are considered separately in DIgSILENT PowerFactory probabilistic simulations. Moreover, analysis has been conducted under different EV penetration levels (e.g. 25%–100% with increments of 25%). Figures 7–10 show the average transformer loading, failure rate and voltage levels at each terminal.

For each simulation, the transformer loading was recorded, and the average transformer loading for 1000 Monte Carlo simulations under different EV penetration levels are shown in Figure 7. The transformer loading shows that the EV penetration is directly proportional to transformer loading. For example, under 25% EV penetration, the transformer loading is 30%, which increased to 50% when the EV penetration reached 50%. Both distribution types indicate similar results

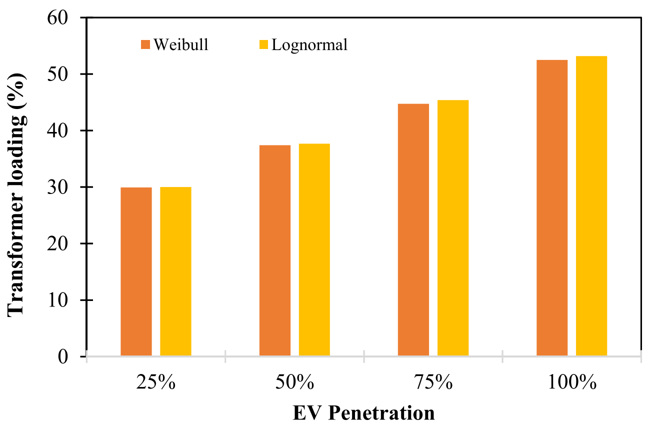


FIGURE 7 Average transformer loading under different electric vehicle penetration levels.

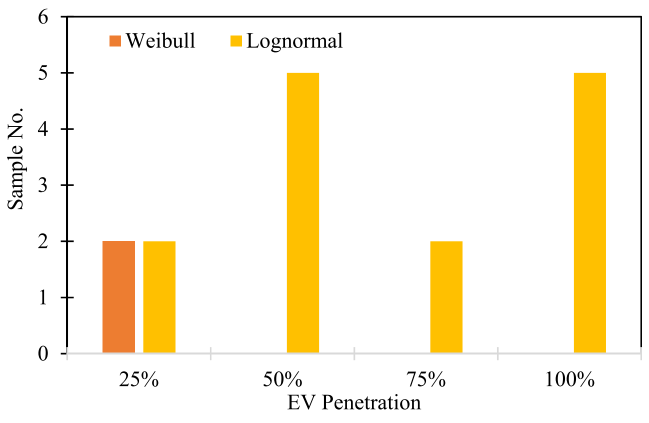


FIGURE 8 Sample failure under each distribution.

with the transformer loading increase above 50% under 100% EV penetration.

Failure rate represents the undesirable conditions where load flow does not converge. The lognormal distribution shows a higher failure rate as the penetration level increases, and Weibull shows a zero-failure rate as the EV penetration increases (see Figure 8). Thus, making Weibull a more suitable distribution for this study.

Due to the household load and EV charging power being the same across all terminals and phases, the plot across each phase is the same with a boxplot representation in Figures 9 and 10. The voltage level decreases downstream of the feeder. Also, the voltage levels do not exceed 1.10 pu. However, the voltage levels drop below 0.96 pu as it reaches terminal five (i.e. TA5), which is the feeder's midpoint. From the plot, it can also be observed that after the EV penetration increases beyond 50%, terminals above the midpoint, that is, TA5 to TA8, decrease below 0.96 pu.

There is a minimal difference between the voltage profiles generated from the two PDFs. However, due to the slightest failure rate observed for the Weibull distribution, it has been used for the rest of the study.

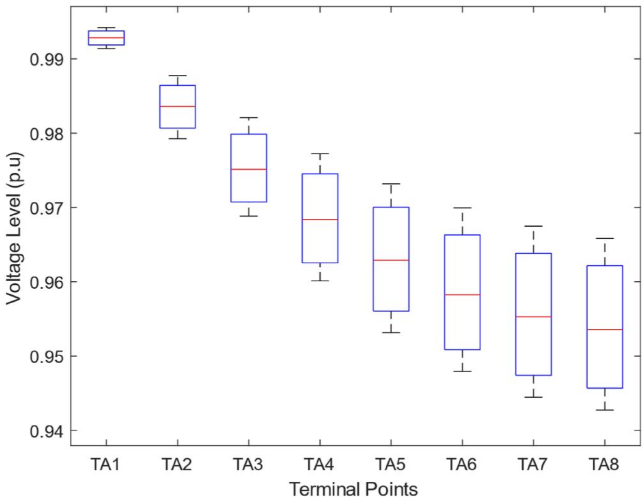


FIGURE 9 The voltage variation in each terminal with the Weibull distribution for electric vehicle charging (TA represents the terminal, so TA1 represents terminal 1 in Figure 4).

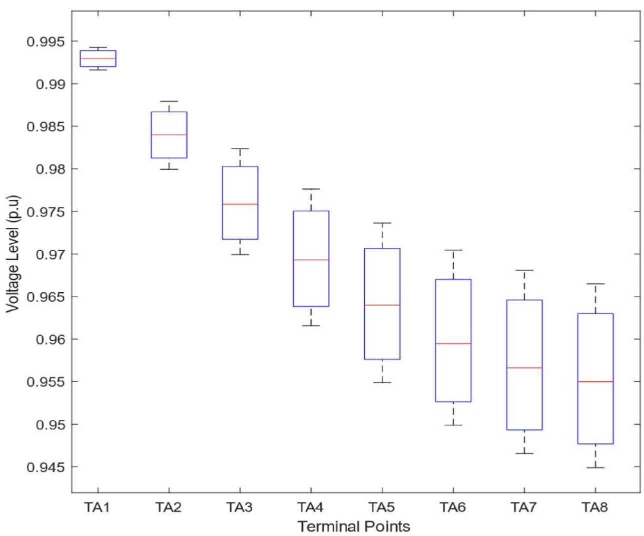


FIGURE 10 The voltage variation in each terminal with lognormal distribution for electric vehicle charging (TA represents the terminal, so TA1 represents terminal 1 in Figure 3).

3.3 | Household load profiles

To produce a more realistic scenario, the household load was varied across each phase while each household has a unique load profile (e.g. Profile-1 for households connected to phase-A, Profile-2 for phase-B and Profile-3 for phase C). The load profiles are shown in Figure 11. These load profiles represent a typical residential load profile where peak periods are from 5:30–11 pm and off-peak periods are after midnight until 6 am. Each profile is assigned to households in each phase and then probabilistic simulation was conducted with the Weibull distribution representing the EV charging load.

Figure 12 shows the per-phase loading at the transformer, which increases uniformly as EV penetration increases. The

FIGURE 11 Household load profiles.

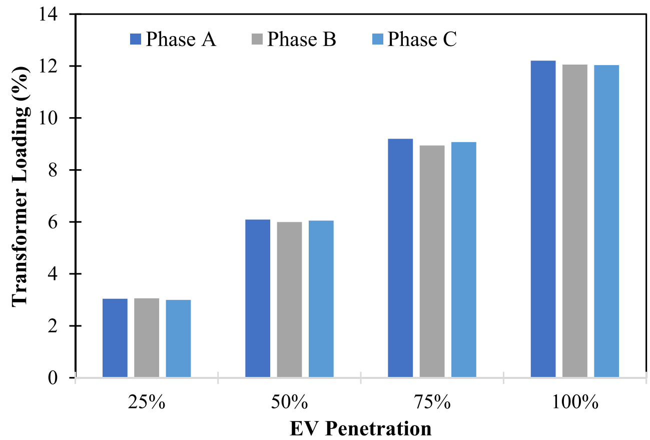


FIGURE 12 Transformer loading per phase for household load-profile simulation.

transformer loading at 100% EV penetration is four times the transformer loading at 25% EV penetration; whereas, for the simulation done in Section 3.2, the transformer loading at 100% EV penetration is 1.7 times the transformer loading at 25% EV penetration.

The voltage unbalance factor (VUF) is calculated using the National Equipment Manufacturers Association definition, and is given by:

$$VUF = \frac{\text{Maximum Deviation of the Mean from } Vab, Vbc, Vca}{\text{Mean of } Vab, Vbc, Vca} \quad (5)$$

The VUF is calculated for the start of the feeder (TA1), middle of the feeder (TA4) and end of the feeder (TA8) under each EV penetration level. The VUFs are shown in Figure 13.

According to Figure 13, the end of the feeder indicates a much larger voltage unbalance compared with the start of the feeder. For example, at 25% EV penetration, it indicates a VUF of 0.023% at the start of the feeder, and it has been increased to 0.064% at the end of the feeder. Moreover, high EV penetration scenarios have resulted in a slightly lower VUF level. However, VUF levels are far from the maximum limits stipulated in standards for these scenarios.

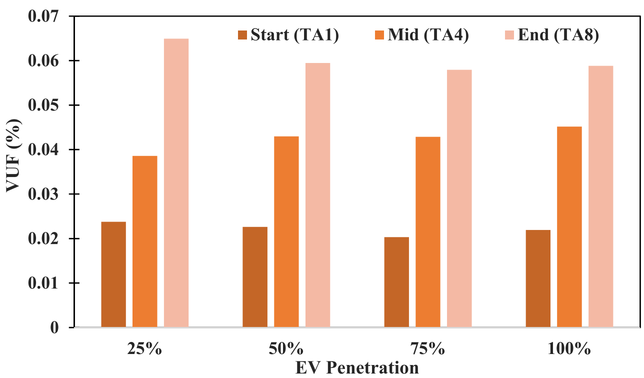


FIGURE 13 Voltage unbalance factor for household load-profile simulation.

The load profiles show a significant impact on the voltage distribution across the feeder, since the household load varies during the day. The voltage levels across each phase can be seen to be within the maximum and minimum voltage level threshold, as shown in Figure 14.

3.4 | Vehicle to grid (V2G) simulation

The V2G scenario was simulated using the Weibull distribution. The effect on the transformer loading is observed as well as the voltage levels across the feeder. Figure 15 illustrates the transformer loading for both V2G and G2V. It must be noted that the household load is kept at 2.4 kW under the V2G scenario. According to Figure 15, under V2G scenarios, the transformer loading has significantly reduced as it caters for the local load. Since the local load is constant, it does not capture the actual effect of V2G on the transformer loading. However, it is more beneficial to implement V2G under high local load conditions to relieve the transformer loading.

It can be observed that there is an opposite effect with V2G compared to G2V scenarios. According to Figure 16, the voltage level increases across the feeder as the EV penetration

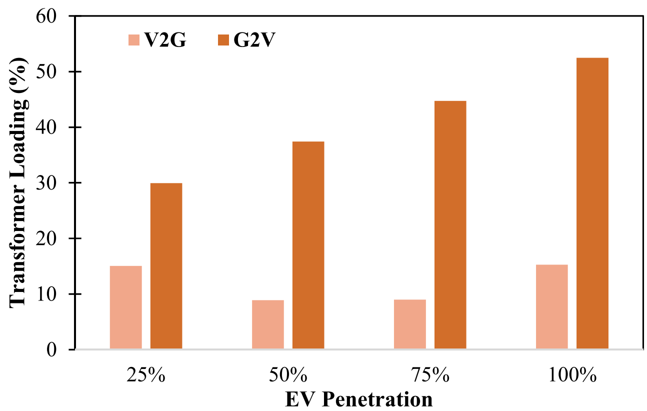


FIGURE 15 Transformer loading of the vehicle-to-grid (V2G) versus grid-to-vehicle (G2V).

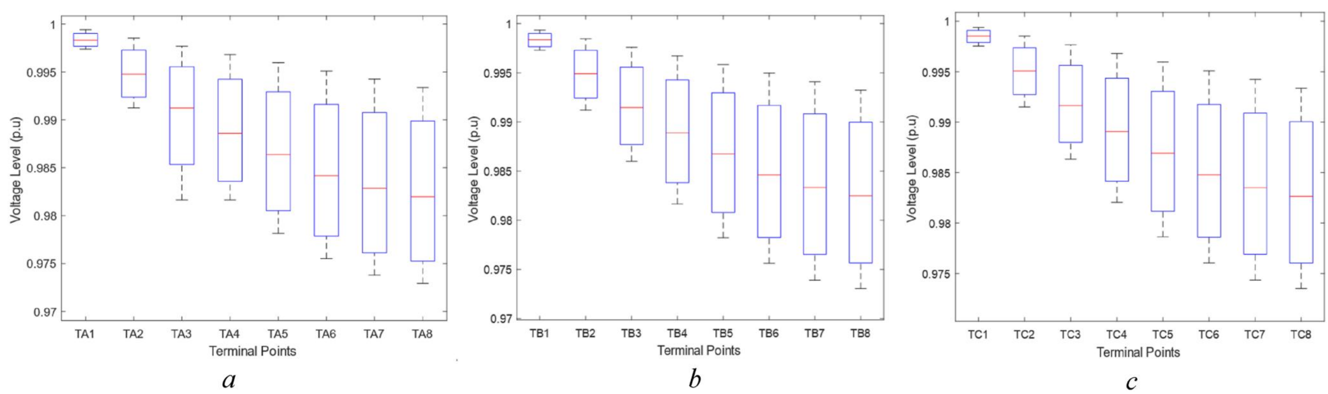


FIGURE 14 Voltage distribution across each terminal for each-phase, (a) phase-A, (b) phase-B, (c) phase C.

increases. However, the voltage levels of the feeder stay within the maximum and minimum limits stipulated in standards.

4 | CASE STUDY: IMPACT OF EV ON THE REAL RESIDENTIAL LV FEEDER WITH SOLAR-PV GENERATION

This case study was formulated further to verify the findings from the standard network study and analyse the effect of solar-PV generation. The Weibull PDF was used to represent EV charging. The EV charging loads are randomly assigned to each household in the real LV feeder (Figure 5) to achieve 0%, 25% and 100% penetration levels. The EV penetration is defined based on the same definition as in Section 2.3.3. The following scenarios were analysed in this case study:

a) Different solar-PV penetration levels
b) Smart-PV inverter with volt-var control
c) V2G with and without smart inverter volt-var control

4.1 | Different solar-PV penetration levels

Following solar-PV generation levels are analysed with EV charging scenarios:

i. 0% solar-PV generation (base scenario)
ii. 25% solar-PV generation (late afternoon during the summer)
iii. 100% solar-PV generation (during mid-day)

The same power output is applied to all solar-PV systems under each generation scenario, and all PV systems were operated at unity power factor. Figure 17 shows the mean terminal voltages under various EV and solar-PV generation scenarios. It must be noted that the terminal voltages are the mean voltage of 1000 voltage values obtained from the Monte Carlo simulation.

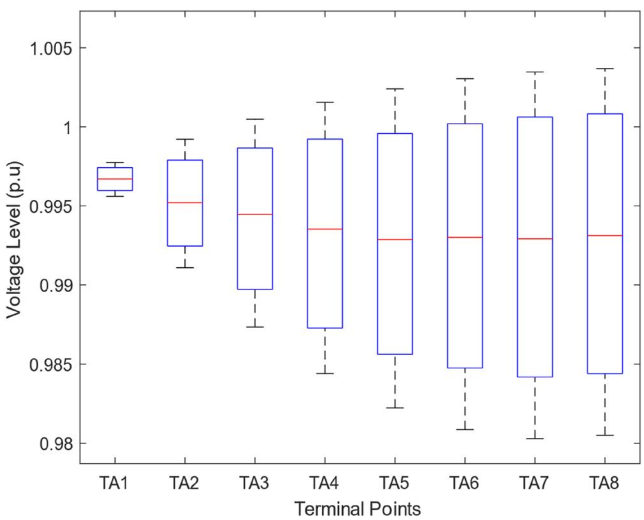


FIGURE 16 Voltage distribution across each terminal for V2G.

According to Figure 17, high PV scenarios are likely to increase the terminal voltages despite the EV load in each terminal. For example, under the 0% PV and 100% EV scenarios, the terminal voltage was 0.9987 pu, which has increased to 1.005 pu under 100% PV and 100% EV scenarios. However, it is unlikely that 100% PV generation is present when 100% EV load exists in the feeder. However, 25% PV generation is possible during the summer months when 100% EV load is in the feeder. Under such a scenario, the voltage was at 1 pu, indicating how PV generation can harmonise the adverse effect of the EV load.

A boxplot of transformer loading for each scenario is illustrated in Figure 18.

According to Figure 18, PV generation has assisted in reducing transformer loading, particularly under high EV scenarios (e.g. 100% EV load). For example, under 25% PV generation, it has reduced transformer loading by 7% on average for 100% EVs in the feeder. Under 100% PV generation, transformer loading has decreased by approximately 24%, with 100% EVs in the feeder. Therefore, probabilistic

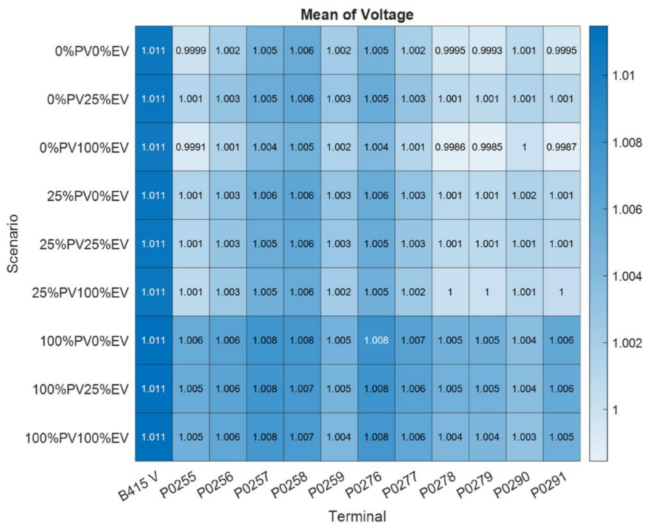


FIGURE 17 The mean terminal voltages for electric vehicle and solar-PV scenarios.

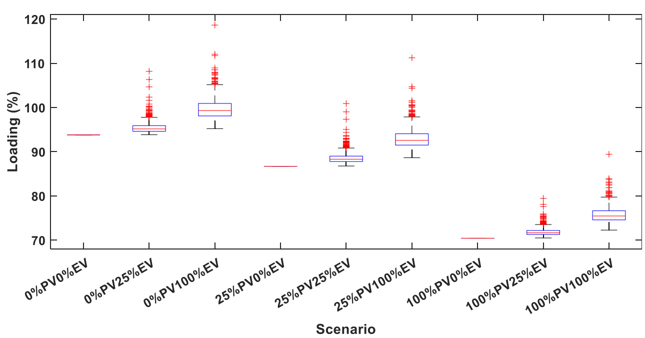


FIGURE 18 Transformer loading for electric vehicle and solar-PV scenarios.

analysis confirms the positive effects of PV generation under high EV penetration in the feeder.

4.2 | Smart inverter scenario for solar-PV

Smart inverters can provide volt-var control, injecting or absorbing reactive power to regulate the terminal voltage within a defined limit. IEEE Std. 1547 and AS4777.2 specify volt-var set points [21, 22] the inverter should follow when injecting or absorbing reactive power for voltage regulation. This paper adopts the volt-var settings, and the minimum reactive power capability standard specified in AS4777 (see Figure 19).

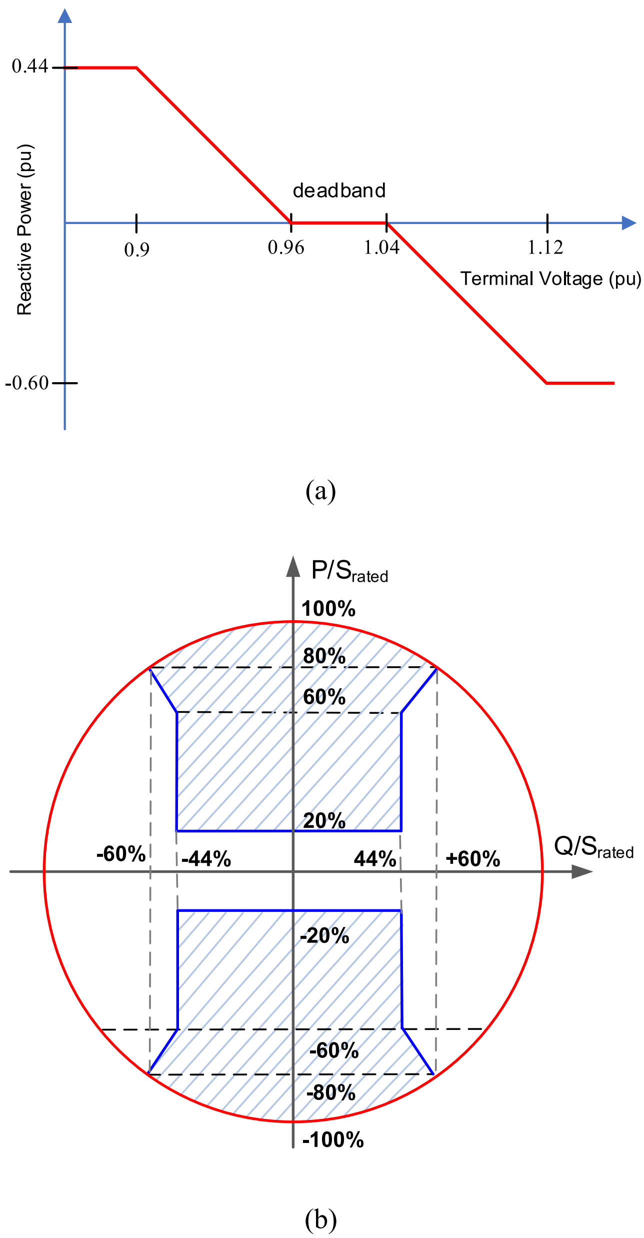


FIGURE 19 AS4777.2 Inverter specifications, (a) volt-var control setting, (b) inverter minimum P-Q capability.

Simulations have been conducted for the 100% EV scenario under 25% and 100% solar-PV generation levels. Figures 20 and 21 show the terminal voltage boxplots.

According to Figure 20, the terminal voltage variation along each terminal has reduced after implementing the volt-var control at solar-PV inverters, for example, the terminal voltage has decreased approximately by 0.16% with the volt-var control. However, that reduction has been reduced due

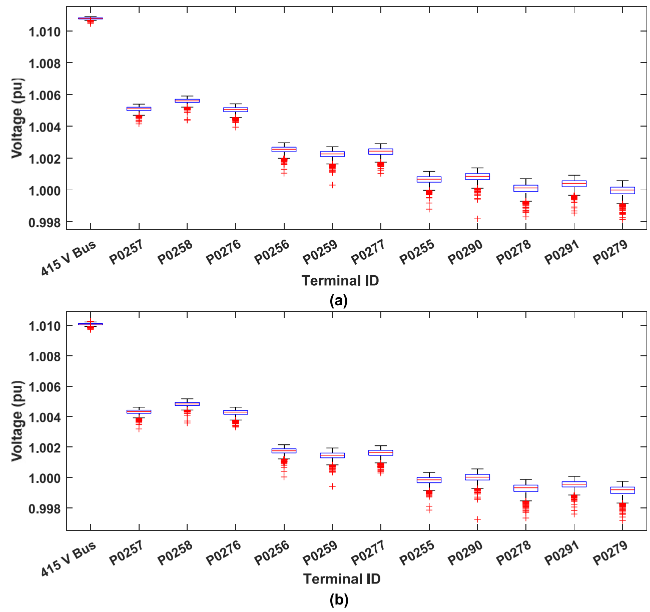


FIGURE 20 Terminal voltage boxplots with 100% electric vehicle and 25% solar-PV generation in the feeder, (a) without volt-var control, (b) with volt-var control.

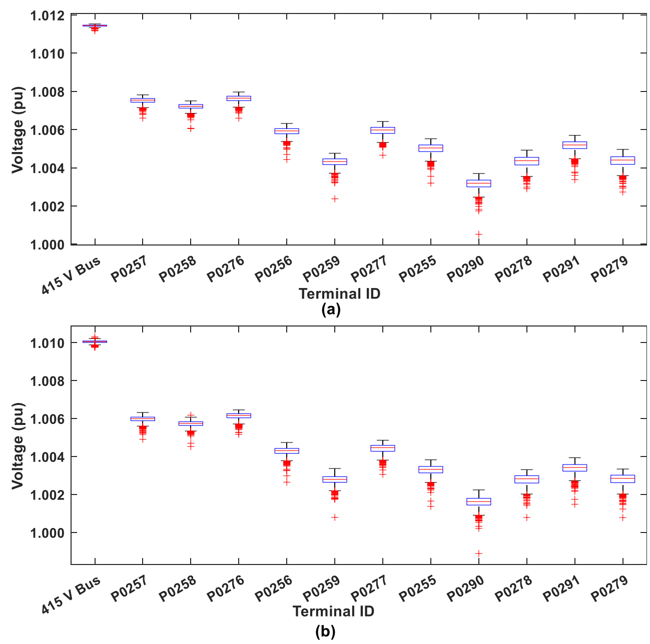


FIGURE 21 Terminal voltage boxplots with 100% electric vehicle and 100% solar-PV generation in the feeder, (a) without volt-var control, (b) with volt-var control.

to high PV generation as only a less reactive power headroom is available under 100% PV generation. In terms of transformer loading (see Figure 22), it does not have much effect at 100% PV generation; however, transformer loading has shifted slightly towards the rated loading level under volt-var control.

4.3 | V2G with and without volt-var control

The V2G scenario was simulated with 100% EVs operating in V2G mode. Several solar-PV generation levels (e.g. 25% and 100% solar generation) are simulated with and without the volt-var control functionality of the inverter. Figures 23 and 24 illustrate the boxplot of bus voltages obtained from Monte Carlo simulation under V2G with and without volt-var control.

According to Figures 23 and 24, the terminal voltage spread has reduced after implementing the volt-var control at the inverter. For example, the voltage recordings between 25% and 75% have decreased by ≈30% (difference relative to the nominal 1 pu) after implementing the volt-var control, and thus a relatively better voltage regulation can be achieved. However, due to the low X/R ratio (<1) of the LV network, the voltage regulation employing reactive power is not very effective compared to the HV network. Since active power is more dominant due to high resistance in the LV network (since $R.P > Q.X$). The failure rate has also been reduced by 40% after enabling the smart inverter capability. Since the

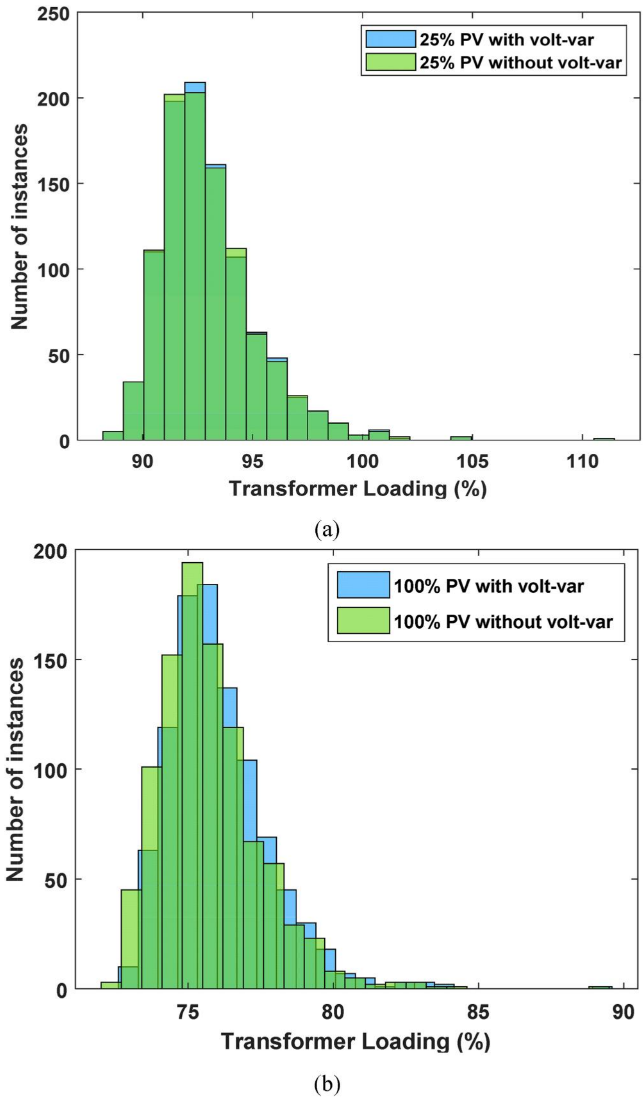


FIGURE 22 Transformer loading with and without volt-var control, (a) 25% PV generation, (b) 100% PV generation.

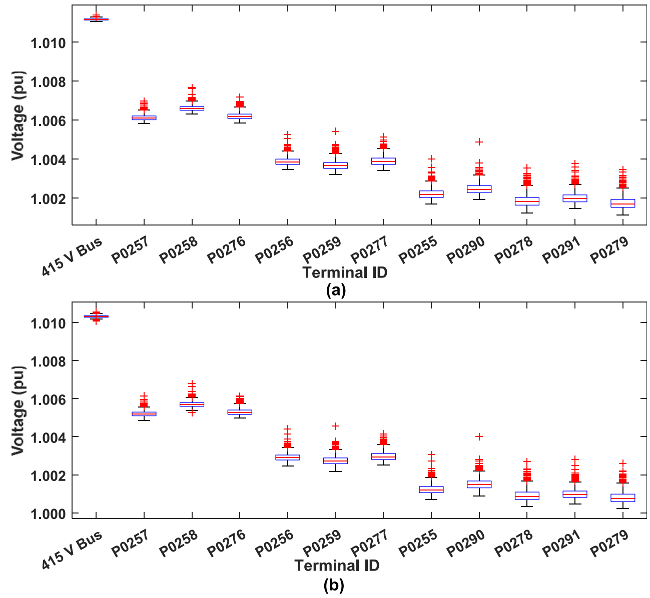


FIGURE 23 Terminal voltage boxplots with 100% electric vehicle in V2G mode and 25% solar-PV generation in the feeder, (a) without volt-var control, (b) with volt-var control.

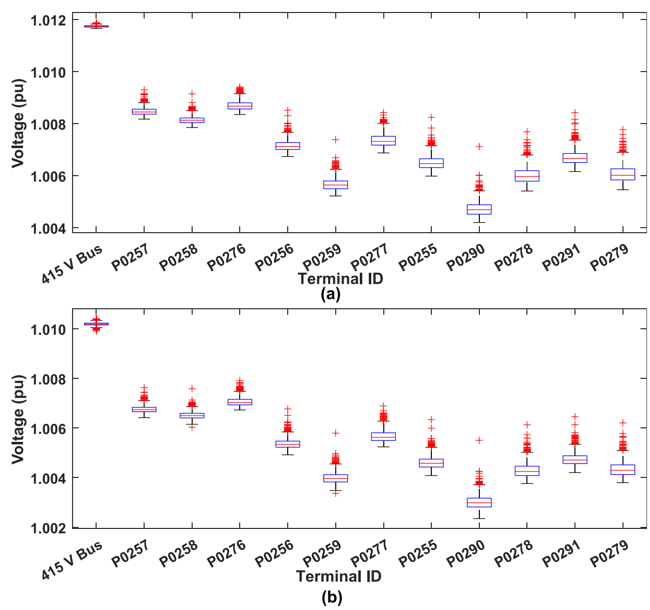


FIGURE 24 Terminal voltage boxplots with 100% electric vehicle in V2G mode and 100% solar-PV generation in the feeder, (a) without volt-var control, (b) with volt-var control.

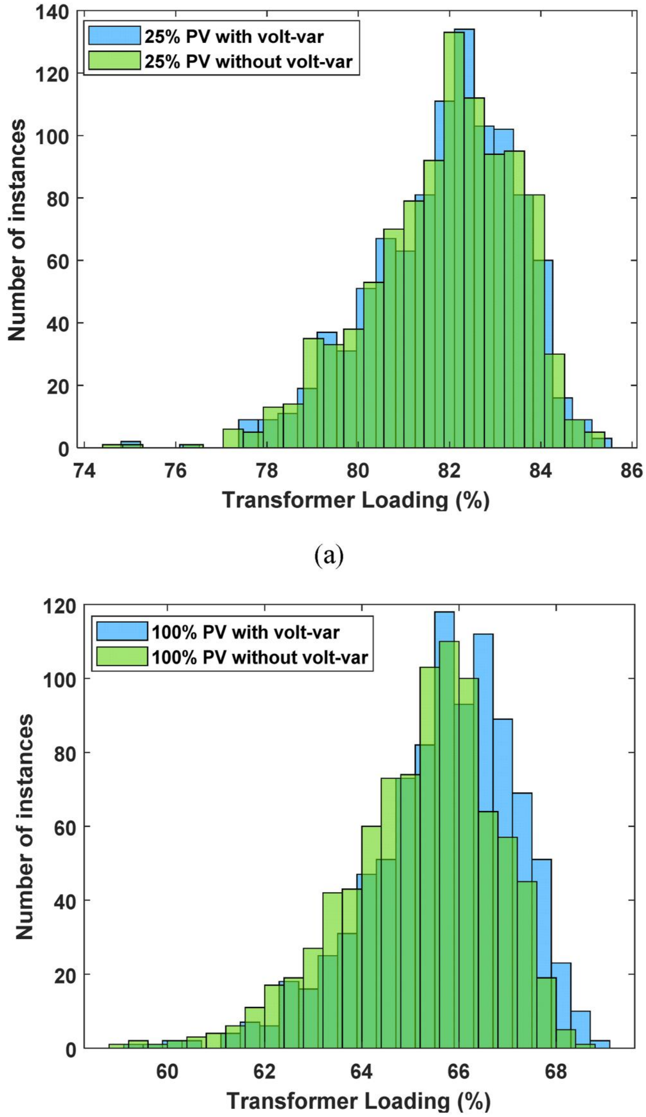
failure rate is directly associated with undesirable operating conditions, such conditions can be reduced with the volt-var control.

Finally, the transformer loading has been analysed for the scenarios and they are shown in Figure 25. Transformer loading has reduced with the higher solar-PV generation. However, with the volt-var control, transformer loading distribution has skewed towards 100% loading, as more reactive power is transferred under the volt-var control mode through the transformer.

5 | DISCUSSION

The probabilistic EV impact analysis framework can be extended to any LV network to assess the EV impact on the network. However, DNSPs need to acquire more accurate charging energy and charging duration data to produce the probability distribution function for EV charging power. As DNSPs are increasingly utilising the smart metres in customer premises, they can be used to capture these data; however, smart metres should be configured to capture data at high-resolution. Otherwise, high-resolution data acquisition systems can be utilised to capture charging data. Since the proposed method employs 1000 samples to run the probabilistic simulation, the computational burden may increase by 10–20 times more than a simple load-flow simulation. However, it can be mitigated by utilising multi-core computing architecture. Moreover, the load and solar-PV generation data can also be represented as a probability distribution function in these impact studies. However, this analysis did not consider it, as it purely focuses on the probabilistic nature of EV charging and V2G. However, it may increase the computational burden further.

In terms of smart inverters, they can also provide some voltage control in distribution feeders using their reactive power control capability. However, the voltage control bandwidth of reactive power is limited, since the LV distribution feeders are predominantly resistive. Therefore, active power control methods are more effective for the LV grid, and hence smart charging methods which actively control the active power should be deployed to tackle voltage control challenges.



(a)

(b)

FIGURE 25 Transformer loading with and without volt-var control under V2G, (a) 25% PV generation, (b) 100% PV generation.

6 | CONCLUSIONS

This paper has investigated the impact of EVs on low-voltage networks using a probabilistic simulation framework. Probabilistic impact analysis of EVs' integrated into LV networks shows the unpredictability of the loading per feeder with approximately a 20% increase in transformer loading, as EV penetration increases from 25% to 100%. Also, V2G simulation has resulted in an interesting outcome on how EVs can work in a smart grid with just a 1% increase in transformer loading from 25% EV penetration to 100% EV penetration. Voltage unbalance reduced slightly under a high EV penetration level; however, the downstream of the feeder has shown a much higher VUF level compared with the upstream.

A case study developed based on a real residential LV distribution feeder with solar-PV generation has shown how solar-PV generation can assist in reducing the adverse effects of EV charging. However, it is limited to a certain PV generation (e.g. 25%) in summer months as most EV loads are likely to appear in the evening or late afternoon hours. However, if the charging stations are connected to the LV residential feeders with solar-PV generation, they can exploit the benefits of solar-PV generation. Also, the study has shown how the volt-var functionality of the solar-PV inverter can help improve the feeder voltage profile under EV charging and V2G; however, volt-var support is constrained by the low X/R ratio of the LV feeder.

AUTHOR CONTRIBUTIONS

Matthias Hungbo: Conceptualization; data curation; formal analysis; investigation; methodology; writing—original draft.

Mingchen Gu: Conceptualization; methodology; supervision; visualization; writing—review and editing. **Lasantha Meegahapola**: Conceptualization; investigation; methodology; resources; supervision; visualization; writing—review and editing. **Timothy Littler**: Methodology; writing—review and editing. **Siqi Bu**: Writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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