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Impact Assessment of High-Power Domestic EV Charging
Proliferation of a Distribution Network

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Impact assessment of high-power domestic EV charging proliferation of a distribution network

Arsalan Zaidi, Keith Sunderland, Michael Conlon

Abstract: Transport electrification is becoming the mainstream as a means to improve efficiency, performance, and sustainability of transportation systems. Electric vehicles (EVs) can help to de-carbonise the environment, but a downside is the technical issues presented to the low-voltage distribution network. To quantify the stochastic nature of transport-affected electrification, probabilistic load flow is employed. Monte Carlo-based simulation is applied to accommodate the probabilistic uncertainties associated with variable EV charging patterns. This study considers high-power charging (up to 11 kW) at the domestic level while monitoring power quality variations (voltage drop, voltage unbalance factor, voltage sag) standards. This work focuses on the Irish and UK, distribution system operator’s—transmission system operator’s perspectives, as it will help to identify the likely impacts due to high-EV charger proliferation at household locations. The results indicate that if a 3.68 kW charger is used at the domestic level, it is possible for 40% of total household consumers to connect EVs directly to the distribution network without any power quality breaches. Furthermore, the proliferation of EV can be increased up to 100% if constrained to the start, and middle portions of the network (relative to the feeder substation transformer). For higher charger capacities (up to 11 kW), a bottleneck is presented regarding a resultant voltage unbalance factor.

1 Introduction

The proliferation of electrification within the transport sector can help to reduce fossil fuel consumption as well as carbon emissions. However, analogous to the scheduling challenges associated with the transport sector, electrical vehicles (EVs) can also exert unprecedented challenges on the planning and operation of power systems, whereby supply and demand must be balanced on a moment-by-moment basis.

The increasing proliferation of low-carbon technologies (LCTs) generated at the distribution level is forcing the traditional power supply networks through a paradigm shift. The consumers at the distribution level are no longer pure consumers as they play a more active role as a ‘presume’. LCTs such as EVs can provide ancillary services to the distribution level, and the technical impacts of these on the distribution level may propagate to the transmission level. For that reason, coordination between the transmission system operator and the distribution system operator (DSO) is required. The smart solution is to explore the possibilities of reducing the technical issues at the distribution level. So that the impact of technical issues cannot propagate to the transmission network (TN), the DSO needs to understand the penetration limits of LCTs before technical issues become manifest [1]. This understanding can subsequently be employed to quantify the impact of technical issues in terms of the number of customers affected. There are challenges due to the lack of real-time monitoring (observability) at distribution networks (DNs) and their impact on TNs [2]. For example, the uncertainties associated with LCTs affect DSO operation and planning policies, while utilising the existing assets. In this work, the maximum utilisation of existing assets with respect to different EV charging levels is considered. Mathematically based scenarios are generated to describe the impact of EV chargers on the network. Probabilistic analysis is used to discover the number of customers affected with respect to a penetration level of EV so that conclusions are based on the penetration level that the DN can sustain without any sustaining detrimental technical issues.

1.1 Technical standards

For any DSO managing EV engagement technical issues and more specifically, the power quality (PQ) is of primary concern as it needs to be maintained throughout the network as prescribed by network standards. Voltage drop and voltage unbalance are the main concerns associated with PQ in the LV network with EVs [3]. An unbalanced connection of EV load (allocated to each individual phase) can lead to increased levels of voltage unbalance in LV feeders. The level of voltage unbalance is dependent on the location, size of the battery, and the length and impedance of the feeder. This is particularly the case with a voltage unbalance caused by increased single-phase connected EV. The degree of unbalance is usually defined by Chandran et al. [4] as

\[
\text{VUF\%} = \frac{V_n}{V_+} \times 100 \tag{1}
\]

where \(V_\text{n}\) is the negative sequence component and \(V_+\) is the positive sequence component of the voltage. According to the IEEE standard [5], voltage imbalance must be limited to 2% in low-voltage and medium-voltage networks for 95% of the time. In the context of Irish/UK DN, the voltage unbalance limit is 1.3% [6].

The EN 50160 standard [7] stipulates the nominal voltage (\(U_\text{n}\)) in DNs as 230 V (between phases and neutral). Under normal operating conditions, including situations arising from faults or voltage interruptions [7, 8], voltage deviations up to 10% in low-voltage grids, for 95% of the time, are acceptable. Furthermore, the standard prescribes that all 10 min, root-mean-square (rms) values of the supply voltage must be within 10% of \(U_\text{n}\).

Voltage sag, as defined by IEEE, is a reduction in voltage for a short time. The voltage reduction magnitude is between 10 and 90% of the normal rms voltage. The duration of a voltage sag event, by definition, is <1 min and >8 ms or a half cycle of 50 Hz electrical power [9]. Large and sudden deviation of voltage for short periods is a known PQ event [10]. Further PQ events can be classified into normal, which are expected events and abnormal events [9]. For instance, to quantify the abnormal events, short circuits and earth faults are considered. The most common type of

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abnormal events that can occur in DN include unsymmetrical single line to ground (SLG) faults. Such abnormal events lead to severe voltage sags. In this work, voltage drop and voltage unbalance are considered along with voltage sag due to SLG faults.

1.2 Literature review

In Ireland, the DSO can only facilitate slow chargers to be installed at domestic installations. Slow charging (up to 3.68 kW) can take 10–12 h to replenish a completely discharged battery and fast charging (up to 50 kW) points are limited in number. Fast charging points (non-domestic) are limited due to maximum import capacity (MIC) restrictions associated with the electric network at each connection point. Recent advancements in battery technology suggest that EVs can store energy at higher rates with higher ampere-hour (Ah) capacities will be available for vehicles. For instance, a 40 kWh battery capacity is already available in the market. Electrical buses, for instance, have battery capacities that are in the order of 200–300 kWh [11]. Currently, it is not practical for EV users to connect 40 kWh batteries for 10–12 h with a 3.68 kW single-phase charger [12]. Recent research suggests if the charge is stored in the battery for long periods of time, storage capability deterioration will be experienced by the batteries with time [13]. The proliferation of EVs is limited due to the repercussions of practical implementation. For instance, the vehicle-to-grid (V2G) concept. Despite the benefits of the V2G concept [14], implementation can significantly reduce battery life [15]. Furthermore, the V2G concept utilises extra cycling. So opportunities to use an EV battery for grid balancing, even when at constant power, will cause the EV battery cell performance to reduce significantly [15]. To be more specific, the battery of an EV with V2G technology could reduce the working lifespan of an EV battery pack to under 5 years [16].

Over the last decade, significant research focus has been engaged in terms of understanding the impact of charging EVs with respect to power systems. In [17], a probabilistic approach for optimal charging is presented using the Monte Carlo simulation (MCS). An optimal charging pattern is proposed based on charging points at hours when the energy price is low. In [18], the role of reactive power to reduce the voltage magnitude violation is monitored. In [19], a comprehensive detailed analysis is presented in terms of battery state of charge (BSOC) based on driving patterns but voltage unbalance factor (VUF) calculations and results are not presented. In [20], a detailed examination of LCTs, which includes different penetration levels, is discussed, although the study is limited to voltage and thermal limit violations. The study utilises 5 min resolution input data for each individual LCT, at each penetration level in 20% increments. The same author also proposes a mitigating solution in terms of three-phase LCTs connection, feeder reinforcement, and on-load tap changer transformers along with a cost-benefit analysis [21].

In [22], the hosting capacity of existing assets is defined based on the penetration level of EVs. However, the work does not consider the VUF. Based on the analysis and results presented in this presented work, the authors assert that the voltage level and VUF are the primary concerns.

In [23], the grid voltages are analysed according to the probabilistic and deterministic limits of the EN50160 standard, for a 100% EV penetration rate. A scenario-based modelling approach is considered. The VUF is calculated and presented. However, the results do not replicate the probabilistic facilitation of hosting capacity. In a deterministic approach, it is not possible to appreciate how many customers will be affected by different EV penetration levels.

In [24], the steady-state time-variant proliferation of EVs is considered in the analysis to estimate the critical number of EVs that can be integrated into a DN. The hosting capacity of an existing asset is not defined based on the penetration level of EV. All the studies [19, 21–25] consider probabilistic and deterministic approaches to provide planning models of the DN. The authors herein propose an approach using a predefined penetration level for EV chargers and how much EV charging impacts the existing assets. Moreover, the hosting capacity of existing assets based on the percentage of customers will also be affected.

In the past, researchers also utilised a combination of deterministic and probabilistic approaches to appreciate the technical issues arising from the integration of LCTs in DNs [23, 26]. While there are two common approaches adopted by different researchers, there is a general trend in researcher approaches. Most of the researchers are using deterministic approaches with the random selection of input data profiles [27].

1.3 Contribution

The majority of researchers in the literature estimate the performance of DNs in terms of PQ variations such as voltage drop, voltage unbalance, cable loading etc. Limited studies are carried out to quantify the performance of networks in terms of extreme condition events such as voltage sag and swell. In terms of a research gap/contribution, the authors combine the realistic topology of the Irish DN and use an MCS to predict the influence of PQ variations and events of EV charging on the legacy grid. This method aims to assist the DSO in the assessment of different EV chargers’ impact on the network. Different voltage metrics are studied, allowing a better understanding of the different EV chargers and their effects on the network. This work can further facilitate novel approaches for DSO to implement an energy transitive framework featuring the presence of utility-owned EVs; as a novel planning model based on programming, which is suitable to properly utilise their existing (and future) assets.

The remainder of this paper is organised as follows. Section 2 presents the proposed network and load modelling. Section 3 describes the solution methodology and the load flow analysis using 100 repeated iterations for MCS for each 5 min interval throughout the day in a probabilistic manner. In Section 4, the results are presented. Due to the probabilistic nature of analysis, cumulative density functions (CDFs) and complementary CDFs (CCDFs) are used to represent the results. Some relevant conclusions are drawn in Section 5.

2 Data formulation

2.1 Network modelling

The network model is implemented on the DigSILENT power factory platform. There are 74 customers, connected from a 10/0.4 kV transformer in a radial network topology. In this regard, the LV DN considered in [28], as provided in Fig. 1, is employed. The network consists of nine (three-phase) pillars, namely, Pillars B–J, through which customers are connected. These pillars subsequently facilitate a radial connection to the substation transformer (Fig. 1). Pillar B is nearest to the transformer and Pillar J is the furthest away from the transformer. The pillars are separated by two consumer connections (domestic installations), each with the distinct earthing provision terrestrial neutral combined and separated earthing sytem (TN-C-S). Service cabling, from pillars to consumers is 25/16 mm² concentric neutral [28]. The cabling from the substation transformer to the first pillar (and each pillar thereafter) is either 185/70 mm² cross-linked polyethylene or 70 mm² paper-insulated (NAKBA) [28]. Fig. 1 illustrates the network structure from the transformer down to the consumer with the pillar/consumer earthing provisions. The earth electrode impedances are modelled as 5 Ω resistances at customer connections and 1 Ω resistance at the pillars. In the analysis presented, and for brevity, there is a focus on the start of the network (Pillar B), the middle (Pillar E), and the end (Pillar J) to describe the potential issues/concerns. Furthermore, only the important specification of the network is presented in this section.

Full technical details and modelling approach are discussed in [28]. In Ireland, consistent with EN50438, microgeneration is defined as generation units that can produce 25 A at 230 V or 16 A at 400 V, as for the guidelines published by ESB Networks (Irish DSO) [29]. It is worth mentioning that 11 kW (single-phase) connected loads are in excess of guidelines published by ESB, under
current regulation. Twenty per cent EV load penetration is allowed with a charging rate of 3.68 kW.

As defined in the EN50160 standard [7], the voltage at every bus of the medium- and low-voltage network should be within ±10% of its nominal value, with ±6% being employed by the network designers.

2.2 EV and residential load modelling

The household load demand profile was obtained from the DSO. The household load is represented by an average after diversity maximum demand value of 0.49 kW per customer. This is based on an annual consumption of electricity of 4300 kWh in Ireland [7] and a power factor of 0.95 (inductive) for each household load. In Fig. 2, the maximum load profile with and without EVs load is illustrated with one EV charging scenario is presented, to represent the diversification of load. The maximum load on the network section (without EVs) is 80 kW at 21:00. The maximum peak load value inclusive of EVs is 150 kW at 23:00. The maximum energy consumed by each EV battery is 3.68 kW for 5 min, with a 3.68 kW charger [30]. The same approach is adopted for 7 and 11 kW charger load, which can take up to 7 and 11 kW for 5 min, respectively. For brevity, only a 3.68 kW EV charger is considered and the impact on the load profile is explained in detail and presented in Fig. 2. The demand profile is created through a freely available tool developed by the Centre for Renewable Energy Systems Technology at Loughborough University [31]. This tool can generate random load profiles based on the average diversity demand of consumers and it is employed here to generate domestic household profiles.

2.3 Probabilistic representation of BSOC

In this work, the statistical analysis presented by Richardson and Taylor [32], corresponding to a recent 1-year field trial of EVs in Dublin, Ireland, is used to create the profiles. A probability density function (PDF) is applied to the network such that a mean BSOC of 10.75 kWh and a standard deviation of 6 kWh are selected for initialisation [33]. According to the current guidelines, as provided by the DSO, the proliferation of EV across the network should be limited to 20% [34]. The proliferation of EVs is likely to increase by 50% by 2030 [34]. However, if one considers the arguments supporting increased EV integration (such as CO₂ abatement, the development of a green economy, adherence to EU regulations etc.) it is plausible that future energy charging scenarios will include 100% EV penetration [34].

The Nissan LEAF 3 ZERO has a range of 400 km, through a 62 kWh battery [35]. The Nissan LEAF (2018) has a 230 km range, through a 40 kWh battery [35]. The average distance passenger cars travel in Dublin is 15 km/day in 24 min [36] and such distances require 34.5 min or 2070 s to charge on daily basis (using a 3.68 kWh/single phase charger). One-in-five journeys made by Irish people last year were for distances of <2 km yet over half [36] still use the car for such journeys. In most of the European countries, battery sizes up to 40 kWh will be sufficient to overcome daily travelling requirement.

However, it is considered here as being appropriate to examine the worst future energy scenarios to completely capture the impact of charging (extreme condition). The approach to define the probability of EV BSOC and apply it for the initialisation of EVs is taken from the method outlined by Richardson et al. [33].

For probabilistic load flow (PLF), the following procedure is used to implement the input EV data. By using the battery characteristics (20 kWh), the BSOC and PDF stipulate the energy requirements associated with a pool of 100 slow charging residential EV profiles. All the 74 vehicles are required to be charged in a day. Seven EV profiles do not require charging out of 74 randomly generated EV profiles. If, all seven EV profiles are selected in random selection out of 74 required then maximum EV charging penetration is 90–95% otherwise in most of the cases,
The amount of energy required by the cars is randomly selected from Table 1. For instance, six EVs have 2 kWh of initial BSOC, and these six EVs required 18 kWh/EV to replenish completely.

Once 100 randomly EV charging profiles are generated, then 74 EV profiles are randomly selected out of the 100 EV profiles. There are only 74 household customers available in the DN (Fig. 1).

Each EV profile has a 5 min resolution; 288 readings throughout a day.

For every 5 min resolution input reading, 100 different combinations are considered through MCs.

In the simulations, to make the EV charging more realistic, an EV will remain connected until it is fully charged.

The charging time is, therefore, the connection time and the total charging period.

In Fig. 3, the initial BSOC of 74 EVs, connected randomly across the DN, is considered. As illustrated in Fig. 3, three of the EVs have 20 kWh of initial BSOC (20 kWh battery). For example, if seven EVs have 0 kWh of initial BSOC (20 kWh battery and 20 kWh of energy is required from a 3.68 kW charger), 5 h is required for charging as shown in Table 1 [30]. It is noted that a 20 kWh battery size is considered in [29], Richardson et al. work. However, due to the recent advances in battery size, a 40 kWh battery capacity is utilised in this work. The 40 kWh battery initial state of charge (SOC) is obtained by linear interpolation of a 20 kWh battery size (as an estimation) forcing modification impacts the replenish time of the battery. The changes in energy requirements, based on total battery capacity, are presented in Table 2 [37]. Seven EVs have 0 kWh of initial BSOC (40 kWh battery and 40 kWh of energy from a 3.68 kW charger). Then for each phase, the number of EVs connected, total battery capacity, total BSOC, and energy required are calculated. It is noted that each phase will have a different number of EVs connected and different energy requirements. For instance, Phase C in Table 1 facilitates 200 kWh for 24 EVs. On average, therefore, it facilitates 8.3 kWh, each requiring 200 min of charging with a 3.68 kW charger to replenish the battery completely. For an individual car example with a 40 kWh battery and an EV BSOC of 60% (24 kWh), to facilitate the 40% battery capacity 16 kWh is required. A 11 kW charger can provide 16 kWh of energy in 90 min. Similarly, 3.68 kW can provide 12 kWh of energy in 3 h as shown in Table 1 [30]. Once the battery on a particular phase is fully replenished it will be automatically disconnected from the network.

This modification impacts the replenish time of the battery. The changes in energy requirements, based on total battery capacity, are presented in Table 2 [37].

### 3 Method

The deterministic load flow approach cannot consider the probabilistic aspects associated with the proliferation of LCTs. Deterministic load flow is used for an adequate starting point. It is challenging to predict customer behaviour accurately, especially in the case of EVs, and, hence, a probabilistic approach is required to quantify the impact of EV proliferation. The DN considered in the simulation is the representation of a small portion of an urban DN. It is consistent with larger (holistic) Irish/EU DNs. In Northern American DNs, demographical influences result in changes in the network structure. As is noted in the literature, the North American DNs can sustain single-phase EV charger ratings up to 19.5 kW. In the European context, however, EV chargers are limited to 4.5 kW at a domestic level [22] due to different network configurations.

#### 3.1 Probabilistic impact assessment

The random allocation of EV load profiles throughout the day is explained in Fig. 4. There are 100 datasets available for EV profiles. Out of these 100 EV profiles, 74 EV profiles are randomly selected. One pool contains 288 inputs, representing the load demand of EV in 5 min resolution over 24 h per day. The process

- Battery initial BSOC is defined based on Fig. 3, to facilitate 100 EV initial BSOC.

#### Table 1: Charging specification of EV

<table>
<thead>
<tr>
<th>Distance travel, km</th>
<th>Charging energy, kWh</th>
<th>230 V/10 A (2.3 kW)</th>
<th>230 V/16 A (3.68 kW)</th>
<th>230 V/16 A (11 kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>1.4</td>
<td>00:37</td>
<td>00:23</td>
<td>00:08</td>
</tr>
<tr>
<td>20</td>
<td>2.8</td>
<td>01:14</td>
<td>00:46</td>
<td>00:15</td>
</tr>
<tr>
<td>50</td>
<td>7.1</td>
<td>03:04</td>
<td>01:55</td>
<td>00:38</td>
</tr>
<tr>
<td>100</td>
<td>14.1</td>
<td>06:08</td>
<td>03:50</td>
<td>01:17</td>
</tr>
<tr>
<td>150</td>
<td>21.2</td>
<td>09:12</td>
<td>05:45</td>
<td>01:55</td>
</tr>
<tr>
<td>200</td>
<td>28.2</td>
<td>12:17</td>
<td>07:40</td>
<td>02:34</td>
</tr>
</tbody>
</table>

#### Table 2: Initial BSOC of EV (40 kWh battery)

<table>
<thead>
<tr>
<th>Number of EVs</th>
<th>Combined battery capacity, kWh</th>
<th>Combined initial BSOC, kWh</th>
<th>Total energy required, kWh</th>
</tr>
</thead>
<tbody>
<tr>
<td>phase A</td>
<td>24</td>
<td>960</td>
<td>670</td>
</tr>
<tr>
<td>phase B</td>
<td>26</td>
<td>1040</td>
<td>974</td>
</tr>
<tr>
<td>phase C</td>
<td>24</td>
<td>960</td>
<td>760</td>
</tr>
<tr>
<td>total</td>
<td>74</td>
<td>2960</td>
<td>2404</td>
</tr>
</tbody>
</table>
to obtain different EV datasets with respect to uncertainties associated with EVs is explained in the next section. Different types of EV chargers are considered (3.68, 7, and 11 kW), while the maximum possible penetration level (up to 100%) is considered for each case study. A 100% EV proliferation means the maximum penetration possible as one EV per household. Once the household load and EV load profiles are assigned to each individual household in the network, power flow is calculated using DlgsILENT programming language (DPL).

3.2 MCSs impact assessment

For each successive iteration, the load profiles (customer load and EV profile) are reset to include a new specific MCS profile. The MCSs are used to randomly assign the charging patterns for the EVs over a 24-h period. Once the pattern is selected, the BSOC is checked every 5 min. It is assumed that once the battery is connected to the network, it will remain connected until it is fully charged. Random selection of the EV charging pattern implies an uncontrolled charging pattern is utilised. For the simulations considered, all residential households are randomly assigned an EV charging profile with different SOC. The breakdown of EV allocation is based on a probabilistic distribution as well as the energy requirement of the EVs. The organisation of this distribution per phase is presented in Table 1.

The steps over each MCS iteration – given a particular EV charging level and consumer load – are summarised in the flowchart presented in Fig. 5. The associated steps are considered for different EV charging levels. Each iteration generates random input variables cognisant of theMIC for each network connection. MCS iterations and EV/customer loading are bound by the predefined limits as defined by the DSO code (EN5160). The maximum number of iterations is limited to 100. Justification for the number of iterations employed in the MCS is a significant consideration in terms of computational overhead. Hundred iterations are utilised in these simulations as a sufficient number in terms of convergence and accuracy. A comparison of MCS using 100 repeated iterations and 1000 repeated iterations were considered. The total square error was found to be 0.002, implying that the difference is limited to 0.2% for all 100 Monte Carlo considerations. A similar consideration in terms of solar photovoltaic connections in different feeders is tested by Pukhrem et al. [38], with an error difference of 0.0016 being recorded. Based on the evidence available in the literature, 100 MCSs are employed in the work presented here.

3.3 Allocation of battery charging time

The term ‘rectangular distribution’ used in Fig. 5 represents the general nature of battery charging, i.e. once a battery is connected it will remain so until it is (completely) replenished. For the sake of simplicity, the average EV load per phase is calculated based on the initial BSOC in Table 1, to represent the diversity of the EV load. For example, Table 1 suggests 24 EVs require 290 kW on Phase A. One EV requires 12.08 kW power approximately. The initial BSOC at Phase A is 670 kWh for 24 EVs. The initial BSOC of one EV connected to Phase A is on average 28 kWh. If the battery state remains below 95%, then it will remain connected until it reaches the desired value.

4 Probabilistic nature of the analysis

The statistical nature of the analysis from the MCSs implies that the results need to be presented in a probabilistic way, in particular, the probability associated with the occurrence of technical issues such as voltage drop at each phase and VUF at the pillars (as three-phase sources). The nature of the results is such that they can be used to determine whether a certain EV penetration level is within acceptable limits for the DSO. In other words, by quantifying this probability, the DSO might conclude that it is feasible to accept penetration levels that represent a low probability of technical issues (line voltage drop, voltage sag, and VUF) instead of opting for significant network reinforcements (if available) or investigations of other solutions. The probability of occurrence associated with the voltage drop and VUF is presented for a particular network scenario and then, CDFs are considered to determine the probability of encountering certain problems in a particular portion of the network (position: start, middle, or at the end of the network portion under consideration). Thus, a DSO can establish the extent of a potential PQ problem based on the corresponding percentage of EVs that are integrated across the network.

Fig. 5 MCS assessment framework
connection scenarios (e.g., 60% or 80%) can be accommodated by the network without voltage breaches being incurred. It is important to note here, if a voltage drop breach occurs at a specific pillar, it will limit EV penetration level throughout the network.

Consideration of the worst-case study will facilitate a comparison of the results obtained from the probabilistic study in further assessing the impact metrics due to the increased proliferation of EV. For the metrics, three worst-case scenarios can be considered. Case study 1 considers a 3.68 kW charger, i.e., a 100% penetration level of EVs. In case study 2, a 7 kW charger is considered. Finally, in case study 3, a 11 kW charger is considered.

4.2 Case study 1: 3.68 kW charger

For the case study 1, all the 74 customers have EV chargers installed in their premises, one EV charger can consume up to 3.68 kW at a particular instant. The rate of battery charging depends on the rating of the EV charger rather than battery capacity. Battery capacity sizes are influential primarily during the battery-charging period. Different penetration levels of EVs are considered during the MCS with maximum and minimum EV load peaks being considered over the 24 h analyses (5 min) time periods.

For simulation, the nominal voltage is set as 1.05 p.u. The under-voltage limit is 0.95 p.u. in all simulations. For instance, in consideration of Fig. 6, for Phase A at Pillar J, the probability of 1 p.u. voltage is 0.7 (approximately). Furthermore, at Pillar J and with respect to Phase B, the probability of the voltage being 1 p.u. is 0.5 approximately.

In Fig. 7, the voltage unbalance profile over the benchmark for the test DN on different pillars for a 3.68 kW EV charging scenario is illustrated. It is evident that the VUF value is significant at Pillar J, as the probability of the VUF exceeding 1.3% is 0.4. This result suggests that if the network has 100% EV connections (one per 74 customers), the probability of no households having a VUF PQ issue is 0.4. In terms of a DSO perspective, this implies that the network can accommodate only 40% arbitrary EV penetration across the network, to facilitate an acceptable VUF. Based on this result, the DSO can decide what level of VUF will be tolerated in the network. For example, in a planning context, the DSO may set the VUF maximum limit up to 0.5%, then 10% proliferation is permitted throughout the network.

4.3 Case study 2: 7 kW charger

EVs are connected to the network as a single-phase load. Therefore they can cause voltage unbalance. In Fig. 8, which illustrates the impact of 7 kW chargers, voltage breaches are shown for Pillar J, Phase B, and Phase C. The probability of under-voltages <0.95 p.u. is 0.2 (approximately). In Fig. 9, the probability of VUF exceeding 1.3% is 0.27 and 0.5 at Pillar J and Pillar E, respectively. In the context of Irish/UK DN, a voltage unbalance limit is 1.3%.

4.4 Case study 3: 11 kW charger

In Fig. 10, the voltage metrics on different pillars for 11 kW EV charging scenarios are presented. The probability of an under-voltage below 0.95 p.u. at Pillar J is 0.4 (approximately). The manifestation of voltage breaches is evident at Pillar J and the probability of VUF breach at Pillar J is 0.2. It is important to mention here, a 11 kW charger is not allowed for installation in domestic premises by DSO (ESB Networks). For example, from a planning perspective, the DSO aims to set the VUF maximum limit to 1%. Then 10% of EV penetration is allowed throughout the network.

4.5 CCDF analysis

For each case study, the voltage unbalance is computed and quantified against the UK/Irish standard of 1.3% for 95% of the defined time period. Thus, the percentage of occurrence of VUF that exceeds the threshold value is quantified. The graphical plot of the percentage of customers affected versus the percentage of VUF is shown in Fig. 11, as a CCDF. The corresponding CDF facilitates a measurement of the probability of under-voltage occurring at the

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**Fig. 6** CDF of system indices for under-voltage metrics at 3.68 kW charging

**Fig. 7** Percentage of VUF at Pillar B, Pillar E, and Pillar J at 3.68 kW charging

**Fig. 8** CDF of system indices for under-voltage metrics at 7 kW charging

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**4.1 Cumulative distribution functions**

CDFs can be extracted for each EV charging level (namely 3.68, 7, and 11 kW); one for each metric (voltage drop and VUF). In the context of voltage metrics, ‘x’, represents the voltage per unit (p.u.) and the corresponding CDF or $F(x)$ allows a quantification of the voltage magnitude probability. In total, there are three different positions namely Pillars A, E, and J in the network, each position has three different phases namely phases A, B, and C, so subsequently nine CDFs for each case study (such as 3.68 kW). These CDFs enable the probability of the voltage drop at a specific location for each case study to be understood. For example, in Fig. 6, the probability of a voltage drop is <0.95 p.u. in the network, with 100% EV penetration, is 0.05 (approximately). Therefore, if a voltage breach for the worst condition (100% penetration) impacts 5% of the customers, then all the other EV connection scenarios (e.g., 60% or 80%) can be accommodated by the network without voltage breaches being incurred. It is important to note here, if a voltage drop breach occurs at a specific pillar, it will limit EV penetration level throughout the network.

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site for each case study. Again, from Figs. 9 and 12 (VUF probability associated with 7 and 11 kW chargers), it is apparent that VUF breaches will be experienced by customers. The meaningful replication of the percentage of customers affected by the different types of chargers, namely 7 and 11 kW, is provided in Fig. 11. The percentage of customer violations is represented by the random variable \( x_s \). \( F(x_s) \) represents the CCDF and it is evaluated at \( x_s \) in two different changing levels (7 and 11 kW). These customer violations are considered at three different locations, namely Pillar B, Pillar E, and Pillar J; all considered in terms of 7 and 11 kW chargers. It can be noted here, the importance of VUF at different locations. For instance, for Pillar B, the VUF remains within limits for 7 kW charger rating as illustrated in Fig. 9, but this is not the case at pillars E and J, at 100% EV penetration level. The CCDF represents how frequently a random variable exceeds a particular limit. For instance, from Fig. 11, in consideration of an 11 kW charger and specifically

4.6 Voltage sags (predictable extreme conditions)

For instance, if there is an evening when EVs are charging as usual, but there is a higher than normal electricity demand (for instance, a public holiday), the DN could become overloaded and fail. Other examples include lightning and switching surges, causing stress to the steady-state voltage in the network. In network planning, it is important to define the possible extreme conditions and estimate the DN response during these conditions. Such predictable extreme conditions are introduced in the network with 11 kW EV chargers if all 74 EVs are connected simultaneously.

Another example of an extreme event could be a SLG fault during the peak EV charging time. A short-circuit study of a SLG fault at Pillar E for Phase A is considered to establish the ramifications. In this regard, a fault time duration (<1 min), location (Pillar E), and fault clearance are considered. A SLG fault study was performed in DigSILENT Power Factory, utilising the dynamic simulation language toolbox. As shown in Fig. 13, highlighted in the red box, the SLG fault event caused the voltage on Phase A to drop to 0.84 p.u. at Pillar J with the 11 kW charger. At Pillar E, the voltage drop was 0.88 p.u. approximately. Fig. 13 illustrates the short-circuit event occurring at Pillar E (middle of the network) and the maximum deep voltage sag is at Pillar J (end of the network). It is apparent that the voltage level remains within limits at Pillar B during a short-circuit event. The shallow voltage sag is observed near the transformer (Dy configuration). Under such abnormal events (extreme conditions), large reactive power flows are required to facilitate voltage recovery post-fault. High reactive flow, can generate high inrush currents from the fault,
which can damage electrical equipment [38]. During the simulation, it was observed that the fault impedance (distance from the transformer to fault location) has a significant role in limiting voltage sag depth. If the fault impedance of the network is high, the voltage sag magnitude remains high (shallow sag is observed). Short-circuit fault analysis is out of the scope of this work.

4.7 Transformer loading

In the network under analysis, the power rating of the transformer is 0.4 MVA. The thermal loading of the transformer is monitored under different charging levels namely, 3.68, 7, and 11 kW chargers, at 100% EV penetration level. The thermal loading of the transformer is presented in Fig. 14. In the case of the 3.68 kW charger, the transformer loading remains between 5 and 25% approximately. However, for the 11 kW single-phase charger scenario, the loading goes up to 48% approximately (as illustrated in Fig. 14). For this particular network section, the transformer loading remains below 50%. Transformer loading results are calculated but not analysed probabilistically because, in this particular feeder, there are no customers affected by the loading problem as it never goes >50% in the analysis presented.

The loading of the transformer is calculated from the PLF capability in DigSILENT power factory. The loading of the transformer remains <50% throughout the day, even at maximum EV charging load. Therefore, significant cable loading throughout the network is highly unlikely. In Fig. 14, the transformer loading is increased significantly using 11 kW EV chargers instead of 3.68 kW chargers. For instance, as shown in Fig. 14, at 18:00, the loading of the transformer with 3.68 kW EV chargers is ~15%, at the same instant with 11 kW chargers, it is ~25%.

5 Conclusion

In this work, EV proliferation (up to 100%) is considered in a low-voltage DN with respect to different charger levels. A MCS is chosen as a tool for considering the probabilistic aspect associated with EVs. The existing assets of the DN are analysed to define the maximum stress it can sustain in terms of EVs penetration. Based on the results, the DN can face PQ issues in terms of line voltage drop and VUFs, for increasing EV load. From a DSO perspective, EV customers are only allowed to use a 3.68 kW charger in domestic premises. The analysis suggests that 40% of EV proliferation in the network does not cause any sort of technical issue, with respect to the EN50160 standard. It is important to quantify the technical issues in the network before proposing any solution. This network can sustain 40% EV penetration without any network modification or mitigation measures. The proliferation of EVs and a higher rate of EV charger are inevitable and therefore DSOs must act proactively to define limits for their networks. In a DN-design context, it is important to consider the predictable extreme conditions. During extreme conditions, the voltage level drops to 0.88 p.u. If the voltage level remains 0.88 p.u. for more than 1 min, the network can become unstable. The network designer must need to consider the extreme condition scenarios in the distribution grid design. This work does not consider a smart charging or time sequencing charging solution. Smart charging techniques are quite promising but the communication protocol required to monitor load demand are difficult to implement practically. Custom devices (static VAR compensator (SVC) or static synchronous compensator (STATCOM)) can provide alternative solutions. They are costly but fast response times are possible.

In terms of voltage unbalance, the increase in voltage unbalance at higher charging rates is due to unbalanced loading. Overall, the VUF of the system changes substantially and could cause significant violations with respect to 7 and 11 kW chargers. In conclusion, the proliferation of EVs poses quite a significant concern in terms of PQ assurance throughout the system. From this probabilistic study, VUFs and voltage unbalance violation and voltage level violations are less problematic. This work can be used as a means to identify the likely impacts due to high EV charger proliferation in the realistic/practical network. This method enables us to quantify the likely impacts of different EV charger ratings available in the market.

The PLF technique can give relatively accurate results. On the other hand, a potential disadvantage of the method is that the result is meaningless if the conditions of the distribution of the input values and the range of mathematical modelling are not accurate. MCSs can become very time-consuming. The time to compute the outcome of a scenario will increase as the complexity of the used model increases. Besides, it may take a large number of scenarios to keep the uncertainty of the final results within acceptable levels [39]. To reduce the number of scenarios per simulation it is possible to use so-called variance reduction techniques [39]. Future work will investigate methods to integrate PLF within time sequence charging.

6 References


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