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IMPACT ANALYSIS OF PLUG-IN ELECTRIC VEHICLES ON THE REAL RESIDENTIAL DISTRIBUTION NETWORK

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Highlights

- A generic and comprehensive impact analysis framework is proposed to be applied to low-voltage networks to investigate an evaluation of the integration of small-scale renewable energy systems and/or new forms of demand such as electric vehicles.
- The influence of the transformer loading on secondary substations as well as the effects on low voltage customers, feeders and energy losses are analyzed separately for different cases whilst assessing the corresponding dependencies – crucial for a realistic quantification.
- It demonstrates the effectiveness of the proposed indicators with a UK case study that considers real Low Voltage Networks (typically, 0.4 kV), as well as realistic time-varying residential demand and Electric Vehicle Profiles.
- The discussion section is also presented with the corresponding caveats and suggestions.

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ABSTRACT: The growing share of Electric Vehicles (EVs) in the personal automobile market is expected to accelerate in the years to come. With increased demand at a household level, technical problems such as transformer and feeder overloading are likely to emerge. Therefore, this highlights the need for a comprehensive impact analysis framework for EVs to overcome the challenges ahead. A smoother transition, exploiting scalable performance indicators, to Low Voltage (LV) networks with this new form of demand could be achieved as imminent problems can be computed in a realistic manner. To this end, the impact analysis framework is proposed and the corresponding performance indicators are formulated to be used by researchers and/or Distribution Network Operators (DNOs) for different purposes. Under different scenarios, the impacts of EVs on the real underground unbalanced three-phase network are comprehensively explored considering household voltage profiles, transformer-loading, utilization of feeders, and daily total energy losses. For the summer and winter seasons, three cases covering all possible circumstances are investigated: without EVs, with EVs, and a worst-case scenario where all EVs connect at the same time. From the study, it can be deduced that the impact of EVs on the network and household voltage could reach unacceptable levels, and diversifying the connection times of EVs is vital to coping with potential problems posed by residential-level participation in EVs.

Keywords: *Plug-in Electric Vehicles, Low Voltage Network, Impact Analysis, Thermal Overloading, Performance Indicators*

1. INTRODUCTION

The concerns associated with reducing reliance on fossil fuels and decarbonizing the personal automobile market, together with the falling prices of electric vehicles and government incentives, have paved the way for the boom of electric vehicle uptake in recent years. Consequently, investment in EVs and their batteries increased 19 times more in 2019 compared to 2018 in the European Union alone [1]. Some countries have already reached a significant share/penetration of vehicles running on electricity. For instance, the proportion of EVs in the personal automobile market in 2019 was 56%, 25.5%, and 15% in Norway, Iceland, and the Netherlands, respectively [2]. Despite global car sales declining by 16% due to the pandemic-related worldwide downturn, electric car registrations grew by 41% in 2020 [3]. However, this opportunity is likely to result in some technical issues (such as voltage drop and thermal overloading), as residential peak demand is expected to coincide with the new form of demand posed by EVs [4–7].

Given that traditional distribution networks are not designed to deal with these new forms of demands, some technical problems might eventually emerge due to significant peak demand hours [8]. Since householders with EVs are likely to charge their automobiles at home, the corresponding infrastructures are highly likely to be the first place affected (in particular, European-style LV networks on which hundreds of customers are connected to the grid). It is, consequently, essential to quantify the impact of the adoption of EVs on customers and the network-level to propose efficient and scalable solutions through which greater the hosting capacity of the network is gained.

In general, the impact analysis and various solutions in the literature have been documented. These can be categorized under three main headings: optimization-based solutions, control-based methods, and

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deterministic or probabilistic impact analysis studies at the residential and/or network level.

The first group aims to provide impact analysis and solutions with various advanced optimization techniques [9–11]. These analyses typically require charge status, extensive information, visibility and communication technologies, and real-time pricing [12–14]. However, this does not yet fully correspond with real-world conditions, as acquiring all this information is not cost-effective and, therefore, is not readily available in a straightforward manner.

The second method, control-based solutions, typically aim at voltage or congestion mitigation (conductor and transformer levels) [15–18]. For voltage impact analysis, the primary objective is to reduce the voltage magnitude per unit, while current reduction or utilization reduction is employed to address thermal overloading. However, achieving this requires both data from the network and a communication system for remote control. Therefore, similar to the optimization-based solutions, in the absence of real-time data, corresponding communication channels and interoperability issues make these approaches challenging to be viable. The control actions can also be achieved through Machine Learning approaches (e.g., employing nodal voltage and its sensitivity to the design controller) [19]. Furthermore, some methods might require additional specific control elements such as phase-shifting ability [20].

The third common method is to perform a deterministic or probabilistic (DoP) impact analysis [21–24]. Most of the studies documented in the literature focus on DoP. The majority of these studies are on assessing/mitigating thermal overloading on the transformer, lines, and customer voltage profiles [25–28]. However, for utilities, especially in terms of voltage, the penalties are given based on the existing voltage standards of the relevant countries. Therefore, related studies should be evaluated in this context. In addition, thermal overloading poses a risk to the corresponding assets. Moreover, these analyses are to be generic, in turn, they must be expressed mathematically. Thus, it can be adapted in other countries with minor setting modifications. In addition, most studies have not examined low-voltage networks, where the effects are expected to emerge first [29]. This is likely to create hesitation in terms of the applicability of the relevant solutions. Also, some studies using simplified models may not disclose their particularities [5].

However, none of the aforementioned studies address mathematically expressed dynamic voltage calculation as performed in real life scenarios. Furthermore, none of the studies conduct a comprehensive analysis that simultaneously examines both customer and network-level technical issues.

1.1. Contributions

In this paper, a generic and comprehensive impact analysis framework is proposed to be applied to low-voltage networks to evaluate the integration of EVs. In addition, this framework could be applied to quantify the impact of battery energy storage systems, small-scale renewable energy systems, and new forms of demand, such as electric heat pumps. This framework allows Distribution Network Operators (DNOs) to identify the networks with technical problems in advance, providing them with sufficient time to implement potential solutions.

This impact analysis framework includes the realistic dynamic voltage calculation according to European standards (EN 50160). Furthermore, simpler and applicable calculations for network energy losses are mathematically expressed for the planning stage. Consequently, the impact analysis combines the utilization of feeders and the transformer, voltage issue (voltage drop), and network energy losses which in turn, is able to realistically quantify network and customer-level technical issues.

For the case studies, therefore, this study aims to mimic real-life applications by considering a fully modeled three-phase four-line real LV network, generating realistic high resolution (1-min) plug-in electric vehicle profiles and obtaining 1-min demand profiles.

The remainder of the paper is organized as follows: An overview of the proposed methodology is presented in section 2. Modelling and analysis considerations, together with performance indicators, are provided. In section 3, the results and discussion are presented for the case study. Finally, section 4 concludes the study.

2. MATERIAL AND METHODS

The methodological framework proposed comprises three stages and is illustrated in Fig.1. In the first stage, a fully modeled LV network and household demand profiles are needed. Once EVs are considered for the analysis, corresponding EV profiles are taken into account. Given uncertainties surrounding the usage of demand and EV profiles, the analysis needs to be tailored to each household. For illustrative purposes, the worst-case scenario may include only one EV profile. While this might not accurately reflect real-life conditions, the objective is to provide insights into potential outcomes when all customers behave in a similar manner.

In stage two, three-phase four-wire power flow analyses are carried out. In stage three, performance indicators are obtained and compared against the explored cases.

A generic synthetic LV network model is given in Fig.2, where the measurement points are in place to allow the capturing/computing of the aforementioned indicators.

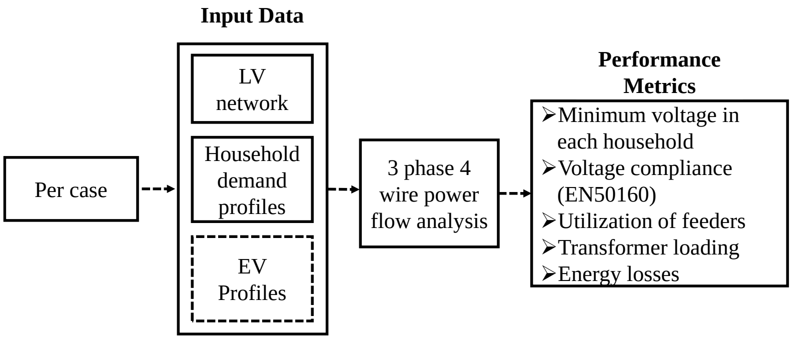

Figure 1. Flow chart for the performance assessment framework

The measurement point at the secondary side of the transformer provides active ($P^{tr_{sec},\varphi}$) and reactive ($Q^{tr_{sec},\varphi}$) power, and current drawn by each feeder ($i_t^{F\_head,\phi}$).

Furthermore, measurements at household connection points provide corresponding daily voltage profiles (Vh_N^{φ}). This enables the calculation of the corresponding performance indicator.

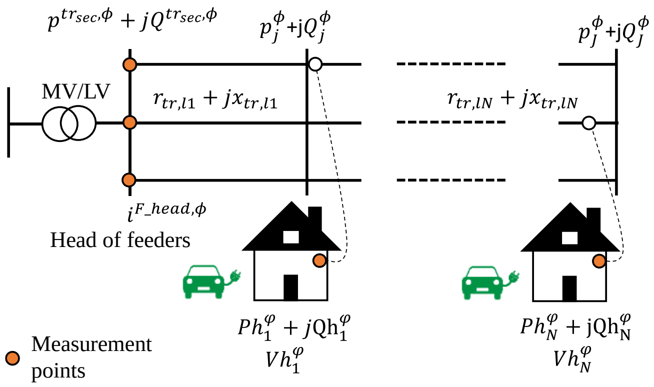

Figure 2. Layout of synthetic LV network

2.1. EV modeling considerations

For EV impact analysis, typically real data is employed. By means of long-term charge measurements for EV cars, starting charging time and energy demanded during a connection are typically captured. Along with these, considering the constant charging rate and the battery capacity, EV profiles can be modeled accordingly. For this study, the detail of the modeling is provided in section 3.

2.2. Performance indicators

To assess the performance of EVs on the network, voltage, utilization of feeders, transformer loading, and energy losses are analyzed. This approach aims to provide a thorough analysis of each component within the studied network.

One of the striking features in the transition to LV networks with emerging technologies such as EVs is voltage instability. Voltage rise or drop may exceed the statutory limits. Given that EV and household demand profiles are analyzed on the network, it is essential to apply a voltage drop equation.

For an exemplary two-bus system demonstrated in Fig.3, voltage drop from Bus_j to Bus_{j+1}, for the phases (i.e., φ), is shown as $\vec{V}_j^{\varphi} - \vec{V}_{j+1}^{\varphi}$, which can be expressed by power flow between buses as in (1).

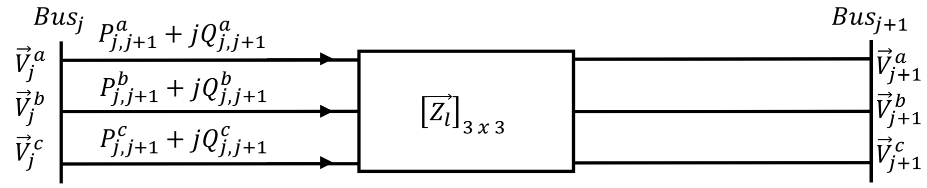

Figure 3. Exemplary two-bus system

$$\begin{bmatrix} \vec{V}_j^a \\ \vec{V}_j^b \\ \vec{V}_j^c \end{bmatrix} - \begin{bmatrix} \vec{V}_{j+1}^a \\ \vec{V}_{j+1}^b \\ \vec{V}_{j+1}^c \end{bmatrix} = \begin{bmatrix} (P_{j,j+1}^a + jQ_{j,j+1}^a)/\vec{V}_j^a \\ (P_{j,j+1}^b + jQ_{j,j+1}^b)/\vec{V}_j^b \\ (P_{j,j+1}^c + jQ_{j,j+1}^c)/\vec{V}_j^c \end{bmatrix}^* x \left[\vec{Z}_l\right]_{3x3} \tag{1}$$

For each phase, this three-by-three matrix equation can be transformed into the form in which only the corresponding current and impedance could be utilized as in (2).

$$\vec{V}_j - \vec{V}_{j+1} = \left[\frac{(P_{j,j+1}^a + jQ_{j,j+1}^a)}{\vec{V}_j \angle \theta_j}\right]^* x\, \vec{Z}_l = \vec{I}_{j,j+1} x\, \vec{Z}_l \tag{2}$$

It is crucial to compute voltage drop (or rise) more realistically, as DNOs are legally obliged to keep their end users' voltage profile within the statutory limits (e.g., according to BS EN50160). According to regulation, 95% of the measured supply voltage (10-min average r.m.s. value) must be within 1.1 p.u. and 0.9 p.u. of nominal voltage. In addition, all measured supply voltage must never breach 1.1 p.u. and 0.85 p.u. of nominal voltage.

To comply with statutory obligations, the following three steps proposed in [30] are adopted. In the first stage, a 10-min average of household demand profile-based decisions are made (e.g., 144 decisions for 1440-min resolution). Due to the fact that day-long analysis is adopted, in this study, the corresponding regulation is adapted as daily. As such, in each time of t (time of measurement), a 10-min average of voltage profile (i.e., $av(Hd_t)$) a day is greater than 1.1 p.u. or less than 0.9 p.u., then, the associated time (i.e., i) is flagged as 1(i.e., problem arisen), if not, i is defined as 0. This is mathematically expressed in (3).

Considering all-day-long analysis, for each 10-min average a value is assigned, in turn, a set of binary decisions $(i.e., TP_i^{Daily})$ is given, for a certain customer.

$$TP_i^{Daily} = \begin{cases} 1, & if\ av(Hd_t) \geq 1.1pu\ \vee if\ av(Hd_t) \leq 0.9\,pu \\ 0, & else \end{cases} \quad \forall\, t\, \in T \tag{3}$$

In stage two, the final daily decision is made for a given customer. In accordance with EN50160, in the first stage, if any 10-min average of voltage profile (i.e., $av(Hd_t)$) is higher than 1.1 p.u. or lower than 0.85

p.u., the customer is identified as a customer with a voltage problem.

When all 10-min average voltage profile decisions ($\sum_i TP_i^{Daily}$) is greater than five percent of the duration of household demand resolution (D^{HDR}), then, a voltage problem is identified, otherwise, no voltage problem is considered for a given customer.

Considering all customers for the given network, the recurrent process in stages 1 and 2, is carried out for all customers ($\sum H_n$) on the network, in stage three as in (4).

$$H_n = \begin{cases} 1, & \sum_i TP_i^{Daily} > 0.05\ x\ D^{HDR} \\ 1, & if\ any\ , av(Hd_t) \geq 1.1pu\ \vee av(Hd_t) \leq 0.85\ pu \\ 0, & \sum_i TP_i^{Daily} < 0.05\ x\ D^{HDR} \end{cases} \tag{4}$$

Finally, the percentage of the total customer number ($\mathrm{T}_{\mathrm{cus}}^{\mathrm{per}}$) with voltage problems are identified. This process can also be adopted to feeder-by-feeder calculation in (5).

$$\mathrm{T}_{\mathrm{cus}}^{\mathrm{per}} = \frac{\sum H_n}{N\ x\ 10^{-2}}, \forall\ n \in N \tag{5}$$

Given that thermal overloading might affect the first feeders more than the corresponding transformer, it is crucial to calculate the utilization of feeders. Therefore, for a given time period (t), the average current drawn by the head of each feeder (i.e., considering all phases, ϕ) is captured and divided by ampacity, and the percentage value is calculated as given in (6). This provides the daily percentage of feeder utilization ($F_{ut}^{D,per}$).

$$F_t^{per} = \frac{av(i_t^{total,F\_head,\varphi})}{FA\ x\ 10^{-2}} \quad , \forall\ t\ \in T \tag{6}$$

A set of feeder utilization is obtained, the maximum one is the feeder utilization.

This is one of the important indicators as it is well known that EVs have an adverse effect on the utilization of feeders, hence, it provides insight into DNOs' understanding as to when their feeders are expected to be reinforced.

Due to the fact that EVs have the potential to increase transformer loading, it is essential to measure this according to profiles' resolution to cater for time-varying impact. Therefore, in each predefined resolution time (t), considering all phases (ϕ) at the secondary side of the transformer, the total active ($P_t^{tr_{sec},total,\phi}$) and reactive power ($Q_t^{tr_{sec},total,\phi}$) is measured and transformed to complex power and divided by transformer capacity (TR^{cap}) so that the corresponding transformer capacity percentage ($TR^{cap,per}$) computed for a given penetration level. The mathematical expression is provided in (7).

$$TR^{cap,per} = \frac{\sum_{t=1}^{T}((P_t^{tr_{sec},total,\phi})^{\wedge}2 + (Q_t^{tr_{sec},total,\phi})^{\wedge}2\ ^{\wedge}(1/2)}{TR^{cap} x\ 10^{-2}} \quad , \forall\ t\ \in T \tag{7}$$

As a result, the impact of EVs on the transformer loading based on resolution is captured. This allows DNOs to be aware of the usage of a transformer for a given LV network and take precautionary measures, if necessary.

Energy losses on the network are expected to increase due to the power drawn by EVs, therefore, the impact of EVs on energy losses could be considered another indicator to be taken into account.

For a given two-bus system in Fig.2, power injection at Bus_i (i.e., $P_{j,j+1}^{\varphi}$ and $Q_{j,j+1}^{\varphi}$) is computed by power balance equations. Since the household demand (e.g., customer number one exists in place) is known (i.e., Ph_1^{φ} and Qh_1^{φ}), the active ($P_{j,j+1}^{losses,\varphi}$) and reactive power ($Q_{j,j+1}^{losses,\varphi}$) losses can be calculated in a straightforward manner (as given in 8 and 9).

$$P_{j,j+1}^{losses,\varphi} = \left(\frac{P_{j,j+1}^{\varphi}}{\vec{V}_j}\right)^2 r_{j,j+1} = P_{j,j+1}^{\varphi} - Ph_1^{\varphi} \quad \forall \varphi \in \phi \tag{8}$$

$$Q_{j,j+1}^{losses,\varphi} = \left(\frac{Q_{j,j+1}^{\varphi}}{\vec{V}_j}\right)^2 x_{j,j+1} = Q_{j,j+1}^{\varphi} - Qh_1^{\varphi} \quad \forall \varphi \in \phi \tag{9}$$

For a network with numerous buses and customers, a simpler method for quantification is needed.

Unlike voltage, utilization, and transformer loading equations in which time is essential for accurate quantification, only the total daily amount is sufficient for calculating energy losses.

Therefore, total daily active and reactive energy losses (i.e., $P_{sum}^{losses,\varphi}$ *and* $Q_{sum}^{losses,\varphi}$) are quantified as shown in (10) and (11) where $\sum_{n\epsilon N} Ph_n^{\varphi}$ *and* $\sum_{n\epsilon N} Qh_n^{\varphi}$ denote the total daily active and reactive demands of all households, respectively. $P^{\,tr_{sec},total,\varphi}$ and $Q^{\,tr_{sec},total,\varphi}$ represent total daily active and reactive power at the secondary side of the transformer, respectively.

$$P_{sum}^{losses,\varphi} = P^{\,tr_{sec},total,\varphi} - \sum_{n\epsilon N} Ph_n^{\varphi}, \forall \varphi \in \phi, n \in N \tag{10}$$

$$Q_{sum}^{losses,\varphi} = Q^{\,tr_{sec},total,\varphi} - \sum_{n\epsilon N} Qh_n^{\varphi} \quad \forall \varphi \in \phi, n \in N \tag{11}$$

3. RESULTS AND DISCUSSION

In this section, the demand profiles, EV profiles, and network employed to assess the impact of EVs on the network is introduced. The tool developed by the Centre for Renewable Energy Systems Technology (CREST) in [31] is utilized for modeling the domestic profiles (one-minute resolution). Each load of individual dwelling is realistically modeled by considering factors such as the number of occupants, the type of day, seasonality, and the corresponding usage of electrical appliances.

For the considered network, the number of occupants per household aligns with UK statistics [32], i.e., the percentage of houses with 1, 2, 3, and more than 4 person/people are 29, 35, 16, and 20%, respectively. Two seasons (summer and winter) are investigated, therefore, for each season, a pool of 1,000-weekday customer profiles (1-min resolution) is created to be employed. For each season (July and February), the average of the created pool is normalized and demonstrated in Fig.3. As the EV statistics (for Nissan leaf brand EV cars) are publicly available in [33], where probability distribution function for daily EV energy requirement and probability distribution function of EC connection times during the field trials are provided. The corresponding figures are provided in Fig.4 and Fig.5. This data is employed to generate a pool of 1000 profiles (1-min resolution). The average of the created pool is normalized and demonstrated in Fig.6. In this study, EV profiles are considered to operate at the unity power factor. The battery capacity is 24kWh [34].Since EVs are connected to the grid at home, only slow charging mode is considered, with a constant charging rate of 3kW. Furthermore, generated EV profiles are randomly allocated between customers to cater for uncertainty.

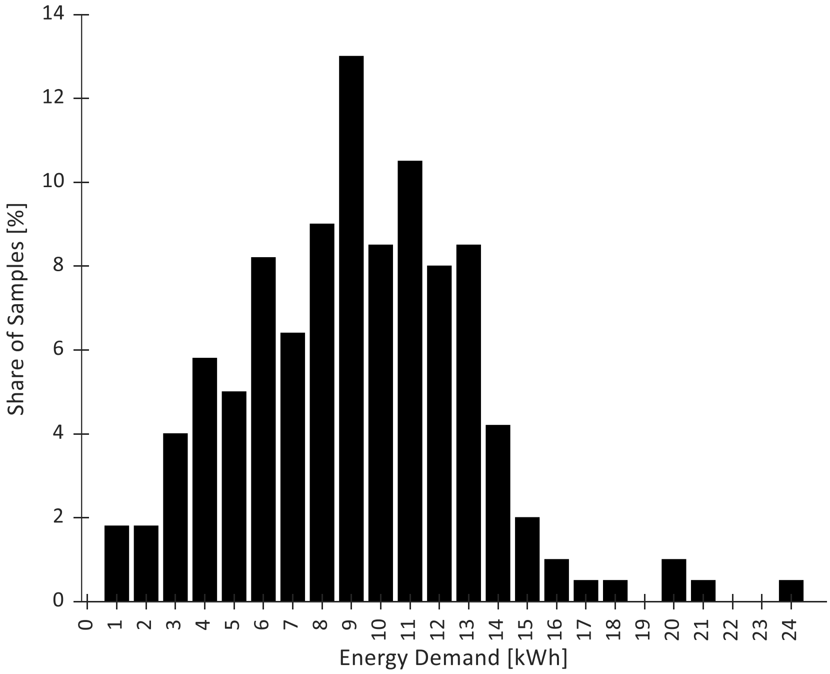

Figure 4. The probability distribution function for daily EV energy requirement.

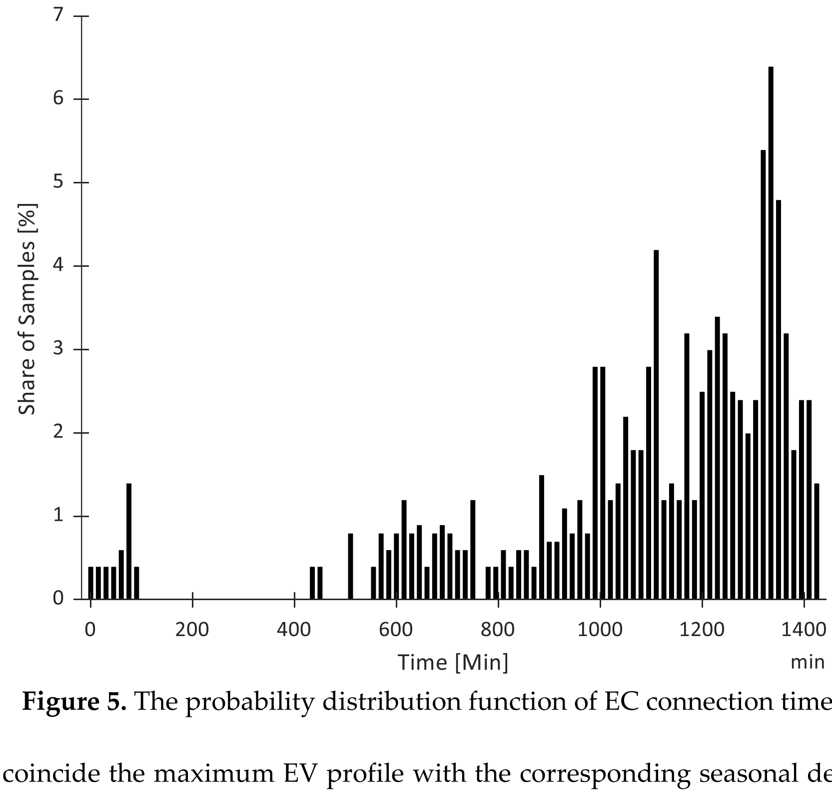

Figure 5. The probability distribution function of EC connection times.

In order to coincide the maximum EV profile with the corresponding seasonal demand profiles, the time of connection is shifted to one and four hours for summer and winter, respectively. Therefore, the effect of EV connection on voltage profiles can be observed. For the worst-case scenario (also referred to as Dumbed Charging), the same EV profile is chosen to be able to connect at the same hours, which also coincides with peak demands. Although it is highly unlikely to observe Dumb Charging under normal conditions throughout the year, it may happen in exceptional cases (e.g., after a sports event, etc.)

In this section, the real underground residential UK LV network (feeder by feeder) from the North West of England, part of the Low Carbon Networks Fund Project 'LV Network Solutions', is used [35]. It is modified as an LV network to assess the network-based impact analysis shown in Fig.7. The network consists of six LV feeders (three-phase four-wire), each of which is shown with different colors. A total of 351 customers are connected to feeders through single-phase connections.

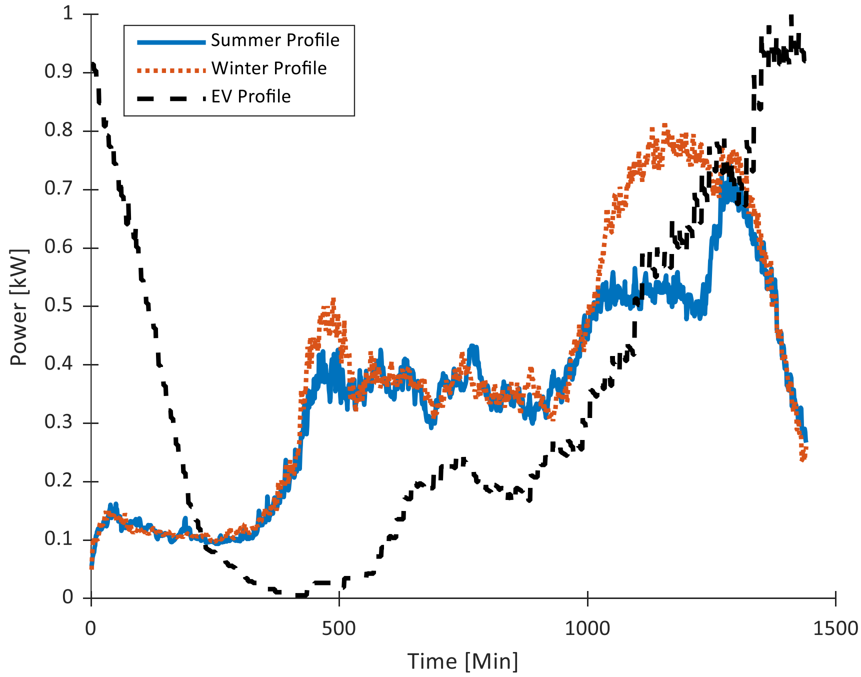

Figure 6. Normalized average of EV, summer, and winter demand profiles.

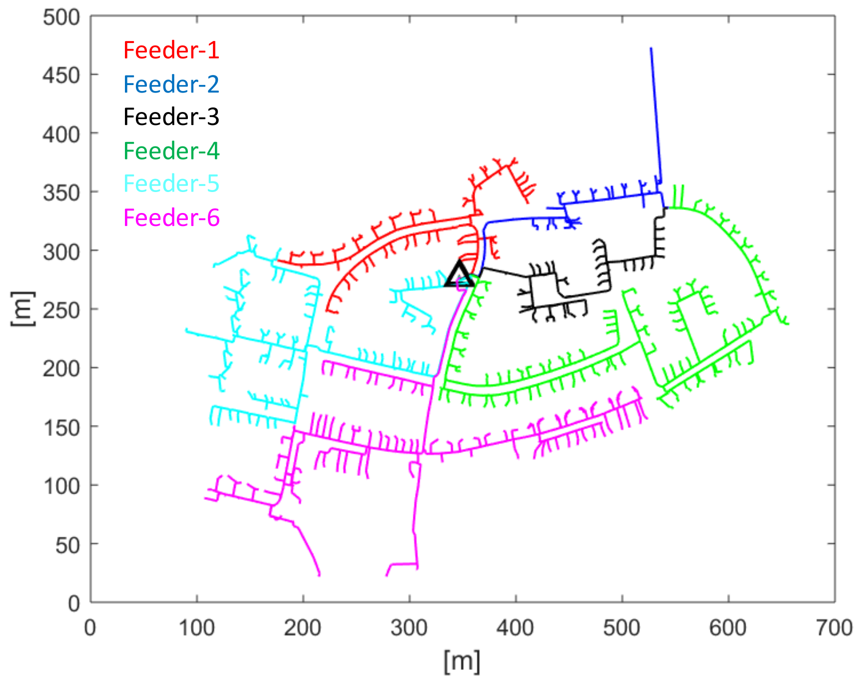

Figure 7. Studied real LV network on which feeders are shown in different colors and the secondary substation is represented by a triangle.

The corresponding transformers (illustrated in the triangle) have a voltage ratio of 11 kV to 0.433 kV (8.7% offload tap boost), which is typical in the UK [36]. The capacity of the transformer is 500 kVA. For simplicity purposes, the voltage at the primary side of the transformer is considered fixed at 1 pu.

3.1. Results

In this section, a realistic three-phase four-line time series unbalanced power flow analysis is carried out through OpenDSS to assess the impact of EVs on the network along with customer voltage profile considering different scenarios. The results and corresponding discussions are provided.

In order to assess the impact of EVs on the voltage, the analysis of with and without EVs, and the worst-case scenario is carried out for summer and winter. For the without EVs cases, only demand profile impacts on the network and the customers are quantified considering seasons. For the 'with EV' and 'worst-case' scenarios, each dwelling has an EV connected in a certain time period of the day (the worst-case scenario considers the same connection time of EVs).

The minimum voltages of households throughout the day for each case are captured and compared against each other to provide insight into how EV profiles' effects are on the voltages shown in Fig.8.

The results show that the reduction in minimum voltages for all feeders analyzed varies according to the location of households (a total of 351 customers). The more demand drawn from households indicates the lower voltages.

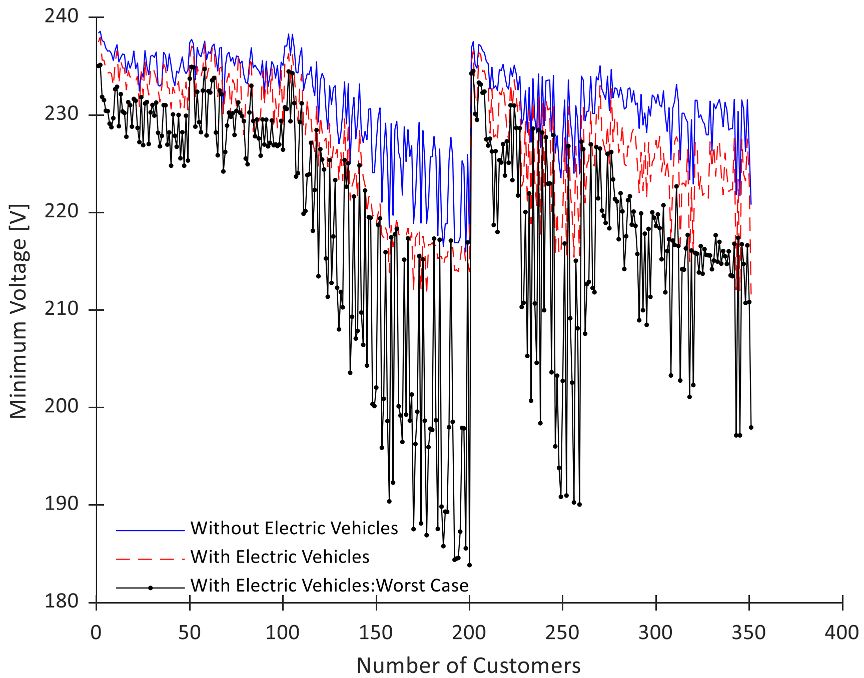

Figure 8. The minimum voltage at each household on the network for without, with, and worst-case study.

Due to the nature of EVs, the current drawn by dwellings is expected to increase. Therefore, voltage profiles along the feeders are to be affected. The change in voltage profile along with the feeders with EVs in winter is, for Feeder-4, demonstrated in a time series manner in Fig.9.

It is evident that the change in voltage profiles of households from the transformer to the end of the feeder increases. It is a fact that customers with the largest distance from the transformer are expected to be the most challenging dwelling in terms of voltage (i.e., relatively large voltage drop). Crucially, voltage drops are primarily observed at late hours when most EVs are connected. It is noteworthy that, according to EN50160, none of the customers experience voltage problems in the case of employing without EVs and different EV profiles for summer and winter. Whereas, in the worst-case scenario, a total of 44 and 51 customers are affected by voltage problems (i.e., breaching the statutory limits) for summer and winter, respectively.

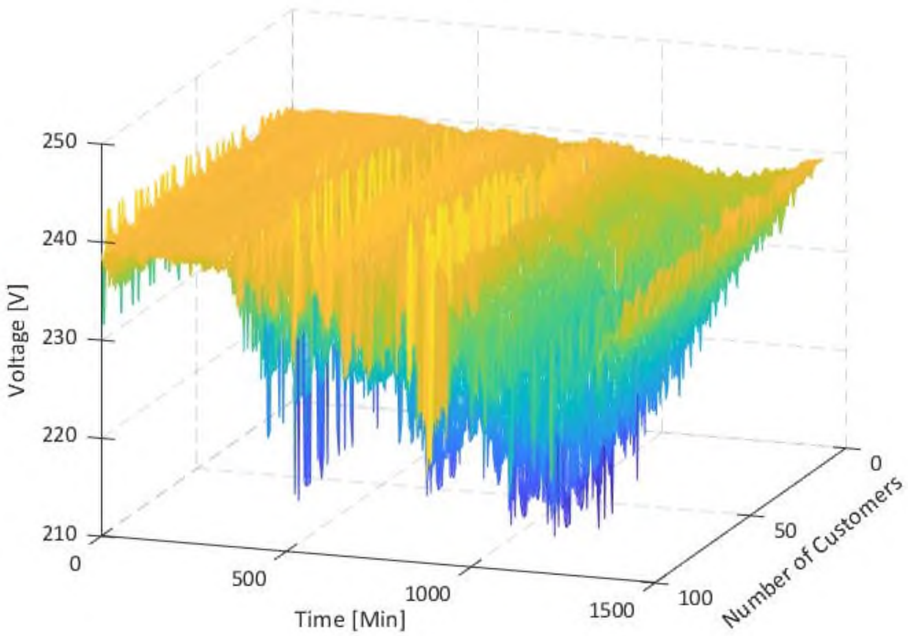

Figure 9. Daily min-by-min voltage profiles of households from the transformer (customer number is labeled as 0) to the end of Feeder-4 (labeled as 100).

The hourly utilization of each feeder considering the seasons and various scenarios is shown in Fig.10. Once feeder utilization exceeds one hundred percent, thermal overloading occurs in the feeder. Note that the utilization percentage of each feeder increases with the adoption of EVs as the currents drawn by households increase. For the worst-case analysis, Feeders from 4 to 6 pose thermal overloading. From the seasonal perspective, the utilization of feeders increases slightly in response to the growth in demand.

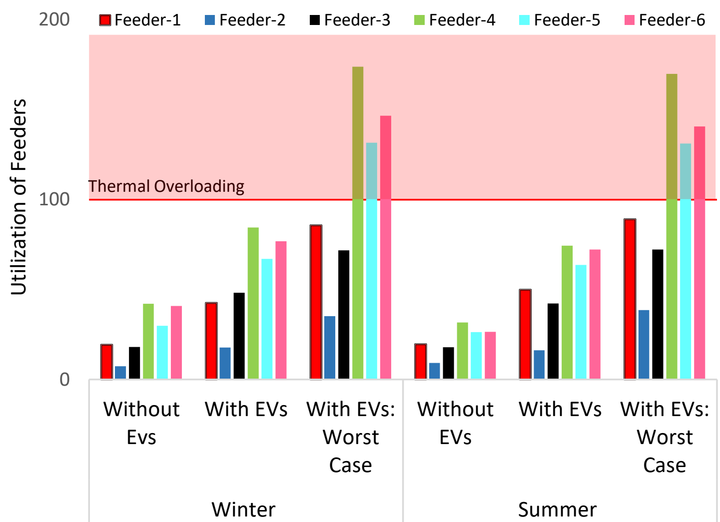

Figure 10. Utilization of feeders for different cases in two seasons.

From utilization feeder impacts, it is obvious that currents drawn by households increase to a great extent with the adoption of EVs. This is, in turn, expected to result in amplification in transformer loading. For the analyzed three cases in each season, the transformer loading percentage is given in Fig.11. It can be seen from the figure that EVs augment transformer loading due to the growth in demand profiles. In the case of the worst-case scenario, thermal overloading exceeds its limit (i.e., 100%), which indicates no headroom is left to host EVs. Furthermore, from utilization impact, only feeders from 4 to 6 are overloaded, yet, the room provided by other feeders is not sufficient for the transformer to overcome overloading.

Another indicator considered is energy loss as it can be expected to increase with greater demand (EVs). Daily total energy losses for the studied network are given in Fig.12. With larger demand (considering EVs and seasonality), daily energy losses are increased, as expected.

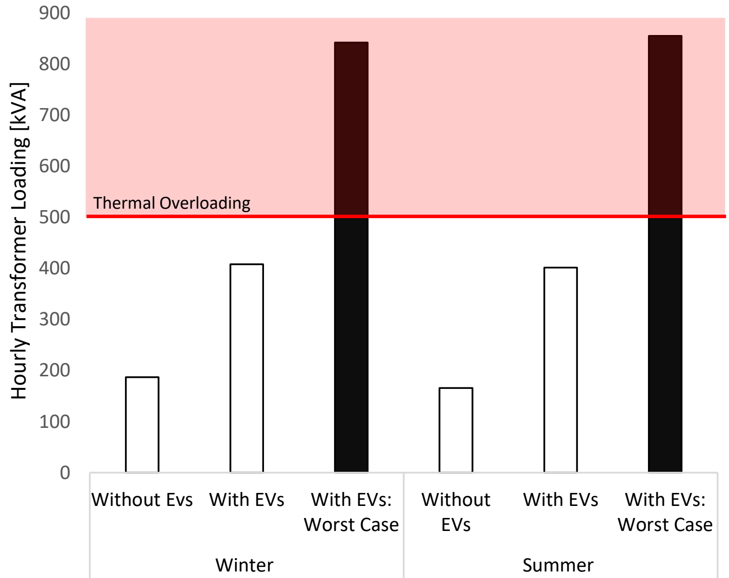

Figure 11. Hourly transformer loading for different cases in two seasons.

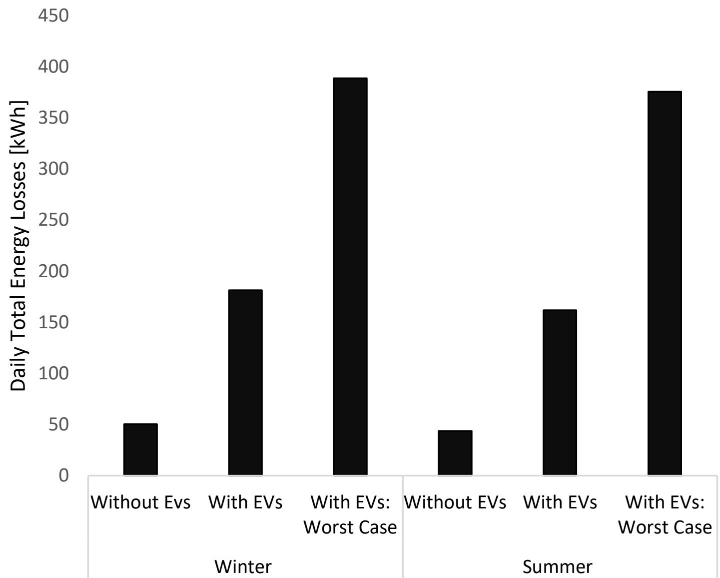

Figure 12. Daily energy losses for different cases in two seasons.

It is noteworthy to highlight that total daily energy losses are to be significantly low compared to total energy drawn by households.

3.2. Discussion

As demonstrated by the results, the impact of EVs on the households and network level depends on seasonality and instances in which how EVs are engaged in the network.

Although impact analysis may be computed from different perspectives, the proposed methodology and formulated performance indicators could be used to assess the impact in a more realistic manner by adopting timely analysis, real-time control of networks and EVs, etc. The resolution of profiles is also key to computing performance indicators, as the realistic manner of calculating voltage issues depends on the average 10-min voltage profile according to BS EN50160.

From a planning/operational perspective, the methodology considers the extent to which feeders are prone to voltage/utilization problems and when the solution could be required to cope with eminent technical problems.

Despite most DNOs currently having little or no measurements from the customers and/or network points, publicly available or generated high-resolution demand profiles can be used to conduct this analysis.

The identical connection time case (worst-case scenario) poses technical problems such as voltage problems, utilization of feeders, and thermal overloading of the transformer. Therefore, DNOs are to be ready for this case even if no technical problem is posed by their networks currently. While this scenario is highly unlikely to occur under normal circumstances, it remains a possibility to occur under some circumstances (e.g., in the aftermath of sports activities in some neighborhoods). This could pave the way for greater investment in charging stations at workplaces and malls. Another topic that deserves to be discussed is the interoperability of EVs with other technologies, such as energy storage systems, to diminish the potential reverse impact on the network.

Additionally, the methodologies developed to enhance hosting capacity in low-voltage (LV) networks with photovoltaic (PV) systems can be extended to the domain of LV networks with electric vehicles (EVs). These include network reconfiguration, the deployment of battery energy storage systems (BESS) to support LV feeders hosting both PVs and EVs, and the implementation of demand response strategies [37–41].

4. CONCLUSION

In this study, the participation of EVs in the real LV network is studied. A pool of EV profiles is generated from real-world statistics. Under three different scenarios, the impact of EVs on the LV networks is investigated in a comprehensive manner considering household voltage profile, the network transformer loading, utilization feeders, and daily total energy losses. Without EVs, with EVs and worst-case scenarios for summer and winter are considered to cover all possible circumstances.

For scalability purposes, all performance indicators are formulated to be used in a straightforward/practical manner by researchers and/or DNOs. Taking into account that the share of electric vehicles will increase in the years to come, the formulated performance indicators promote a smoother transition to this new form of demand at a residential level as imminent problems can be computed and the corresponding solution could be put in place.

The presented case study exemplifies the computation of the formulated performance indicators that could be adopted to any network. The study suggests that diversifying the connection times of EVs is vital to coping with potential problems posed by residential-level EV participation. Therefore, incentivizing householders to shift the connection time of their EVs into the grid could be a potential solution.

Declaration of Ethical Standards

The author followed all ethical guidelines including authorship, citation, data reporting, and publishing original research.

Credit Authorship Contribution Statement

The author is responsible for conceptualization, methodology, software, formal analysis, discussion of the results, writing, reviewing, and editing of the manuscript.

Declaration of Competing Interest

The author declares no conflict of interest.

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