Electric Power Systems Research 212 (2022) 108399

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Assessing the EV Hosting Capacity of Australian Urban and Rural MV-LV Networks

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ARTICLE INFO

Keywords:
Distribution networks
Electric vehicles
Hosting capacity
Network modelling

ABSTRACT

With the expected uptake of electric vehicles (EVs), it is vital for distribution companies to investigate the EV hosting capacity of their networks given the increase in demand. Asset congestion and voltage issues need to be quantified considering both the medium voltage (MV) and low voltage (LV) parts as well as the unbalanced nature of the problem. Since LV models are not available, this paper adopts an approach to expand existing MV-only models by incorporating pseudo-LV feeders. The EV hosting capacity is assessed by exploring multiple EV penetrations and considering their time-varying behaviour during the peak demand day (worst-case scenario). Two realistically modelled Australian MV-LV networks (urban and rural) are used as case study considering EV profiles derived from the Electric Nation project in the UK. The results show the importance of detailed network and EV modelling to adequately inform distribution companies and their EV planning strategies.

1. Introduction

In recent years, many countries have seen a growing uptake of light-duty electric vehicles (EVs) which is expected to surge over the next two decades. Since a large proportion of EV charging might take place at home [1], for instance, after the daily commute of EV users, the additional demand can lead to technical impacts on the very infrastructure EV chargers are connected to: the distribution network. Consequently, there is an increasing concern from distribution companies on impacts such as asset congestion and voltage issues that could result from the widespread adoption of EVs. However, to adequately assess the extent of those impacts and, thus, assess the EV hosting capacity of existing networks, it is crucial to consider different networks types (urban and rural) and use detailed models of all the aspects involved.

Both the medium voltage (MV) and low voltage (LV) parts of the distribution networks must be considered to fully capture the interactions between the voltage levels as well as their three-phase unbalance nature, where many customers (and, EV chargers) can be single-phase connected. Nonetheless, the majority of studies that focus on the MV part [2–4] often neglect the topological and load unbalance, thus, simply model the MV networks using a single-phase equivalent that considers the demand as an aggregated balanced load connected to distribution transformers. On the other hand, those that consider the LV part only [5–11], while adopting three-phase network models, neglect the voltage fluctuations and interactions with the MV part. Consequently, separate MV or LV studies cannot adequately quantify asset congestion and voltage issues.

The time-varying nature of residential and EV demand must also be modelled with as high-resolution as possible to adequately capture the resulting peak demand and the corresponding effects. Although many studies such as [3,9,10] do consider time aspects, it is common to see the use of low-resolution (e.g., hourly) residential and EV demand profiles which can lead to under or over-estimations.

The use of realistic EV demand profiles is, of course, paramount. Some studies [5–7] generate EV charging profiles assuming evenly distributed charging events throughout the day. Other studies [2,3,9,10], aware of the significance of capturing the potential behaviour of EV users, produce EV charging profiles based on travel surveys of conventional vehicles. However, to truly capture the EV charging characteristics (e.g. charging start time, state of charge, and the active charging power), data from EV trials can lead to the most realistic EV profiles [4,12]. Nonetheless, as the EV uptake increases, the latest EV trials can capture user diversity and different charging technologies.

To address the gaps in the literature, this paper first introduces the adopted approach to build realistic pseudo-LV feeders needed to produce integrated three-phase MV-LV models. It adopts the peak demand

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https://doi.org/10.1016/j.epsr.2022.108399
Received 3 October 2021; Received in revised form 16 April 2022; Accepted 2 July 2022
Available online 25 July 2022

day (worst-case scenario) to assess the EV hosting capacity of a given network. Furthermore, a comprehensive EV modelling process is presented with various considerations. The methodology is demonstrated on two real Australian MV-LV networks (urban and rural), anonymised smart metre data, and real EV data from the UK Electric Nation project [13].

2. Methodology

This section briefly describes the adopted approach to produce realistic pseudo-LV feeder models, to carry out time-varying simulations to assess EV hosting capacity, and the considerations to produce realistic EV demand profiles.

2.1. Modelling of Pseudo-LV Feeders

Most distribution companies do not possess detailed network models of their LV feeders (i.e., only models of MV networks are readily available) and, as such, are unable to fully estimate the EV hosting capacity for planning studies. This paper adopts the pseudo-LV feeder modelling approach proposed in [14,15]. It follows LV design principles (e.g., length, conductor size, after diversity maximum demand, etc.) and, thus, three-phase LV networks can be modelled based on the estimated number of customers per LV transformer. Even if the pseudo modelled LV networks are not exactly as in reality, it will allow a better quantification of the impacts closer to LV customers, particularly, voltages at the customer connection points. When these three-phase pseudo-LV feeders are integrated with the corresponding MV networks, the potential issues resulting from the EV demand unbalance can be captured, and thus the assessment of EV hosting capacity can be more accurate.

2.2. EV Hosting Capacity Assessment

To capture the time-varying nature associated with residential demand as well as EV charging demand, a EV hosting capacity assessment is formulated to quantify the EV impacts in time series as proposed by the authors in previous work [16].

For a given distribution network, as shown in Fig. 1, different EV penetrations are explored (starting from 0%, i.e., no EVs). When there are no EVs, profiles of residential loads during the peak demand day

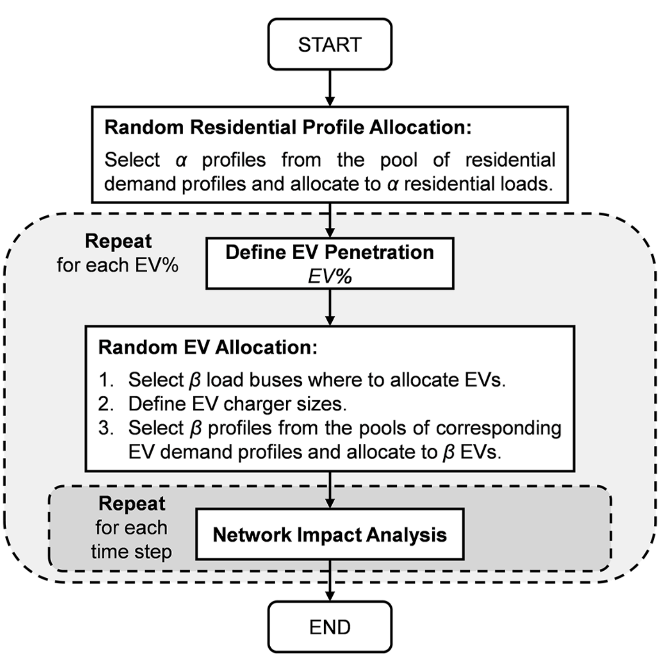

Fig. 1. EV Hosting Capacity Assessment.

(worst-case scenario) are allocated randomly from a pool of residential profiles and kept throughout the assessment. A new (larger) penetration considers additional EVs that are randomly allocated to the houses. The EV charger size is also randomly selected considering a pre-determined proportion (more details in *subsection 2.3*). A pool of EV profiles is also used for the allocation of EVs. For each penetration, a time-series three-phase unbalanced power flow analysis is repeated and, based on the power flow results (e.g., voltages, currents), the EV impacts on the network are assessed in terms of both asset congestion and voltage issues, measured using the following metrics:

- Utilization level (%): Maximum daily utilization of transformers and feeders in both MV and LV parts with respect to their rated capacity.
- Voltage Non-Compliance (%): Percentage of customers whose voltages do not meet the local requirements (e.g., Australian standard AS 61,000.3.100 [17]).

Finally, the EV hosting capacity of a given distribution network is defined in this study as the largest EV penetration that does not compromise the network integrity, i.e., does not lead to any asset congestion or voltage issue.

2.3. EV Modelling

Below are presented the key modelling parameters and the necessary steps to produce realistic EV demand profiles.

- **Charging Start Time and Duration**. The most critical parameters used to describe a certain charging event are the charging 'start time' and 'duration' which reflect the timeframe from charging beginning to end.
- **Daily Charging Times**. The number of times per day EVs are plugged in is important as people may choose to charge their EVs more than once in a day. Therefore, subsequent plug-ins (i.e., more than one) need also to be taken into consideration in EV modelling.
- **Daily Plug-in Factor**. Given the usage pattern and longer EV range, most EVs are not charged every single day. Thus, there is a Daily Plug-in Factor used to estimate the percentages of EVs that will be charged for a certain day.
- **EV Charger Sizes**. The parameters above can only help to define charging status (ON/OFF), while the actual demand is decided by the type of EV charger. For residential charging, there are normally two types of EV chargers available in the market: Levels 1 and 2. In Australia, the demands are approx. 3.68 kW for Level 1 (16A, 230 V) and 7.36 kW for Level 2 (32A, 230 V) [18].
- **Power Factor**. Describes the ratio of active power to apparent power drawn by EV chargers. An on-board EV charger contains an AC/DC converter and has a power factor which needs to be represented.

2.3.1. Step 1: Analyse and check EV data

Australian EV uptake has a lower trajectory than global trends and lacks information characterising its current EV owners. However, given the market similarities, the data from the Electric Nation project in the UK [19] is applicable to Australia and can be used to create EV profiles. Based on more than 30,000 unmanaged EV charging events recorded, here are some key findings from charging behaviour analysis:

- Charging start time is more distributed during weekends, as shown in Fig. 2.
- EVs equipped with Level 2 chargers usually require longer charging duration, as shown in Fig. 3.

2.3.2. Step 2: Define residential EV charger sizes

Since Level 1 provides very slow charging (3.68 kW), it is always applied on EVs with smaller battery sizes (e.g., plug-in hybrid EVs and

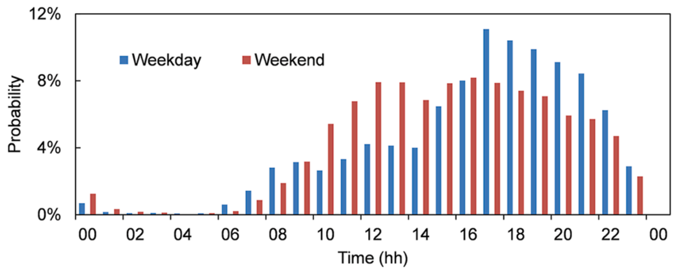

Fig. 2. Charging Start Time: Weekday/Weekend.

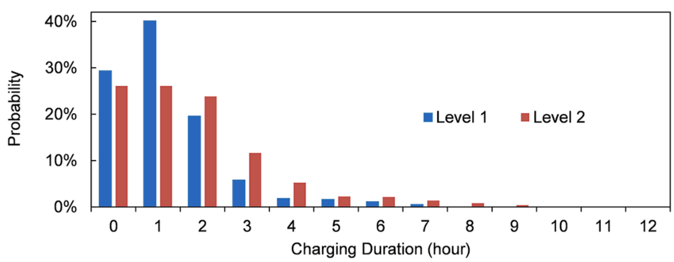

Fig. 3. Charging Duration: Level 1/Level 2.

short-ranged battery-only EVs), and the market share of which is estimated to be around only 20% in 2050 [20]. In contrast, long-ranged EVs equipped with Level 2 charger (7.36 kW) will likely dominate the market, because newly released models are increasing in battery size. Therefore, based on these assumptions, 80% of EVs are assumed to be equipped with Level 2 chargers and 20% with Level 1 chargers.

2.3.3. Step 3: Consider the implications of multiple EVs per house

In this study, residential customers with a second EV are also involved. Therefore, considerations need to be drawn for when multiple EVs are charged concurrently. Considering the import limits for most single-phase connected houses in Australia, it is possible to install two separate Level 1 chargers (Case A) and, one Level 1 charger and one Level 2 charger (Case B), as presented in Table 1. As such, the peak demand for these cases is simply the addition of both EVs.

However, the aggregated power of two Level 2 chargers (14.72 kW) is likely to exceed import limits, therefore a dual-headed Level 2 charger (Case C) is introduced [21]. In this case, if only one EV is charging, it gets the full Level 2 charge of 7.36 kW. However, if charging overlaps, then this is halved until one battery is full or disconnected.

2.3.4. Step 4: Divide data into subsets

According to the charging records, 96% of EVs plug in up to twice a day. Therefore, to simplify the modelling, a filter needs to be applied to extract only charging events for EVs that were plugged in either once or twice per day. Furthermore, given the findings from the analysis carried out in *Step 1*, the data from the Electric Nation project is divided into four subsets differentiating day type (weekday/weekend) and charging level (Level 1/2).

Table 1
Charging Alternatives for House with Two EVs.

Case	1st EV	2nd EV	Chargers	Max Power
Case A	Level 1	Level 1	Separate chargers	3.68+3.68=7.36 kW
Case B	Level 1	Level 2	Separate chargers	3.68+7.36=11.04 kW
Case C	Level 2	Level 2	Dual-headed Level 2 charger	7.36 kW

2.3.5. Step 5: Extract probability distributions

For each of the four subsets, probability distributions for charging ‘start time’ and ‘duration’ are extracted, and the results of subset ‘Weekday Level 1′ is shown in Fig. 4. For the cases when charging occurs twice a day, the plots are presented separately for the 1st and 2nd plug-in events. A prominent start time lag is observed on the 2nd plug-in event.

2.3.6. Step 6: Produce EV demand profiles

With the probability distributions, the charging ‘start time’ and ‘duration’ are randomly selected and combined to produce EV binary profiles. A general charging profile has two statuses: ON/OFF→1/0. Therefore, we need to translate time information into binary profiles. More specifically, assign value ‘1′ to the time-period plug-in and ‘0′ to the period plug-out. However, the actual demand is needed to model EVs in distribution networks. Therefore, the last step is to assign the charging levels (Level 1: 3.68 kW, Level 2: 7.36 kW) to the profiles to translate them into active power demand profiles, which will be introduced in *Section 3*.

2.3.7. Step 7: Apply profiles considering charging limitations

To apply profiles for multiple EVs per household, the charging setup for each house must be considered. As discussed in *Step 3*, the use of separate chargers (Case A and Case B) is unlikely to be a problem and, therefore, charging profiles can be assigned simultaneously. However, the use of a dual-headed charger (Case C) requires adaptation. More specifically, two single Level 2 profiles are aggregated, and the excess demand is deferred, thus extending the total charging duration. The profiles of dual-headed Level 2 charger used in the study are presented in *Section 3*.

2.3.8. Step 8: Extract the daily plug-in factor

As reported in NSW EV Owners Survey [22], EVs are charged only 3 to 4 days of the week, which means that the number of EVs charging in a particular day is always less than the actual EV penetration. Assuming that EVs in Australia will be charged up to 4 days in a week with the same daily charging probability, it turns out that no more than 70% of EVs would have a charging event in a given day. In this paper, this value is referred to as the Daily Plug-in Factor.

2.3.9. Step 9: Consider a power factor

With the development of power factor correction devices embedded in chargers and EVs, the power factor of EV demand can range from 0.98 to 1.0 (lagging) for both Level 1 and Level 2 chargers [23]. For modelling purposes, the value of 0.99 will be used to simulate reactive power absorption.

2.3.10. Step 10: Consider EV penetrations

EV penetration is defined in the study as the percentage of houses with a single EV. This means that with a 100% EV penetration all houses will have one EV. However, since it is expected that eventually around 60% of houses will have two EVs (similar to conventional cars [20]), the maximum EV penetration to be considered in this project is 160%, i.e., every house has one EV, and 60% of them have a second EV.

3. Australian Networks and Profiles

3.1. Urban and Rural Networks

To understand EV hosting capacity on different network types, urban and rural networks are studied. Two 11 kV networks from New South Wales, one from the area called Preston (urban) and one from Hazelbrook (rural), are modelled based on the data provided by the distribution company Endeavour Energy (further details provided in [24]) as part of the EV Integration project [25]. Both networks are three-phase models, and the potential issues resulting from the EV demand

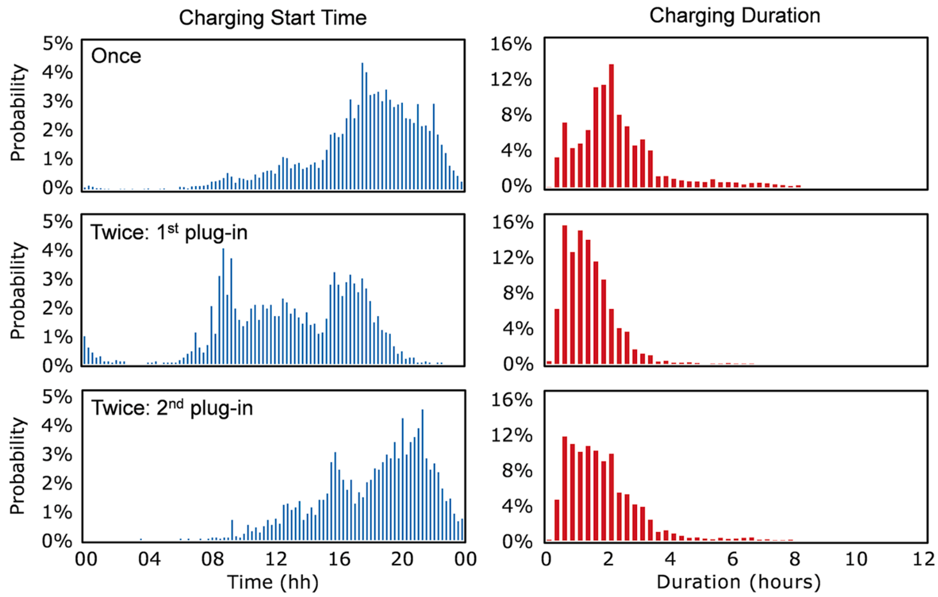

Fig. 4. Sample Probability Distributions: Weekday Level 1.

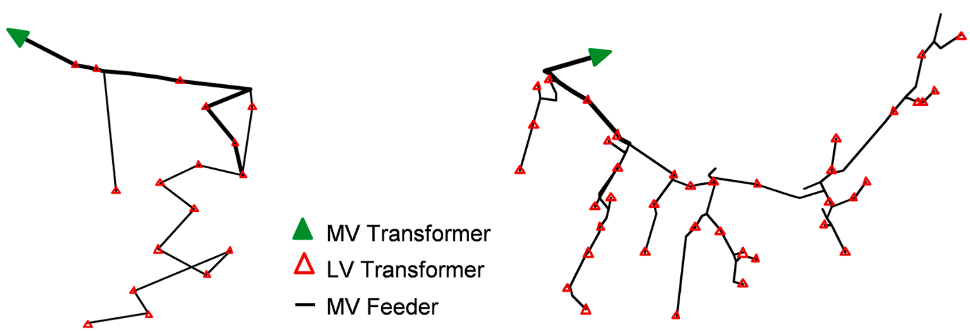

Fig. 5. Network Topologies (not same scale): (left) Urban, (right) Rural.

Table 2
MV Feeder Technical Information.

Feeder Name	Voltage Levels	No. of Cust	No. of LV Tx	MV Feeder Length	PV Penetration and Size
Preston (urban)	33/11/ 0.4 kV	598	17	6 km	30% (Avg 5.8 kW)
Hazelbrook (rural)	66/11/ 0.4 kV	1362	39	20 km	24% (Avg 3.8 kW)

unbalance are inherently captured. The topologies are illustrated in Fig. 5 and more technical details are provided in Table 2. The urban network, as expected, is denser and shorter while the rural network covers a larger area and more customers. Both networks have a significant uptake of rooftop PV systems (as the PV penetration shown in Table II) which will be considered in the modelling.

3.2. Residential Demand Profiles

Anonymised Victorian smart metre data is used to model residential customers [26]. The original half-hourly active power data (from 342 residential customers in the year of 2014) is interpolated to create 1-min resolution profiles. The peak demand day, is important to capture the worst-case effects of EV charging, for the urban and rural networks happen in summer and, thus, residential demand profiles also

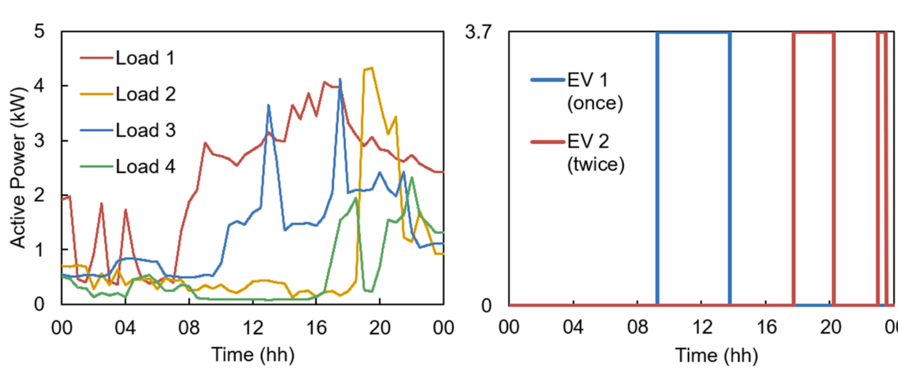

Fig. 6. Sample Weekday Profiles:
(left) Residential Demand, (right) EV Demand.

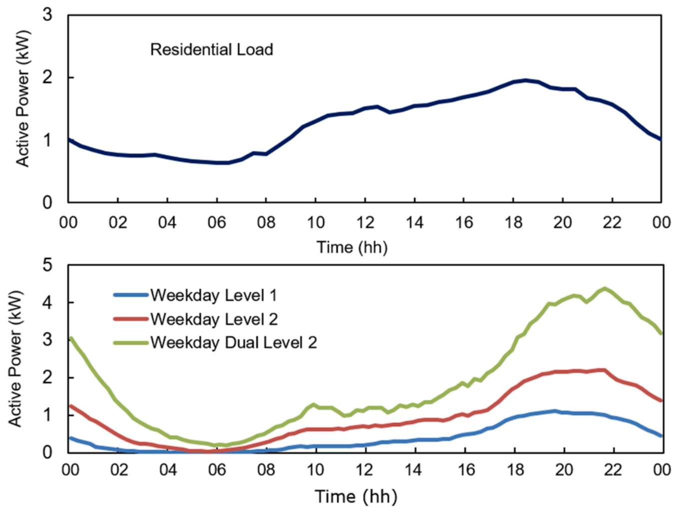

Fig. 7. Diversified Average Weekday Profiles:
(top) Residential Demand, (bottom) EV Demand.

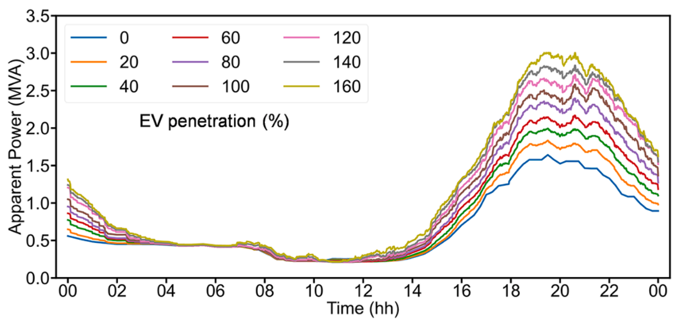

Fig. 8. Urban Network: MV Head of Feeder Aggregated Power.

correspond to summer. To illustrate the 1-min resolution, 24-hour residential demand profiles, sample data from four typical customers is presented in Fig. 6 (left). The diversified average profile is presented in Fig. 7 (top) accordingly.

3.3. EV Demand Profiles

As introduced in the EV modelling, EV charging data is classified into 4 subsets (weekday/weekend, Level 1/Level 2) catering for the variance in charging behaviours. For each subset, 1200 daily demand profiles are

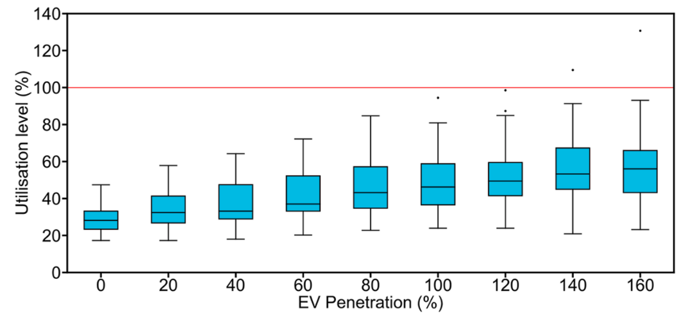

Fig. 10. Urban Network: LV Transfomer Max. Utilisation.

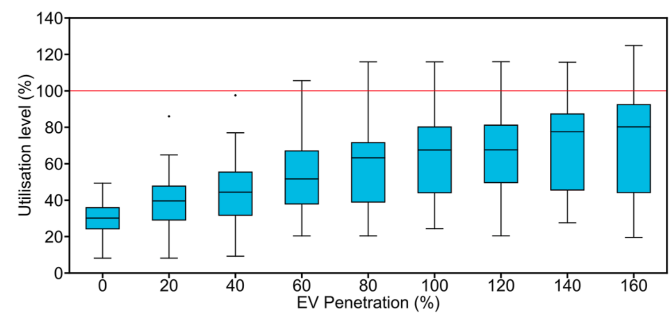

Fig. 11. Urban Network: LV Feeder Max. Utilisation.

created with 1-min resolution. In addition, Level 2 profiles are adapted for dual-headed chargers which are assigned to the charging of two Level 2 EVs. As with residential profiles, weekday profiles of EVs are used in the assessment for this worst-case scenario study. The sample and diversified average profiles are presented in Fig. 6 (right) and Fig. 7 (bottom), respectively.

4. EV Hosting Capacity Assessment

This section quantifies the EV hosting capacity of two Australian MV-LV networks, urban and rural, by exploring EV impacts in terms of asset congestion and voltage issues. An overview of the simulation results is presented for both networks considering multiple EV penetrations.

4.1. Urban Network

Because the peak hours of EV demand and residential demand can coincide during the evening, with more EVs, there is an increased aggregated apparent power (nearly twice at the maximum EV

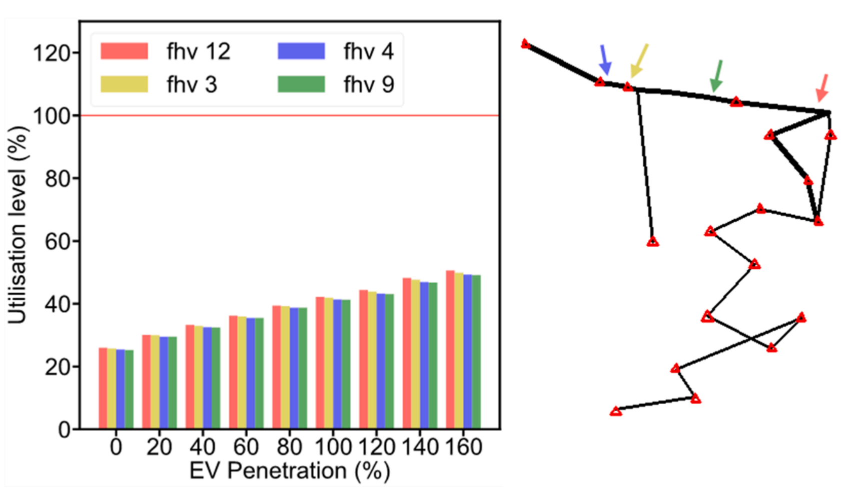

Fig. 9. Urban Network: MV Feeder (top 4 utilised segments): (left) Max. Utilisation, (right) Network Topology.

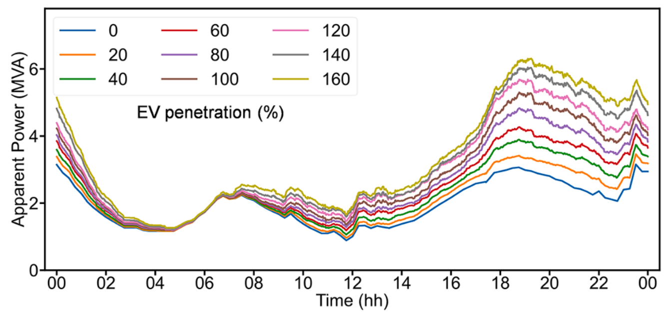

Fig. 12. Rural Network: MV Head of Feeder Aggregated Power.

penetration) seen at the head of the urban MV feeder, as shown in Fig. 8. Although only one MV feeder is considered here, the increase in aggregated power due to the EVs, when combined with other MV feeders, may lead to the congestion of the corresponding MV transformer and, potentially, other assets upstream.

The modelled MV feeder is capable of hosting extra EV demand even when considering the maximum EV penetration of 160%, as seen in Fig. 9, which shows network topology and the top four utilised segments of the MV feeder with respect to their equipment ratings. As expected, those highly utilised segments are close to the head of the MV feeder.

For this urban network, the LV part of the network is more critical than the MV part. The daily maximum utilisation is recorded and presented for LV transformers and LV feeders in Fig. 10 and Fig. 11respectively. There is a large capacity headroom left for the 17 LV transformers in the base case (i.e., no EVs) where loading levels vary between 18 and 50%, and the most critical LV transformer starts to see overloading at 140% EV penetration. In comparison, the congestion issue on LV feeders occurs at lower EV uptake; one out of 29 LV feeders starts to get overloaded at only 60% EV penetration. This trend ends with congestion issues happening on nearly a quarter of LV feeders at the maximum penetration.

Besides asset congestion, voltage issues are also assessed on the customer side, which is rarely seen by any of the 600 residential customers in the urban network even at the maximum penetration. However, given the high PV adoption rate in the network (30%), voltages get very close to both the upper and lower limits for higher EV penetrations. This means that potential adjustments of off-load tap positions (a common solution by distribution companies for voltage issues) to solve PV-related voltage rise could create further voltage drops as the EV uptake continues; and vice-versa.

In conclusion, the first potential issue faced by the network is asset congestion on certain LV feeders, thereby the EV hosting capacity is limited at 40%. With the increase of EV penetration, more congestion problems are expected to happen on LV transformers. Moreover, the increase of EVs in combination with PV uptake will lead to a voltage regulation dilemma in the network, constrained by both voltage limits. Compared to the LV part, the MV feeder is currently capable of heavy EV demand thereby does not limit EV hosting capacity.

4.2. Rural Network

With the increment of EVs, the aggregated peak apparent power at the head of the rural MV feeder is twice the original value (i.e., no EVs) as shown in Fig. 12. As mentioned before, this significant increase in the aggregated power, when combined with other MV feeders, may lead to congestion on the corresponding MV transformer and other upstream assets.

The EV impact on the top four utilised segments within the MV feeder is presented in Fig. 13. Overload of an MV segment starts to occur at 120% EV penetration. This increases to all four segments at maximum penetration. The figure also presents the location of these top four utilised segments in relation to the network topology; as expected, they are close to the head of the MV feeder. The total length of congested MV conductors reaches 1 km (out of 20 km) at 160% EV penetration.

The asset congestion problems are widely observed on the LV part of the network as well. The base loading levels (i.e., no EVs) of 39 LV transformers vary between 40 and 90% as shown in Fig. 14. One of the LV transformers can be overloaded at just 40% EV penetration. By 160%, more than a third of the LV transformers are overloaded. For LV feeders, congestion occurs later as shown in Fig. 15. Some critical LV feeders start to see overloads at 80% EV penetration, which steadily grows in severity up to the maximum penetration, where nearly a quarter of LV feeders have an overloaded segment within them.

The rural network supplies a larger region, compared to the urban network, including over 1300 residential customers and suffers more

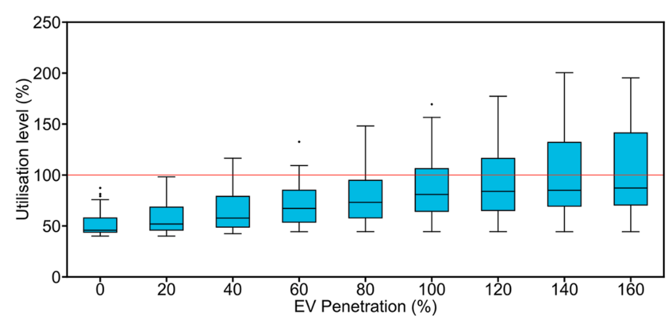

Fig. 14. Rural Network: LV Transfomer Max. Utilisation.

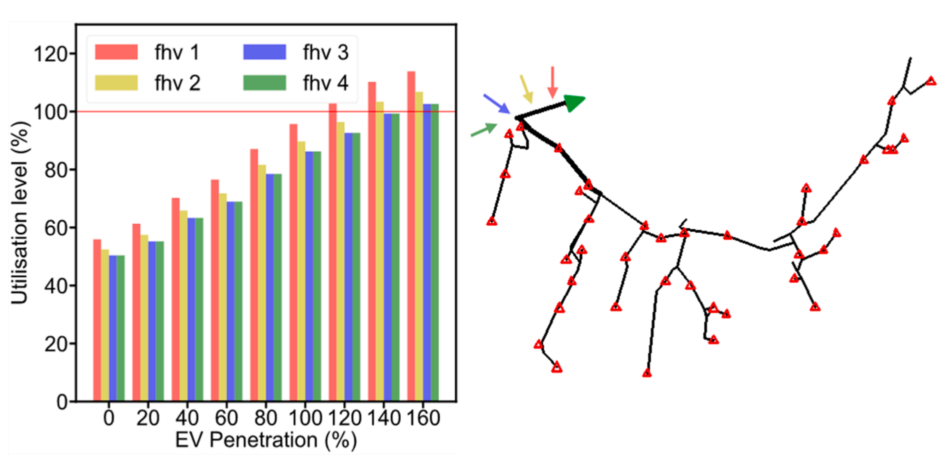

Fig. 13. Rural Network: MV Feeder (top 4 utilised segments): (left) Max. Utilisation, (right) Network Topology.

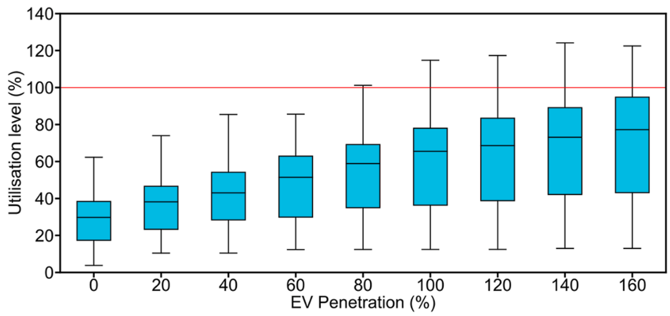

Fig. 15. Rural Network: LV Feeder Max. Utilisation.

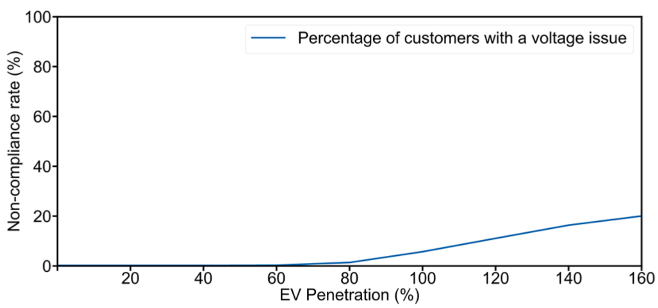

Fig. 16. Rural Network: Customer Voltage Non-Compliance Rate.

significant voltage drops in comparison with the urban network. Fig. 16 shows that customers start to observe voltage issues at 80% EV penetration, ending with approximately 20% of customers experiencing voltage issues at the maximum penetration.

In conclusion, the first technical issue expected to happen in the rural network is asset congestion on many LV transformers, resulting in an EV hosting capacity of no more than 20%. With the increase of EV penetration, congestion on both LV and MV feeders will start to pose challenges to the network operation. Furthermore, the distribution company needs to be aware of the voltage drop issues that may happen to many customers (around 20% at 160% EV penetration).

4.3. Discussion

The EV hosting capacity of the urban and rural networks is 40% and 20%, respectively. In these two networks, different problems are the limiting factors for different EV hosting capacities, therefore making it vital to assess different types of networks when investigating EV hosting capacity. In the urban network, LV feeders were found to be the limiting factor while other assets are well within the limit until very high EV penetration of 120%. The rural network is more problematic in terms of both asset congestion and voltage issues. The first technical issue for the rural network is expected to arise on LV transformers, and the MV part of the network is also posing challenges beyond EV penetration of 100%. Furthermore, voltage issues are expected by over 20% of residential customers by the maximum penetration.

Overall, the rural network is more critical considering the EV uptake trend in the next decades and distribution companies will need to adopt mitigation techniques early for the rural network from both planning and operation perspectives. However, EV uptake in rural feeders may be slower than the uptake within urban feeders.

5. Conclusions

The expected increase in peak demand due to the growing adoption of EVs poses significant technical challenges, such as asset congestion or voltage drop issues, on distribution networks. Distribution companies need to prepare accordingly, and, thus, is vital to investigate the extent to which a given network can have EVs without compromising its integrity; also known as EV hosting capacity.

Since LV models are not readily available, this paper has first introduced the adopted approach to build realistic pseudo-LV feeders needed to produce integrated MV-LV models. An EV hosting capacity assessment is formulated by exploring multiple EV penetrations and considering their time-varying behaviour during the peak demand day (worst-case scenario). Furthermore, a comprehensive EV modelling process is presented with various considerations.

The methodology is demonstrated on two real Australian MV-LV networks, one from the area called Preston (urban, dense and short) and one from Hazelbrook (rural, sparse and long) as part of the Australian EV Integration project [25]. The case study has used the anonymised Australian smart metre data to model residential customers, and real EV data from the UK Electric Nation project [13] to model EVs; which was considered representative of Australian EV users.

The EV hosting capacity of the urban and rural networks is assessed to be 40% and 20%, respectively. In the urban network, LV feeders were found to be the limiting factor of the EV hosting capacity while other assets are well within the limit until very high EV penetration of 120%. The rural network is more problematic in terms of both asset congestion and voltage issues. The first technical issue for the rural network is expected to arise on LV transformers, and the MV part of the network is also posing challenges beyond EV penetration of 100%. Furthermore, voltage issues are expected by over 20% of residential customers by the maximum penetration. The results show the importance of detailed network and EV modelling to adequately inform distribution companies and their EV planning strategies.

Given that EVs are single-phase connected, the demand unbalance can exacerbate the voltage issues in distribution networks. Although this work captured those effects, more studies are needed to investigate in more detail the role of voltage unbalance in EV hosting capacity. In addition, given the increasing uptake of PV systems combined with the adoption of different PV inverter functions (such as Volt-Watt, Volt-Var, export limits), more detailed analyses should be done to adequately capture the interactions with PV.

Credit author statement

Jing Zhu: Conceptualization, Methodology, Software, Validation, Formal analysis,

Data Curation, Writing, Visualization

William J. Nacmanson: Methodology, Writing

Luis F. Ochoa: Supervision

Barton Hellyer: Resources

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work has partly been funded by Energy Networks Australia (ENA), Australia and C4NET, Australia, through project EV Integration, 2020–2022. In addition, the authors would like to thank Endeavour Energy for providing the network model and demand data.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.epsr.2022.108399.

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