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Research Paper

Enhancing electric vehicle hosting capabilities using strategic allocation of charging stations and energy storage systems

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ABSTRACT

This paper introduces an innovative, strength-based, optimal allocation of public electric vehicle charging stations and energy storage systems to enhance hosting capabilities in distribution networks, considering nearby residential and transient customers. Unlike traditional network augmentation, this work emphasizes optimal placement in the early stages of adoption, using voltage deviation and load contribution analysis to enhance hosting capacity. The proposed framework uniquely incorporates diverse regional stakeholder dynamics, often overlooked in existing studies. To address regional challenges, this research integrates Australian-specific EV adoption patterns, plugin uncertainties, and storage export capabilities into its planning model. The stochastic nature of electric vehicle demand is modeled using a Monte Carlo Simulation, providing a probabilistic estimation of hosting capabilities under real-world uncertainties. This stochastic hosting capacity assessment technique addresses voltage and thermal limits, power loss, and voltage imbalances to ensure network integrity and efficient electric vehicle integration. By combining planning-level strategies with stochastic operational insights, this work bridges a critical gap in existing research, offering a scalable and adaptive solution for early-stage penetration of electric vehicles. The results demonstrate that the proposed strength-based allocation, supported by energy storage systems, can significantly enhance hosting capabilities for electric vehicles while aligning with the technical and practical needs of regional distribution networks.

1. Introduction

1.1. Background

Recent initiatives and technological advancements to support net-zero targets by 2050 through the integration of electric vehicles (EVs) have gained popularity worldwide [1]. A recent report from the International Energy Agency reveals that over one in five cars sold worldwide is an EV, with sales expected to reach 17 million by 2024 [2]. While the majority of EV sales occur in China (60%), Europe (25%), and the United States (10%), other regions are also seeing increased model availability and adoption. To respond to the surging EV demand [3], installations of charging facilities continue, although most are still home-based, slow chargers [4]. The demand for fast chargers in multi-dwelling units, workplaces, and transient customers has increased, with public fast charger installations rising 55 percent more than slow chargers by the end of 2023 [2]. While public fast chargers are crucial for improving customer confidence and reducing range anxiety, their random integration into distribution networks can affect hosting capacity by degrading performance constraints such as voltage stability, thermal overload, and power quality issues [5]. To support large-scale EV adoption, enhancing hosting capabilities in the distribution networks has become a key concern for utility operators and policymakers while ensuring techno-economic viability [6,7].

1.2. Related literature

To lay the foundation for enhancing hosting capacity analysis, accurate estimation of hosting capacity is essential. With the rise in global EV adoption, research on EV hosting capacity has grown accordingly. Current estimation approaches generally fall into two categories: model-based and model-free methods [8]. Model-based methods, although computationally intensive and reliant on detailed network data, remain the primary approach due to the limited availability of data in the evolving distributed energy resources (DER) landscape [9]. In

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Symbols and Abbreviations

Symbol/ Abbreviation	Meaning
BEV	Battery Electric Vehicle
C_{batt}	EV Battery Capacity (kWh)
D	Diversity Factor
DER	Distributed Energy Resources
E_d	Energy demand (kWh)
ESS	Energy Storage Systems
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
FI	Flexibility Index
H_{max}	Maximum accommodating capacity (kW)
H_{used}	Used accommodating capacity (kW)
k	Number of EV arrivals
LCI	Load Contribution Index
LL	Localized Loading
L_{ch}	Charging levels
M	Annual driving mileage (km)
N_{EV}	Number of EVs
N_{st}	Number of storage customers
P_b	Load at bus b
P_{com}	Average commercial demand
P_{EVCS}	EV station power demand (kW)
P_{res}	Average residential demand
P.loss	Power Loss
PHEV	Plug-in Hybrid Electric Vehicle
R_m	Maximum EV mileage (km)
S_i	Size of storage unit i
SOC	State of Charge
T_D	Charging duration
UV	Under Voltage
V2G	Vehicle-to-grid
V_b	Voltage at bus b
V_{ref}	Reference voltage
VQI	Voltage Quality Index
$\sum P_i$	Total load at each section
η_i	Charging efficiency
$\gamma_{init}(i)$, $\gamma_{reserve}(i)$	Initial and reserve SOC of storage unit i
γ_i and γ_{max}	Initial and maximum SOC
γ_{res}, γ_{com}	EV density per residence and commercial place
λ	EV arrival rate
μ_d, σ_d	Mean and standard deviation of daily driving mileage
μ_{E_d}, σ_{E_d}	Mean and standard deviation of energy demand

contrast, model-free methods offer simplicity but lack reliability for planning and operational decisions [10]. Model-based approaches can be categorized into deterministic, optimization-based, stochastic, and streamlined methods [8,11]. The deterministic method is commonly applied in EV hosting capacity studies, typically using peak-load conditions without accounting for the dynamic behavior of EV charging [12,13]. Optimization-based methods estimate the maximum hosting capacity under predefined constraints and time frames [14,15]. Stochastic methods improve accuracy by capturing load uncertainties and involve significant computational complexity [16,17]. To resolve computational challenges, a streamlined approach has been adopted in studies, where representative scenarios are selected to reduce computational burden while maintaining reasonable accuracy for planning and operational decisions [18,19]. Although every method has its own merits and demerits, selecting a suitable method is crucial for analyzing EV hosting capacity. Relying on a range of hosting capacity values rather than a single value will certainly help planners and operators with future network augmentation.

Contemporary research on hosting capacity enhancement predominantly focuses on photovoltaic (PV) technologies, with only 13.8% addressing EV-based technologies, as illustrated in Fig. 1(a). Given the rapid growth of EV adoption and its unique impact on both demand and network stress, utility operators are increasing attention to enhance EV-based hosting capacity [8,20]. While the existing body of research falls into three categories, including planning strategies, operational improvements, and technological adaptations [21], as shown in Fig. 1(b), the need to select a proper method is crucial. Improving EV hosting capabilities using operational strategies involves dynamic tariffs [22], demand response [23,24], dynamic pricing [25], and smart charging [26]. Technology adaptation methods such as transformer capacity upgrades [22], feeder reconfiguration [27], power electronic compensator [28], optimal capacitor placement [29], phase-shifting control [30], and transmission expansion [31], are also employed in enhancing EV hosting capabilities. As these methods often involve costly adjustments and technology adaptations, prioritizing planning-level solutions for hosting capacity improvements during the charging station installation is vital to minimize future retrofits and protect stakeholder benefits [32].

Planning-based strategies for optimal allocation have been widely explored to enhance the capabilities of PV and energy storage systems (ESSs) in distribution networks. Studies have examined optimal ESS allocation [33,34], distributed generation placement [35], and optimal PV and vehicle-to-grid (V2G) system integration [4]. Combining PV with energy storage systems [20] and integrating PV with EVs [26] are effective strategies for enhancing PV hosting capacity. Although planning strategies are employed in PV and ESS hosting capacity improvement in recent studies, the optimal placement of EV charging stations (EVCSs) for enhancing hosting capacity has largely been overlooked. There are many methods available for the optimal EVCS allocation, such as the decision-making process [36], spatial coverage analysis [37], customer convenience [38], and techno-economic impacts [39]. Decision-making methods used include analytical hierarchy process [36] and multi-criteria decision-making techniques [40]. Spatial coverage-based allocation uses GIS datasets, factoring in population density, customer proximity, coverage, and road conditions [37]. For customer convenience, a fast-charger distribution aimed at reducing travel time [38], demand-based charger allocation [41], and deep-learning-based forecasting for charger placement to reduce expenditures and meet customer demand [42].

To account for technical impacts in optimal EVCS allocation, studies prioritize minimizing power losses and voltage deviations [43]. In [44], a novel placement index is proposed for the optimal location of EVCS, considering voltage deviations. An EVCS placement model integrates multi-stakeholder interests in optimal planning for selected EV models in the network accounting voltage limits [45]. The optimal allocation of storage systems has been shown to enhance voltage stability and minimize costs [46]. In addition to technical impacts, profit-based allocation [47] and stakeholder-centric allocation [48] are used in the literature. All these methods centered on EV demand, which is inherently stochastic due to plugin diversity and EV specifications. In [18], simultaneous uneven EV charging and customer exports lead to thermal overload and voltage imbalance issues in PV-rich distribution networks. In [49], voltage unbalance and power losses significantly impact network performance when simultaneous EV charging and DER exports occur. While resource allocation in distribution networks has been studied, the integration of stochastic EV demand, regional diversity, and key metrics like voltage unbalance and thermal loading still needs further investigation.

In addition to optimal allocation of EVCS, export capacity from energy storage systems may help in managing demand and improving network performance. Studies [50] have allocated EVCS and ESS based on average consumption and uniform charging levels without

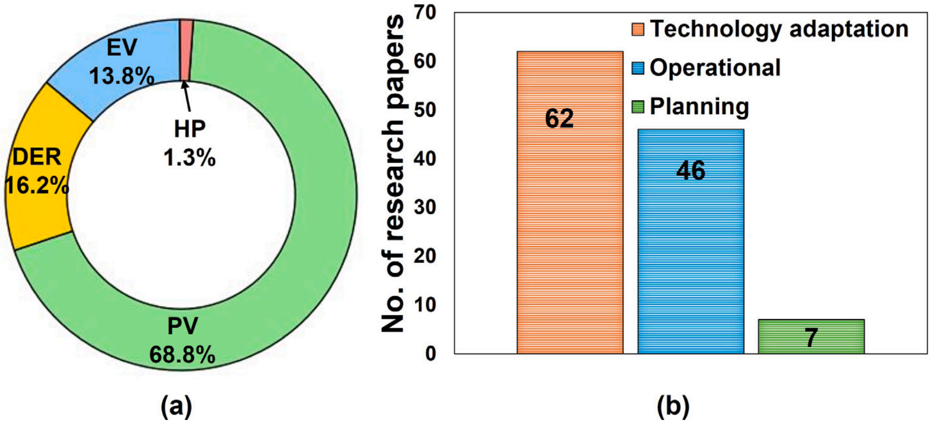

Fig. 1. Hosting capacity enhancement strategies in distribution networks, (a) considered technologies, and (b) enhancement approaches.

accounting for diverse customer preferences. In studies, multi-DERs such as PV-EVCS [51], EVCS-Capacitor [52], EVCS-ESS [53], and ESS-EVCS-DER [54] consider only voltage deviations and power losses as the technical impacts while allocating resources in the distribution networks. The uncertainties consist of storage sizes, adoption rates, and export probabilities in peak hours, which must be considered in assessing storage exports [54]. In [32], stakeholder diversity and priorities in optimal EVCS allocation are emphasized, identifying EV users and network operators as the primary stakeholders. It is essential to consider plugin uncertainties and market dynamics in regional contexts to be more precise in load modeling [55,56]. To include shortcomings in stochastic EV demand estimation in optimal allocation, studies [43, 57] used assumptions and mixed-regional EV plugin variables, which overlook regional contexts.

1.3. Research gaps and contributions

- Estimating EV hosting capacity is complex due to the rapid evolution of EV technologies, varying charging specifications, and diverse user plug-in behaviors [8,11,22]. These characteristics differ significantly across regions, influenced by local policies, vehicle models, and user preferences [20,58]. Therefore, relying on a fixed or average hosting capacity value can lead to inaccurate planning decisions [11,13]. There is a clear research gap in developing robust methodologies that incorporate evolving, region-specific datasets to estimate a realistic range rather than a single-valued EV hosting capacity under uncertainty.
- EV adoption is still in its early growth phase, unlike PV systems, which are more widely deployed. Without forward-looking planning, rising EV load may stress distribution networks, leading to costly upgrades and disruptions [32,59]. In addition, operational and grid reinforcement require costly adjustments, compared to planning-level strategies [60,61]. Therefore, planning-level frameworks are necessary to prevent expensive adjustments and major network upgrades.
- While extensive research exists on enhancing PV hosting capacity through the optimal placement of PV and storage systems [4, 33–35], planning-level interventions for EV hosting capacity improvement remain underexplored. Additionally, the coordinated placement of EVCSs and ESSs to increase EV hosting capacity warrants a thorough investigation.

To address the challenges explored, this paper presents an innovative, strength-based, optimal allocation approach for EVCS and storage systems to improve EV hosting capabilities, considering the diverse regional stakeholder needs in Australian contexts. The specific objectives of this paper are as follows:

- Estimation of stochastic EV demand considering regional plugin diversity and specifications.
- Determination of EV hosting capabilities in a distribution feeder using plugin diversity and specifications from Australian contexts.
- Develop a strength-based optimal allocation algorithm for EV charging stations and energy storage systems in a network, employing network dynamics.
- Demonstration of the optimal allocation of EVCS and storage units to enhance the EV hosting capabilities in the distribution network.

The rest of the article has been organized as follows: Section 2 describes conceptual methodologies for EV hosting capacity estimation and a strength-based allocation process for enhancing hosting capabilities in distribution networks. Section 3 describes the data source, network topology, and required processing work to employ the proposed methodology. It also discusses the calculation of EV customers in different sections, including regional demographics. Section 4 explains the stochastic modeling of EV loads and storage export capabilities by each section, contemplating plugin diversities and specifications. Section 5 explains the results for EV hosting capacity and strength-based allocation using several case studies for the test network. It also discusses practical implications in other regional settings and networks. Section 6 summarizes the findings, limitations, and future research directions.

2. Methodology

This section outlines the methodological framework used to enhance EV hosting capacity, incorporating strength-based allocation and estimating hosting capability. The conceptual methodology is illustrated in Fig. 2, which presents the sequential steps of the proposed enhancement approach. The model is tailored to Australian distribution network contexts and is implemented on a standard test feeder for validation. The stakeholder diversity is developed by incorporating EV model availability, arrival times, charger preferences, and usage patterns into a probabilistic framework. These factors are captured using stochastic Monte Carlo simulations, accounting for regional variations in EV densities and demand from residential and transient customers. Using the derived stochastic EV demand, the strength-based allocation and hosting capacity estimation process is carried out in this paper.

2.1. Strength-based optimal placement

The proposed strength-based optimal allocation of EVCSs and ESSs utilizes an optimization model to identify strong and weak buses within each section of the distribution network. This method utilizes the voltage quality index (VQI) and load contribution index (LCI), ensuring that network performance constraints, such as voltage and thermal

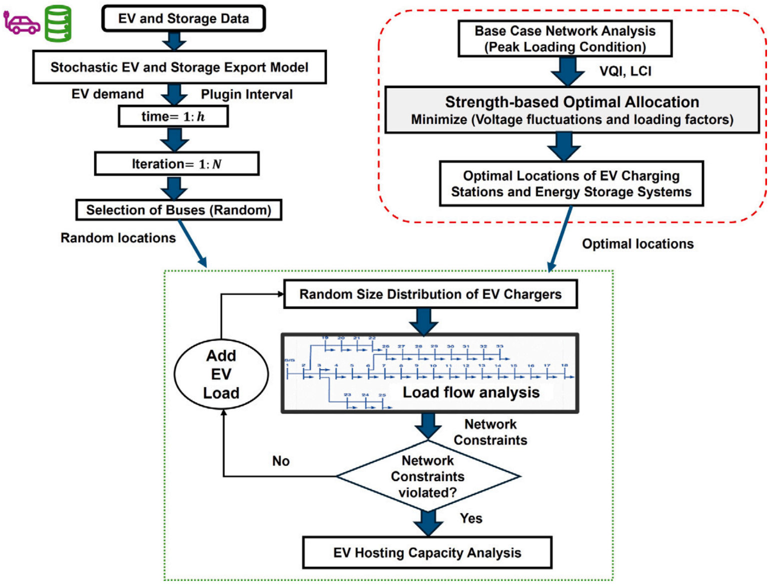

Fig. 2. Conceptual methodology for EV hosting capacity enhancement using strategic allocation of charging stations and energy storage systems in the distribution networks.

limits, power loss, and voltage unbalance factors, are met. The VQI and LCI are calculated for each bus, b, using Eqs. (1) and (2), respectively. Strong and weak buses are identified by analyzing changes in the objective function after applying stochastic load, supported by a voltage sensitivity analysis, as discussed in [62,63].

$$\mathrm{VQI}_b = \frac{|V_b - V_{\mathrm{ref}}|}{V_{\mathrm{ref}}} \tag{1}$$

$$\mathrm{LCI}_b = \frac{P_b}{\sum P_i} \tag{2}$$

where V_b is the voltage at bus b, V_{ref} is the reference voltage, P_b represents the load demand at bus b, and $\sum P_i$ is the total load across all buses. The objective function is first computed using Eq. (3), where both VQI and LCI are normalized, and equal weights of 0.5 are assigned to ω_1 and ω_2.

$$\mathrm{OF}_{\mathrm{init}} = \omega_1 \mathrm{VQI}_b + \omega_2 \mathrm{LCI}_b \tag{3}$$

The stochastic EV load for each section, P_{EVCS}, is applied at randomly selected nodes, and an updated objective function is computed using Eq. (4) following a load flow analysis.

$$\mathrm{OF}_{\mathrm{EV}} = \omega_1 \mathrm{VQI}_b + \omega_2 \mathrm{LCI}_b \tag{4}$$

The final objective function for each bus will be averaged for N iterations and expressed in Eq. (5).

$$\mathrm{OF}_{\mathrm{Final}} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{OF}_{\mathrm{EV,\ i}} \tag{5}$$

The changes in the objective function due to EV loads are calculated using Eq. (6), satisfying key constraints as in Eq. (7).

$$\Delta\mathrm{OF} = \min\left(\mathrm{OF}_{\mathrm{Final}} - \mathrm{OF}_{\mathrm{init}}\right) \tag{6}$$

Constraints:

$$\left.\begin{array}{l} V_{\min} \le V_j(t) \le V_{\max} \\ P_{\mathrm{line}} \le P_{\mathrm{line,\ max}} \\ P_{\mathrm{loss}}^{(i)} \le P_{\mathrm{loss}}^{\max} \\ \mathrm{VUF}_i \le \mathrm{VUF}_{\max} \end{array}\right\} \tag{7}$$

The normalized values of ΔOF are used for evaluating strong and weak buses. Buses with a low score for the changes in the objective function, ΔOF, are considered strong and allocated for EVCS. In contrast, those buses with a high objective function, indicating less capability in handling additional loads, are designated for storage systems.

2.2. EV hosting capabilities

In this paper, the stochastic simulation-based hosting capacity estimation method is used due to the inherent stochastic nature of EV loads. This method is applied in various cases with different combinations of distributed energy resources. It runs a Monte Carlo simulation, spanning over 100 iterations, which generates random EV charging profiles in terms of location and demand for diverse customers based on the probability distribution of EV demand. In addition, random locations are selected at each iteration for analyzing hosting capacity. Then, utilizing strategic allocation of charging stations and energy storage systems, the EV hosting capacity improvement is analyzed. Using Newton–Raphson power flow analysis, the constraints in Eq. (7) are evaluated to determine hosting capacity limits, $P_{\mathrm{EVHC}}^{(i)}$, as in Eq. (8) for each period. The performance indices including voltage limits ($0.90 \le V_i \le 1.05$), overloading limits ($I \le 0.95$), voltage unbalance factors (VUF $\le 2\%$), and power loss (P.loss $\le 8\%$) are checked after load flow analysis at each iteration.

$$P_{\mathrm{EVHC}}^{(i)} = \sum_{j=1}^{N} P_{\mathrm{EV},j}^{(i)} \tag{8}$$

$$\left.\begin{array}{l} H_{\min} = \min\limits_{i} P_{\mathrm{EVHC}}^{(i)} \\ H_{\max} = \max\limits_{i} P_{\mathrm{EVHC}}^{(i)} \end{array}\right\} \tag{9}$$

After all iterations, the minimum and maximum hosting capacity values for each period are obtained as Eq. (9). To measure enhanced hosting capabilities, this work used the flexibility index, FI of the distribution network, as in Eq. (10), where $H_{\max}$ and H_{used} are maximum load accommodating capacity and baseload capacity, respectively.

$$\mathrm{FI} = \frac{H_{\max} - H_{\mathrm{used}}}{H_{\max}} \times 100 \tag{10}$$

3. Data collection and processing

This section includes data collection and processing for EV specifications, plugin uncertainties, and network characteristics.

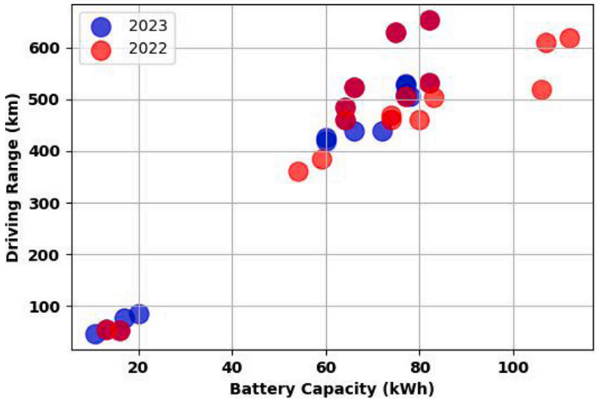

Fig. 3. Top-selling 20 EVs available in the Australian markets in 2022 and 2023.

3.1. EV specifications and plugin uncertainties

In this work, the specifications of the top-sold twenty EVs include battery capacity, C_{batt} and driving range, R_m, which are collected from the Australian EV Council report published in 2023 and 2024 [64] and shown in a scatter plot in Fig. 3. These EVs are accounted for by incorporating regional trends in electric vehicle adoption, which reflect a realistic increase in battery capacity driven by technological advancements and the availability of new models. The global average battery capacities for PHEVs and BEVs in 2025 are expected to be around 11 kWh and 45 kWh, respectively [65]. Based on the scatter plot provided in Fig. 3, it is seen that the average battery capacity for PHEVs and BEVs is 10.45 kWh and 58.35 kWh, respectively. Based on Australian EV models, the combined average battery capacity for PHEVs and BEVs is 50.88 kWh, consistent with the global average.

In addition to EV specifications, plugin uncertainties are considered in this paper are arrival rate (λ at time t), daily driving mileage (d), initial and final SOC (γ_i and γ_{max}), and choice of charging levels, L_{ch}, as in Fig. 4 [60]. These plugin behaviors are collected from the Australian EV customer plugin report and the Australian Bureau of Statistics. The arrival distribution for the Australian EV users is collected from the report [66]. According to Australian statistics, more than half of EVs are charged during the day, and a quarter are charged overnight [66]. In addition, the mean arrival time is around 3–4 PM, according to the Australian study based on 1069 charging sessions for 30 days [18]. The arrival probability distribution for EVs is shown in Fig. 4(a), following a Poisson distribution as Eq. (11) with different arrival rates for the evening, overnight, and daytime.

$$P(k;\lambda t)=\frac{(\lambda t)^k e^{-\lambda t}}{k!} \tag{11}$$

where $P(k;\lambda t)$ is the probability of observing k EV arrivals in an interval t, λ is average arrival rate, and k is the number of EV arrivals.

$$f(d)=\frac{1}{d\sigma_d\sqrt{2\pi}}\exp\left(-\frac{(\ln d-\mu_d)^2}{2\sigma_d^2}\right) \tag{12}$$

The driving patterns for EV customers are collected from the Australian report [66] and the calculated mean and deviation parameters. The calculated mean and standard deviation are used in Eq. (12) to find the probability distribution for daily driven distance, d. Fig. 4(b) shows the probability distribution, $f(d)$, of EV driving patterns in Australia, which follows a log-normal distribution. The mean and standard deviation of the daily driven distance are μ_d and σ_d, respectively. The average daily distance driven by Australian passenger EVs is 36.59 km over 365 days, while it is slightly lower for passenger cars, with 33.15 km based on annual usage statistics [67].

Table 1
Summary of EV distribution by each section.

Section	Residential customers	Commercial customers	Total EVs
1	400	37	827
2	270	25	560
3	224	21	463

In this work, the initial and final SOC of arrived EVs is assumed to be within 20% and 90% limits [59]. The initial SOC, obtained from studies, follows a normal distribution with a mean of 45.9% and a standard deviation of 12.8%, respectively [18]. The charging levels available in Australia are Level 1 (3.6 kW), Level 2 (7.4–<22 kW), and Level 3 ($\geq$ 50 kW). In this work, charging level preferences are obtained from a report published [66]. Fig. 4(d) shows the percentage of customers who came to public charging stations looking for fast (Level 3) and slow (Level 2) chargers. In the case of public charging facilities, it is seen that about 70% of customers are connected with Level 3 charging and 30% with Level 2 charging in Australia.

3.2. Test network

The research uses the IEEE-33 bus system to allocate charging stations and energy storage systems for public and shared spaces, as illustrated in Fig. 5. The distribution network, with a total load of 3715 kW, 2300 kVAR, and 4369.35 kVA, is modeled using loads and parameters from [68] using the Panda Power tool in Python. The network is assumed to be from a suburban region where both commercial and residential loads are present, with 85% of the load accounting for residential loads. The initial base load profiles for a typical day, displayed in Fig. 6, are used to determine the peak demand of the test network for allocating charging stations and storage systems.

Australian energy demand statistics estimate the number of household customers in the network. On average, 3–5 kW and 15–25 kW energy demands are found at peak hours in the Australian residential and commercial places, respectively. Not all households use peak power simultaneously, which is accounted for by the diversity factor D, typically assumed to be 0.8. On average, Australian households have 1.6 vehicles, and commercial sites have about three [67]. It is also accounted that in addition to network customers, there will be 10% transient customers coming from nearby areas. The number of EV customers N_{EV} in the network is calculated using Eq. (13).

$$N_{\mathrm{EV}}=1.10\times\frac{P_{\mathrm{total}}}{D}\left(\frac{0.85\gamma_{\mathrm{res}}}{P_{\mathrm{res}}}+\frac{0.15\gamma_{\mathrm{com}}}{P_{\mathrm{com}}}\right) \tag{13}$$

where P_{total} is the total network power demand, P_{res} is the average residential demand, P_{com} is the average commercial power demand, γ_{res} is the EV density per residence, γ_{com} is the EV density per commercial place, and D is the diversity factor accounting for non-simultaneous peak power usage.

To improve customer convenience by reducing travel time, this study divides the network into three sections. Table 1 summarizes the EV load distribution for each section, including residential, commercial, and transient customers. Section 1 has the highest number of customers, while Section 3 has the fewest, attributed to increased line impedance for those farther from the feeder's head. The public charging stations are designed to accommodate nearby and transient EV customers, equipped with Level 2 and Level 3 chargers, operating at a power factor of 0.95.

4. Stochastic modeling of EVCS demand and storage export

This section discusses the stochastic model of charging station demand and storage export capabilities. The stochastic demand and exports are then used in optimal allocation and hosting capacity analysis.

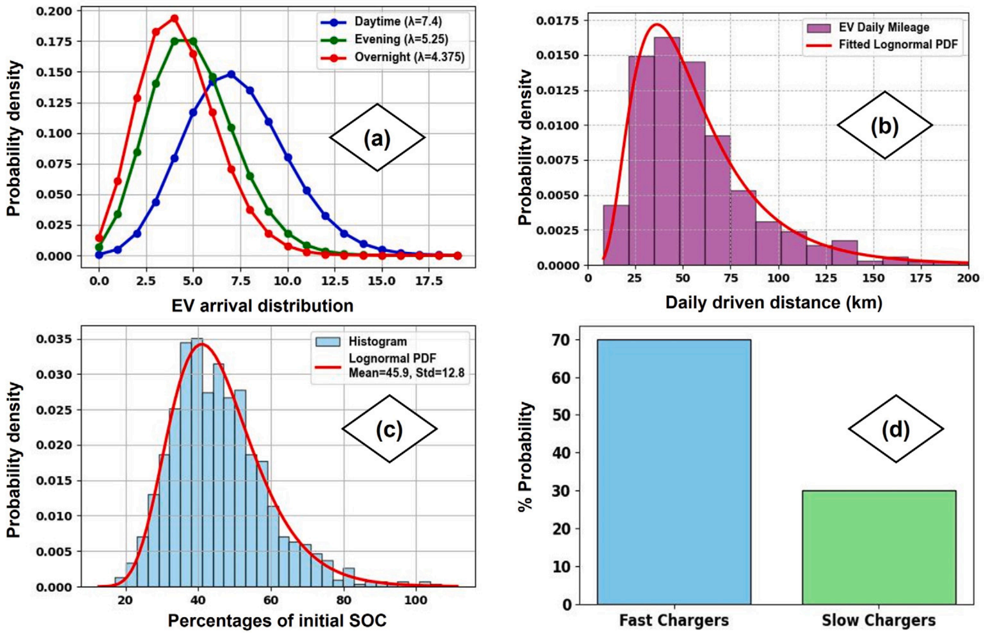

Fig. 4. EV stochastic plugin uncertainties obtained from Australian studies and report (a) arrival times, (b) daily driven mileage, (c) initial SOC, and (d) choice of chargers.

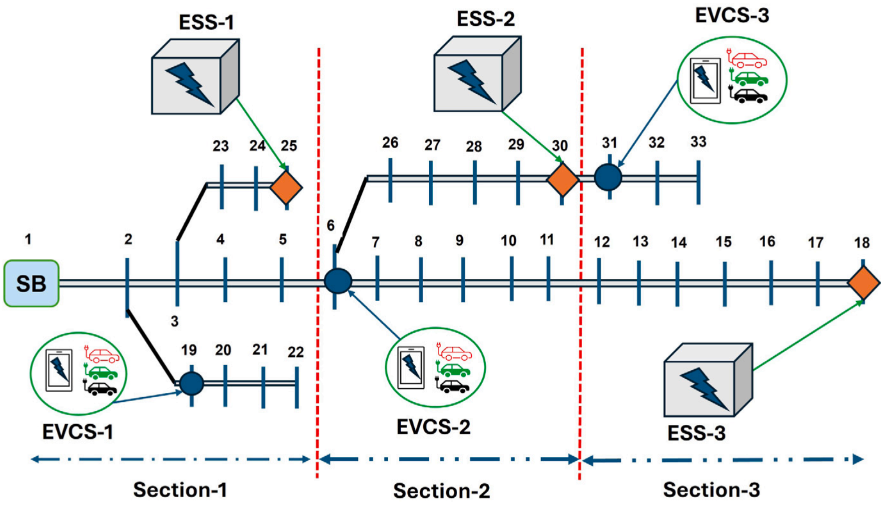

Fig. 5. IEEE 33 Bus system indicating EV charging stations and storage systems.

4.1. Stochastic modeling of EV loads

Due to having diverse plugin behaviors, the EV energy demand, E_d becomes stochastic and is calculated using Eq. (14), incorporating battery capacity, initial and final SOC, represented by C_batt, γ_max and γ_i, respectively. The individual energy demand requested by EV users is computed using a probabilistic Monte Carlo Simulation for 100 iterations. The mean and standard deviation of energy demand are 29.34 kWh and 7.54 kWh, respectively, with the corresponding probability densities shown in Fig. 7.

$$E_\text{d} = C_\text{batt} \times (\gamma_\text{max} - \gamma_\text{i}) \tag{14}$$

The charging duration is calculated using Eq. (15) and depends on charging levels, L_{ch}, and energy requested, E_d, by EV users. The charger efficiency, η_i, is assumed to be 0.95.

$$T_D = \frac{(\gamma_\text{max} - \gamma_i) \times C_{batt}}{\eta_i \times L_\text{Ch}} \tag{15}$$

Based on the energy requirements, E_d, daily-driven distance, d, battery capacity, C_batt, maximum driving range, R_m, the plug-in interval, α, is calculated using Eq. (16).

$$\text{Plugin interval, } \alpha = \frac{E_d}{\left(\frac{C_\text{batt}}{R_m} \times d\right)} \tag{16}$$

The plug-in intervals for EVs in the network are estimated, with an average interval of 5.45 days, as calculated using Eq. (16), which indicates the typical frequency of EV arrivals at charging stations. Additionally, studies [18,69] show that, despite 100% penetration, only 31.76% of EVs arrive at charging stations daily. Using the probability distribution of individual EV demand and the number of EVs in each section, hourly demand for a typical week is estimated, as shown in Fig. 8. Due to changes in demand and driven profiles on weekends, the charging demand is found to be low compared to weekdays. The stochastic total demand for an EVCS over a time interval, $P_\text{EVCS}(t)$ with individual demand for EV, E_d, considering the arrival distribution, is

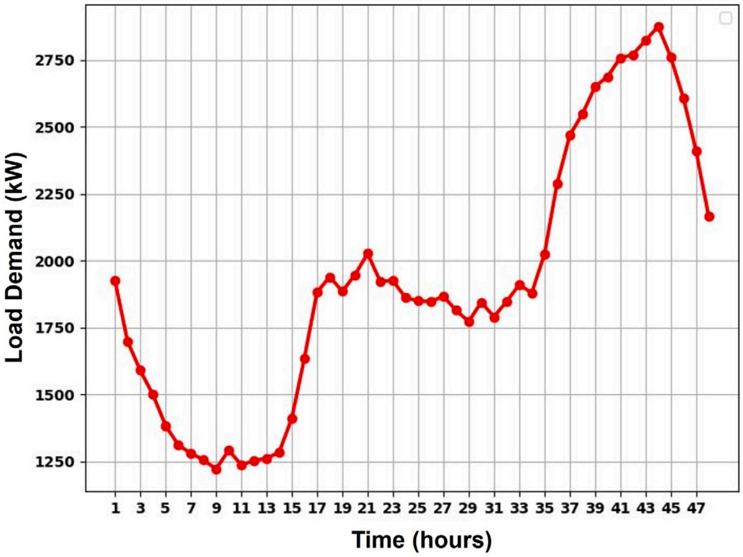

Fig. 6. Baseload profiles in studied IEEE-33 network.

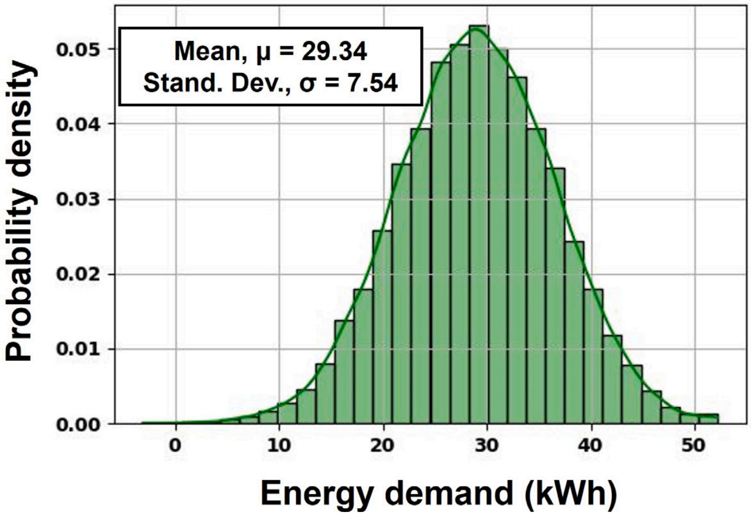

Fig. 7. Probability densities of energy demand.

calculated using Eq. (17).

$$P_{\mathrm{EVCS}}(t) = (\lambda t) \cdot E_d \tag{17}$$

The mean and standard deviation of energy demand for an EVCS, represented by μ_{E_d} and σ_{E_d}, respectively, are estimated from the EVCS demand for 1000 iterations. The expected range of EVCS demand considering mean and standard deviation is shown in Eq. (18).

$$P_{\mathrm{EVCS}}(t) \in \left[(\lambda t) \cdot (\mu_{E_d} - \sigma_{E_d}), (\lambda t) \cdot (\mu_{E_d} + \sigma_{E_d})\right] \tag{18}$$

For different penetration levels, the hourly peak demand is estimated for a typical day, which is presented in the form of a heat map in Fig. 9. For 31.76% EV arrivals, the respective peak demands for Sections 1, 2, and 3 are found to be 516 kW, 375 kW, and 314 kW, respectively.

4.2. Storage export capabilities

This paper considers energy storage systems supported by residential PV and V2G installations from an Australian perspective. The total storage export is calculated based on the storage capacity in kWh, reserved, and initial SOC of each customer storage, using Eq. (19).

$$E_{\mathrm{export}} = \sum_{i=1}^{N_S} \left(S_i \times \left(\gamma_{\mathrm{init}}(i) - \gamma_{\mathrm{reserve}}(i)\right)\right) \tag{19}$$

where N_S is the number of storage units in each section, S_i denotes the size of the ith storage unit in kWh, ranging from 10 to 25 kWh. The storage units are randomly distributed between the minimum and maximum storage sizes. The initial and reserved SOC for each storage unit is denoted by γ_{init} and $\gamma_{\mathrm{reserve}}$, respectively, with values assumed to be 90% and 30% in this work.

To find the number of storage units, in this paper, the statistics from Australia are used. With 3.84 million solar systems installed in a population of 9 million electricity customers, approximately 42.67% of households have solar panels, a figure reflected in this studied network. Additionally, the 2024 Annual SunWiz Australian Battery market reports one storage unit for every six solar installations in Australia. Besides, the V2G facility is not universally available for all EVs, with only three V2G-compatible models (Nissan Leaf, Mitsubishi Outlander PHEV, and Mitsubishi Eclipse Cross) currently on the Australian market. The capacity of commonly used residential storage systems is often

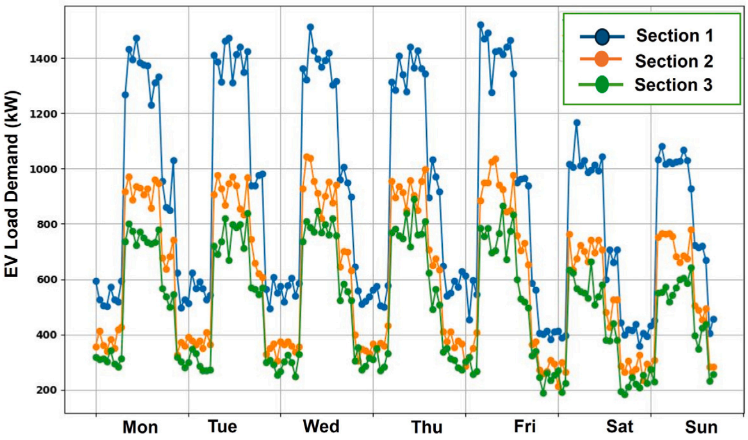

Fig. 8. Hourly EV load demand in charging stations over a week.

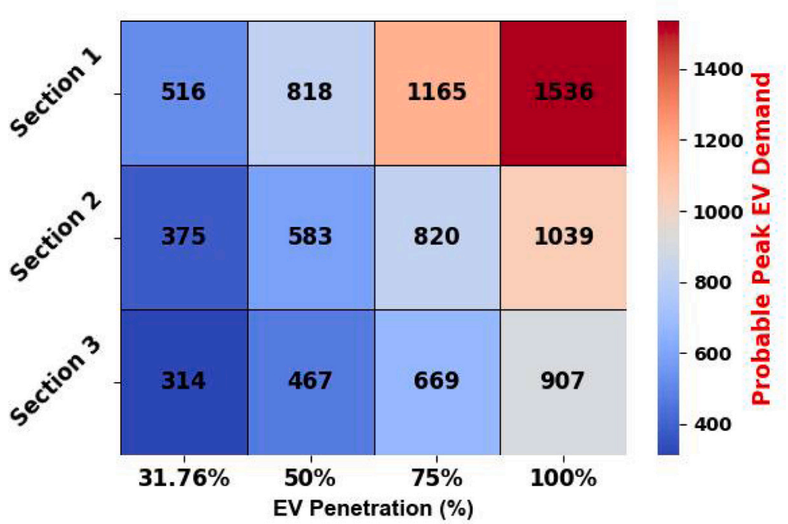

Fig. 9. Heat map showing changes in peak demand for different penetrations.

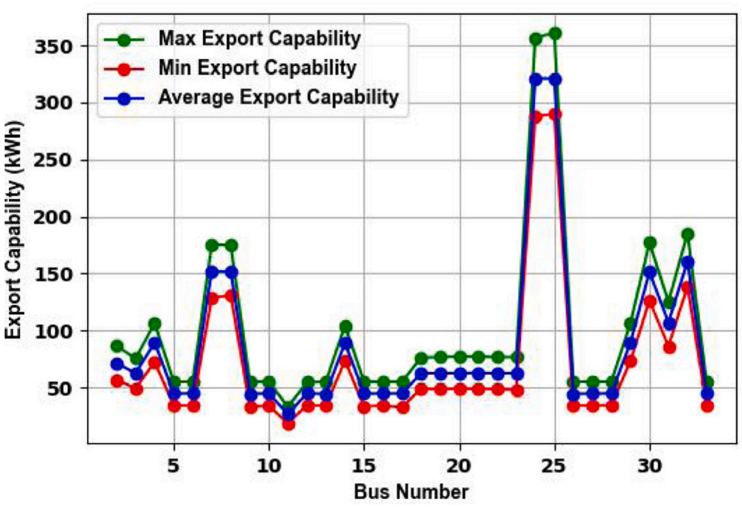

Fig. 10. Storage export capacity for different buses in the IEEE 33 bus network considering Australian contexts.

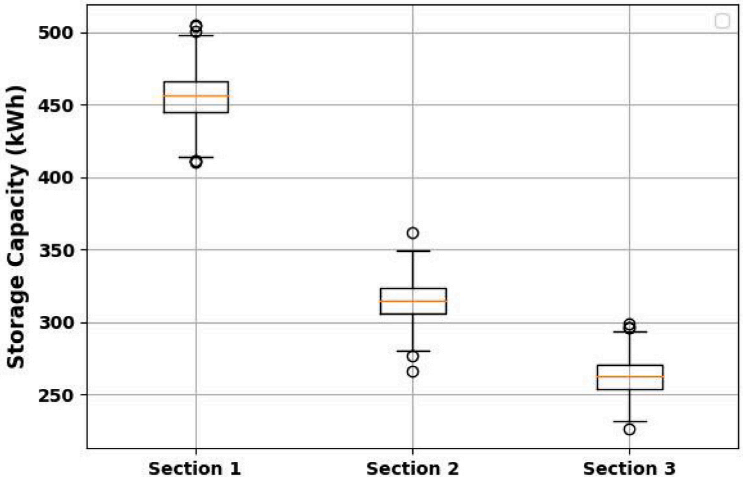

Fig. 11. Storage export capacity for different sections.

insufficient to accommodate the average energy exports from V2G services. To address the scenario, this work assumed only 15% of EVs can support storage through V2G services.

In this work, probabilistic export capabilities for customers are calculated using Eq. (19). It is assumed that 42.67% of customers in the test distribution network have storage units ranging from 10–25 kWh. Fig. 10 shows the maximum, minimum, and average export capabilities in each network node. As the export capabilities depend on the number of storage customers and their sizes, variations in export capabilities are found for each section. Fig. 11 indicates average export capabilities in each section of the network, with Section 1 having the highest and Section 3 becoming the lowest. The number of customer engagements in storage export varies the export capabilities, as seen by Figs. 10 and 11.

5. Results and discussion

This section presents the results for EV hosting capacity across various cases and describes the enhancement of hosting capacity through the strategic allocation of charging stations and energy storage systems. Various cases for EV hosting capacity analysis include base peak load, random EVCS placement, optimal EVCS placement, and random EVCS placement with distributed storage. Additionally, it discusses the transferability of this model to other regional contexts.

5.1. *EV hosting capacity*

In this work, time-series probabilistic Monte Carlo Simulation estimates EV hosting capabilities in the standard IEEE-33 bus network. Unlike deterministic methods that assume fixed values for EV behaviors, probabilistic Monte Carlo simulations account for plug-in uncertainties, providing more reliable estimates of hosting capacity by capturing the variability in EV demand, illustrated in Fig. 7. Using the EV hosting capacity estimation framework described in Section 2, the stochastic hosting capacity values are determined. Fig. 12 illustrates the half-hourly EV hosting capabilities for a typical day in the IEEE-33 feeder, utilizing the load profiles shown in Fig. 6. It is observed that during peak loading conditions, the EV hosting capacity is at a minimum due to undervoltage issues. In this calculation, EV chargers are allocated randomly in size, location, and preferences at each node. To enhance EV hosting capacity during the peak loading period, this paper analyzes multiple case scenarios specific to that time.

While Monte Carlo Simulation effectively captures uncertainties, it increases computational complexity with network size. In this study, convergence was observed after approximately 70–80 runs, indicating that 100 iterations were sufficient to obtain reliable and stable estimates. For larger networks, parallel computing and scenario reduction can be employed to maintain scalability. For precision, a confidence interval-based precision metric is utilized, as defined in Eq. (20).

$$\text{Precision} = 1 - \left(\frac{z\sigma}{\mu\sqrt{n}}\right) \tag{20}$$

where CI is the confidence interval, z is the z-score for the confidence interval. For 95% CI, z-score value is 1.96. μ and σ are mean and standard deviation of hosting capacity values for n iterations. Using the 95% CI, the precision of the hosting capacity estimation was calculated as 0.982 for a mean of 1930 kW and a standard deviation of 195.48 kW over 100 Monte Carlo simulations. This high precision score indicates strong consistency and statistical reliability of the estimated EV hosting capacity under variable loading conditions.

5.2. *Strength-based allocation of EVCS and storage*

The strategic location for charging stations and energy storage systems is identified using the framework described in Section 2. The strength of the node is determined based on the normalized values of changes in the objective function, ΔOF, shown in Eq. (6). For each section of the network, the changes in objective function scores are displayed in Fig. 13. This work uses the Gurobi optimization solver for the mixed-integer linear programming technique to find exact solutions. Based on the results, buses 19, 6, and 31, one from each section, are identified as suitable locations for EVCS placement, revealing a higher capacity to accommodate EV loads with limited impact on network performance. Their selection reflects a balance among available capacity, minimal voltage deviation, and operational resilience.

In contrast, buses 25, 30, and 18 are selected for energy storage system placement due to their higher vulnerability under increased loading, as shown by greater changes in ΔOF. Installing storage at these locations is expected to alleviate local stress by improving voltage stability and reducing overloading, thereby enhancing the overall hosting capacity.

5.3. *Case studies on EV hosting capabilities*

This section examines various scenarios for EV hosting capabilities in the IEEE 33-bus network, with a focus on EVCS and storage allocation. Four case studies are presented: random EVCS allocation without storage, optimal EVCS placement without storage, and optimal EVCS placement with storage. The EV hosting capacity for four cases is analyzed using flexibility indices, as defined in Eq. (10), considering voltage violations, thermal overloading, power losses, and voltage unbalance factors.

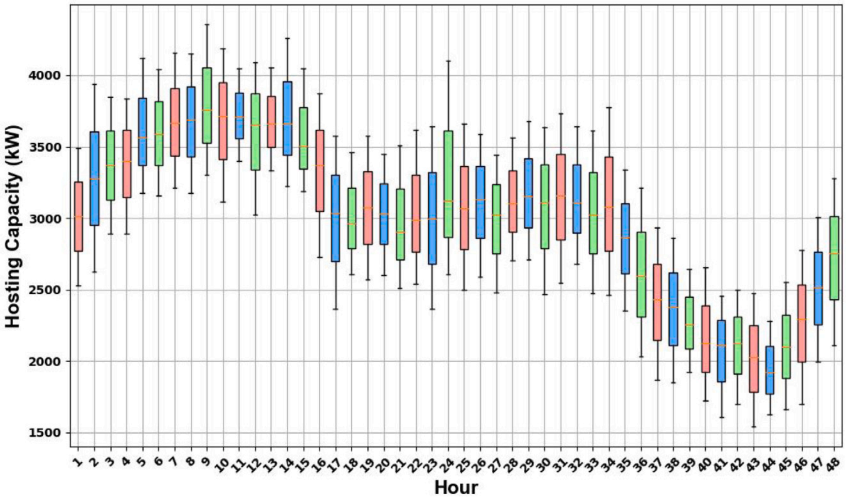

Fig. 12. Hourly EV hosting capacity values for IEEE 33 bus system.

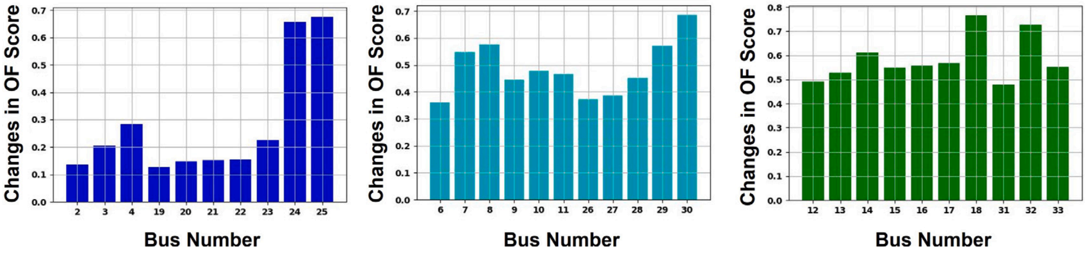

Fig. 13. Changes in objective function values for different buses in three sections.

5.3.1. Case 1: Random placement of EVCS with no storage

In this case, peak-hour EV hosting capacity is determined using the random allocation of EVCS considering stochastic demand for each section. This simulation is carried out for 100 iterations, and in each iteration, voltage limits, overloading, and unbalance are checked. The mean EV hosting capabilities in 20 random trials are shown in Fig. 14. However, the peak hourly demand for different penetration levels is stated in Fig. 8, it is seen that almost all trials of EV hosting capabilities can uphold 31.76% penetration. Out of 20 trials, only six combinations can offer around 50% penetration daily. As the 31.76% plugin possibilities investigated considering EV diversities, it is very important to find strong nodes for placing EVCS. Undervoltage issues dominate in all trials when hosting capacity limits are exceeded. The average flexibility index for this case is about 34.78%, as shown in Table 2. In addition to random charging, in this case, one trial is arranged to find the impacts of placing EVCS at far-away load buses, and it shows lower hosting capabilities, which is below the accommodating power for 31.76% EVs at peak hours.

5.3.2. Case 2: Random EVCS placement with distributed storage

In this case, the random placement of EVCS and distributed storage exports is considered within the IEEE-33 network. Customer-level storage is supported by residential PV and V2G systems. To maintain customer diversity, residential storage capacities ranging from 10–25 kWh are randomly distributed among the customers in each section. Although customer export patterns may fluctuate over time, it is assumed that the majority of customer exports will occur during peak hours due to economic benefits. In Australia, around 3.84 million solar home systems where, out of fourteen, only one residential storage is installed. Besides, the solar installation per customer ratio in Australia is 42.67%. Considering the increasing momentum of storage installations and V2G systems, it is assumed that 42.67% of customers will have storage export facilities, and the probabilistic export capabilities are taken from Fig. 10. It is seen that the number of customers who participated in demand response during peak hours is 139, 94, and 78 from Sections 1, 2, and 3, respectively. These distributed export capabilities are considered in this case, along with the random placement of EVCS with 20 trails. The discharging rate is assumed to be 7 kW and 11 kW with a probability of 0.3 and 0.7, respectively. The flexibility index is improved to 58.96% with the domination of Undervoltage issues, as shown in Table 2; however, due to uneven exports from different buses, voltage unbalance is also relatively higher in this case.

5.3.3. Case 3: Optimal placement of EVCS with no storage

In this scenario, stochastic EV demand is integrated with EVCS at the selected strong buses 19, 6, and 31 determined using the proposed hybrid strength-based approach. No storage is considered in the customer premises for this case. The optimal placement of EVCS in these selected buses in three sections provides enhanced hosting capabilities with a flexibility index of up to 45.24%. Due to adding EVCS at selected locations, localized loading and under-voltage issues are increased in this case, as mentioned in Table 2.

5.3.4. Case 4: Optimal placement of EVCS and storage

In this case, the optimal allocation of EVCS and storage is designed using a centralized approach. Using the proposed method, the strong buses (19, 6, 31) are allocated for installing EVCS, and the weak buses (25, 30, 18) are for supporting the network through storage systems. The export capacities for each section at these weak buses are illustrated in Fig. 11. These export capabilities are derived from the storage systems associated with customers at the respective buses and the participation of V2G customers. Although this placement of EVCS and storage enhanced hosting capabilities through stabilizing voltage during peak hours, losses and localized line loading are increased, as in Table 2. The flexibility index has been enhanced to 78.25%, although the transformer will require an upgrade to accommodate the additional

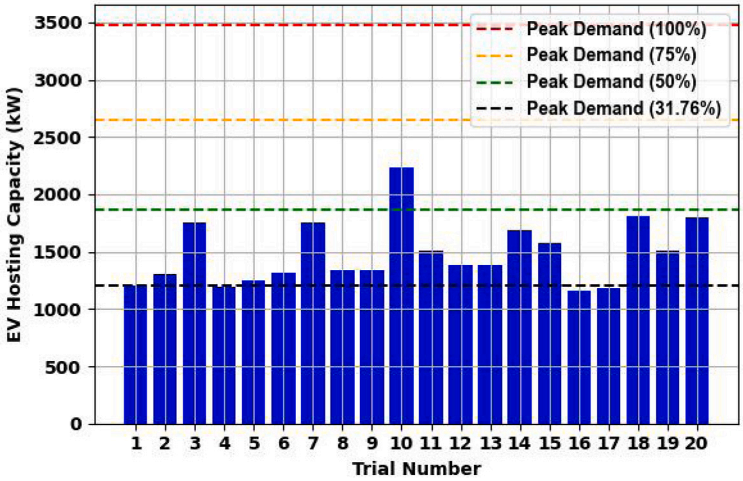

Fig. 14. Peak hour EV hosting capabilities after random placement of charging stations at three sections.

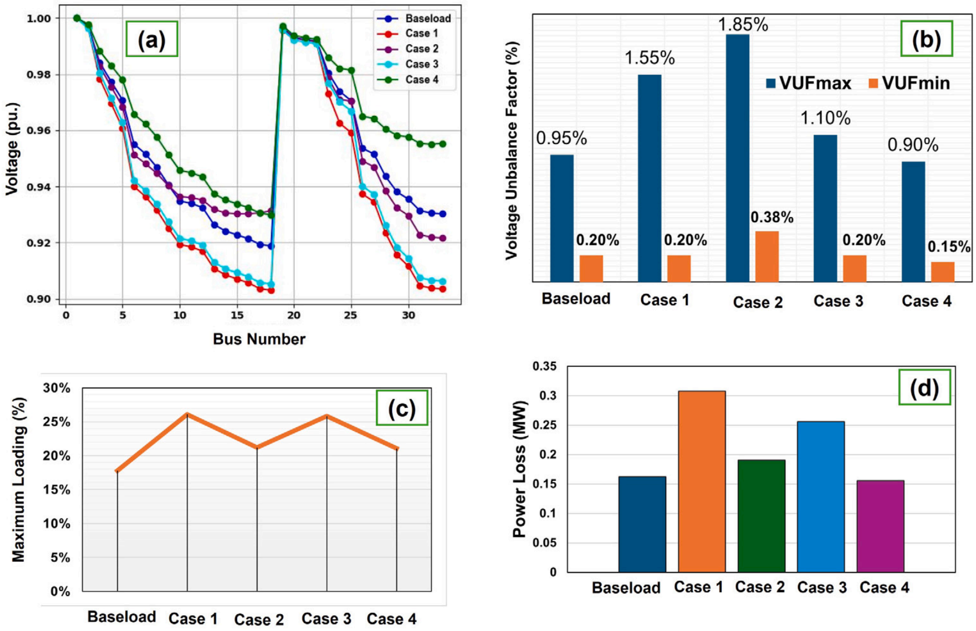

Fig. 15. Impact of different cases in voltage fluctuations, voltage unbalances, loading, and power losses.

Table 2
Comparison of flexibility indices and dominant indices for four cases.

Case	Flexibility index	Dominant constraints
Case 1: Random EVCS	34.78%	UV, VUF, P.loss
Case 2: Random (EVCS + Storage)	58.96%	UV, VUF
Case 3: Optimal EVCS	45.24%	UV, LL, P.loss
Case 4: Optimal (EVCS + Storage)	78.25%	UV, LL

Note: UV (Undervoltage), LL (Localized Loading), P.loss (Power Loss), and VUF (Voltage Unbalance Factor).

imports and exports from DERs. In this scenario, both hosting capacity limits and economic benefits improved while ensuring grid stability.

5.4. Discussion

This subsection discusses the EV hosting capabilities for four scenarios, focusing on the flexibility index and network constraints. Distributed EV hosting capabilities are estimated in this work based on the probability distribution in Fig. 4, using a time-series probabilistic analysis for 100 iterations. Fig. 12 shows the maximum, average, and minimum EV hosting capabilities during a typical day for the given load profile as Fig. 6. It is demonstrated that during peak load periods, the EV hosting capacity is decreased up to 1850 kW by Undervoltage issues with a flexibility index of 39.62%. This flexibility index is greater than the case of random placement due to a reduction in localized loading and under voltages. Also, distributed charging utilizes the network infrastructure more broadly, leveraging the entire distribution system rather than concentrating on a few locations, which improves overall hosting capacity. However, considering the optimal placement of EVCS, the hosting capacity is relatively low.

Fig. 15 provides a comparative analysis of four cases (Case 1 to Case 4) alongside a baseline scenario (Baseload) in terms of voltage profile, voltage unbalance factor, maximum loading, and power loss. In Subplot (a), the voltage profile shows that the baseload scenario maintains the highest voltage levels, while Case 1 suffers the greatest voltage drop across the buses, indicating higher grid stress. Case 4 performs better with a more stable voltage profile and less power losses, suggesting optimal conditions for EVCS integration. Subplot (b) reveals the voltage

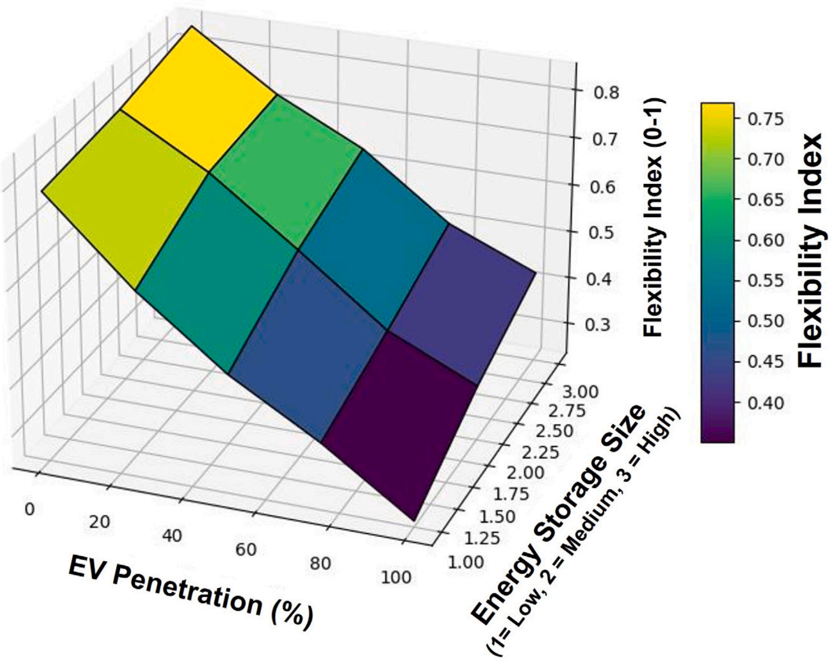

Fig. 16. Impact of EV penetration rates and storage size in flexibility provisions.

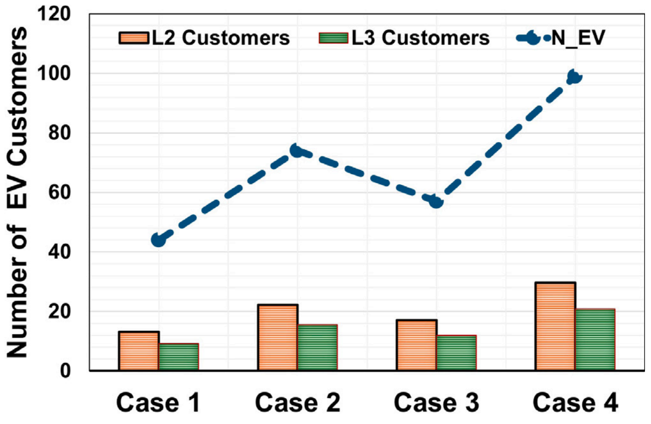

Fig. 17. Hosting capabilities of EV customers in different cases during peak hours.

unbalance factors, where Case 1 exhibits the highest VUF$_{max}$ of 1.55%, indicating significant voltage imbalance, while Case 4 shows the lowest imbalance with VUF$_{max}$ of 0.90%, reflecting better load balancing. In Subplot (c), maximum loading in the feederhead is observed for different cases, which is similar in all Cases. For case 3, during the optimal placement of EVCS, the localized loading and undervoltage issues increased. Finally, subplot (d) compares power losses, with Case 1 experiencing the highest loss, indicating inefficiencies, whereas Case 4 shows the least power loss, making it the most efficient installation for enhancing hosting capabilities. Overall, Case 4 demonstrates the best performance across all metrics, while Case 1 reflects the most stressed and inefficient grid conditions.

The surface plot in Fig. 16 shows how EV penetration (%) and size of the energy storage systems at optimal locations affect the flexibility index on a scale between 0 to 1. As EV penetration increases, the flexibility index decreases, indicating reduced hosting capability. However, increasing storage size mitigates this impact, enhancing flexibility at each penetration level. The use of these energy storage systems in varying proportions has a direct impact on network performance and necessitates network upgrades.

Fig. 17 shows hosting capabilities regarding the number of EV customers in the distribution feeder, contemplating Level 2 and Level 3 customers. It is seen that compared to random charging stations, optimal placement can host more EV customers. When integrated storage in addition to optimal placement of charging facilities, the hosting capabilities increased significantly up to 78.25%, as displayed in Case 4. Increasing storage exports significantly increases flexibility within the distribution networks, as demonstrated in Case 4. The results show that combining optimal EVCS placement with storage systems can boost hosting capacity by up to 22.5% compared to the standalone optimal placement method. These customer exports stabilized voltage limits; however, power losses and thermal loading are increased.

Currently, fixed export limits and dynamic export limits are employed by the network operators. However, in this case study, the discharging rates are considered 7.4 kW and 11 kW with a probability of 0.3 and 0.7, respectively. Based on the fixed and dynamic export limits, the export limits might vary and act differently on the impacts of networks for specific penetration. To limit power losses and thermal loading caused by customer exports, upgrading network infrastructure and stakeholder-focused export opportunities are needed to enhance further hosting capacity.

During peak hours, the average maximum EV load demand reaches 1536 kW, 1039 kW, and 907 kW for 100% penetration, as shown in Fig. 9. Although some studies suggest that 100% of EVs might plug in daily, optimal planning shows this scenario is often unrealistic due to varying plug-in intervals. Previous research has shown that customer plugin uncertainties lead to different plug-in intervals for customer groups, with only 31.76% of EVs recharging daily [18,69]. To improve accessibility for the customers, in this research, 10%, additional transient customers are also included. Considering higher penetration without accounting for plugin diversities unnecessarily increases the demand and corresponding investment for installing charging facilities. Therefore, an EVCS design based on stochastic regional custom er plugin patterns and market trends are crucial to optimizing resource allocation and infrastructure development.

5.4.1. *Comparison with existing studies*

Several studies addressed the enhancement of EV hosting capacity in distribution networks through various strategies. In [70], a synergistic demand response and Volt/VAR control method improved distributed generation and EV hosting capacities by 49.2% and 61.2%, respectively, in the IEEE-33 network. Another study [27] reported a 31.27% improvement in EV hosting during peak load periods through optimal feeder reconfiguration. In [71], a coordinated charging strategy in the IEEE-123 node test feeder achieved a 43.2% increase in EV hosting capacity compared to uncontrolled charging. These results mostly correspond to the static assumption or mixed-regional statistics for EVs, and consider voltage limits as the dominant constraint.

Additionally, in [22], Monte Carlo simulation was used to estimate EV hosting capacity under a random charging scenario, revealing a limitation of around 40% due to transformer and line constraints. The study suggested that incorporating On-Load Tap Changer regulation could enhance hosting capacity up to 80%. However, this analysis was based on static EV battery capacity and did not account for regional variations in EV specifications or plug-in behaviors. In contrast, the proposed planning-based framework employs stochastic simulation with realistic regional variations in EV characteristics and plug-in demographics to the IEEE-33 bus system. By optimally allocating EVCSs and ESSs, this work demonstrates hosting capacity enhancement up to 78.25% without costly adjustments and network reinforcement, offering a more context-aware and scalable enhancement strategy.

These comparisons validate the significance of including strength-based allocation and regional variations in EV hosting capacity studies. The proposed approach aligns with the early adoption criteria and in some cases outperforms existing strategies by incorporating realistic behavioral and locational diversities, thereby demonstrating a more holistic and practical framework for EV hosting capacity enhancement.

5.4.2. Transferability and applicability of the proposed model to other regional contexts

Although this study is developed using Australian data, such as EV adoption patterns, storage penetration, charging preferences, and vehicle specifications, the proposed framework is designed to be adaptable and scalable for use in other regional contexts. The core elements of the model, including the stochastic simulation of EV demand, the strength-based optimal placement algorithm, and the integration of local energy storage systems, are methodologically generalizable. These components rely on region-specific DER specifications and plugin variations, which can be updated to reflect local conditions in other countries or cities. To ensure transferability to different regions, local stakeholders or researchers would need to update several region-specific inputs, including EV fleet characteristics (such as battery size, driving range, and charging behavior), demographic customer distributions, penetration levels, network topology, and ratings. These parameters can be derived from national energy statistics, local utility data, or studies on mobility behavior. Moreover, the modularity of the model allows for integration of country-specific policies, export limit schemes, and customer behavior models, enabling broader deployment. For instance, in countries with higher V2G compatibility or greater rooftop solar penetration, the model can incorporate those characteristics to better assess local hosting capacity enhancement strategies. Therefore, while the current case study is based on Australian conditions, the underlying approach holds promise for use in global urban, suburban, or rural distribution networks, provided that inputs are appropriately localized.

6. Conclusion

This study presents a comprehensive and regionally contextualized framework for enhancing EV hosting capacity in distribution networks through a strength-based allocation of charging stations and energy storage systems. Unlike traditional approaches that overlook regional plugin behaviors and rely on fixed values, this work integrates stochastic EV demand modeling with localized demographic and technical parameters using Monte Carlo simulations, thereby improving the realism and accuracy of hosting capacity estimations. The proposed methodology was implemented on the IEEE 33-bus system, representing a typical suburban distribution network in Australia. By integrating storage systems with PV generation and V2G services, this framework supports not only increased EV penetration but also ensures grid stability, which can be applied to diverse regional contexts. By dividing the network into three sections and accounting for an additional 10% of transient customers, this approach helps improve customer convenience. The strength of individual buses is evaluated using voltage quality and load contribution indices, which identify optimal locations for EVCSs and ESSs. Four case studies, ranging from random to optimal placement, with and without storage, were examined in this paper. The major findings are as follows:

- Random EVCS placement without storage achieved the lowest flexibility index (34.78%) due to undervoltages and localized loading.
- Incorporating distributed storage improved hosting capacity to 58.96%, albeit with increased voltage unbalance.
- Optimal EVCS placement alone raised flexibility to 45.24%, with benefits in reduced power loss.
- The combined optimal placement of EVCS and ESS yielded the highest flexibility index (78.25%), with improved voltage stability and reduced power loss, proving the effectiveness of the planning strategy.

Although this work divides the distribution network into three segments to enhance customer convenience, integrating travel distance as an objective function can provide more realistic modeling. The peak-hour load multiplier is approximately 0.75 but could exceed 1, underscoring the need for cautious EVCS planning in future studies. In addition, a coordinated approach for installing EVCS and storage at selected locations can enhance EV hosting capabilities; however, customer-level exports may still be constrained by the fixed or dynamic export limits imposed by the network, which needs to be considered in future studies. While the proposed optimal allocation approach improves hosting capacity, real-world applications may face challenges due to limited data and region-specific variability. The effectiveness of storage and V2G systems depends on uncertain customer behavior and adoption rates, with only a few EV models currently V2G-compatible in Australia. In this paper, only the top 20 EVs that sold the most were considered, which can be extended to available and future EV models in the regional markets. Future studies should consider these uncertainties and address investment and regulatory needs for coordinated, multi-technology integration in a scalable planning framework within urban, suburban, and remote settings. Although this study focused on standard test feeders, future work should target renewable-rich distribution feeders with real cases to validate and analyze the performance of the proposed method. Investigating temporal and spatial correlations of EVs and storage will enhance realism. Additionally, integrating uncertainty-aware hosting capacity into real-time grid operations and scaling the approach for larger networks are critical next steps.

CRediT authorship contribution statement

Ashish Kumar Karmaker: Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization, Software. **Yang Du:** Writing – review & editing, Visualization. **Sam Behrens:** Writing – review & editing, Supervision, Project administration. **Hemanshu Pota:** Writing – review & editing, Supervision, Project administration.

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.

Acknowledgments

All authors have read and approved the final manuscript.

Data availability

Data will be made available on request.

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