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A holistic review of electric vehicle charging impacts on power distribution networks: Technical challenges, smart mitigation strategies and future directions

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HIGHLIGHTS

- EVs raise voltage instability, thermal stress, and peak demand in distribution networks.
- Review covers smart charging, EV-DG coordination, and network management mitigation.
- Machine learning aids in EV load prediction and smart charging optimization.
- Hosting capacity varies widely; seasonal and behavioral factors are underexplored.
- Future work calls for real-time co-simulation, hybrid modeling, and techno-economic studies.

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ABSTRACT

Electric Vehicles (EVs) have emerged as a pivotal solution in the global transition toward sustainable transportation, offering significant reductions in greenhouse gas emissions and dependence on fossil fuels. The growing adoption of EVs is anticipated to significantly influence electrical power distribution networks. As EV adoption accelerates worldwide, their integration into existing electrical distribution networks poses considerable challenges, particularly concerning load demand, voltage stability. Recent research has increasingly focused on understanding and mitigating these impacts, through a wide array of analytical, simulation-based, and data-driven methods both with and without the implementation of network management strategies. However, a comprehensive, integrated synthesis of these studies linking technical findings with mitigation strategies and practical implications is still limited. Additionally, there is a lack of a thorough review consolidating the existing research on this subject, which is essential for understanding the scope of prior studies. Motivated by this gap, this review paper provides a critical and consolidated examination of the current literature on the impacts of EV on distribution networks. The paper's objective is to assess the comprehensive effects of EV integration and evaluate mitigation strategies across three core domains: network management, EV and Distributed generation (DG) coordination, and regulated charging solutions. The paper also introduces the role of artificial intelligence in enabling predictive, adaptive, and scalable solutions. It highlights key methodologies, data sources, modeling approaches, and the efficacy of various solutions while identifying prevailing research gaps and future directions, including real-time co-simulation, techno-economic assessments, and hybrid planning frameworks. Key outcomes of this study include a unified framework for understanding EV interactions with the grid and distribution network, a comparative analysis of mitigation approaches, and a set of recommendations for advancing research and deployment strategies. These findings aim to inform stakeholders about the latest advancements and support decision-making. The findings are particularly beneficial for utility providers, network planners, policymakers,

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charging infrastructure developers, and researchers seeking to develop robust, data-informed strategies for managing EV impacts and guide them in addressing unresolved challenges.

1. Introduction

The primary source of air pollution is the traditional transportation system that uses internal combustion engines (ICEs) [1]. Electric vehicles (EVs) have gained wider adoption in recent years to reduce air pollution and oil dependency in the transportation sector. The transportation industry is responsible for 24 % [2] of worldwide CO_2 emissions, which contribute to global warming. This has prompted governments to phase out new ICEs vehicles over the next decade. The world's already overburdened power networks will face a serious challenge as a result of the anticipated sharp rise in power demand brought on by this paradigm transition in transportation fuel sources to electromobility. By the end of this decade, EVs are predicted to account for 50 % of new car sales worldwide [3]. This projected growth has spurred efforts to assess EV impacts on the electrical grid and explore ways to accelerate adoption with minimal infrastructure changes.

Several studies suggest that the rise of EV and DG will fundamentally reshape power distribution network design and operation, creating new opportunities [3]. By 2030, global network demand may rise by 5 % to 10 % at a 30 % EV penetration rate, according to a report by the International Energy Agency (IEA) [4]. This increase would be especially noticeable in nations with strong EV adoption rates, including Norway and the Netherlands. According to a different assessment from the National Renewable Energy Laboratory (NREL) [5], by 2050, the network demand in the US would grow by roughly 0.35 % for every 1 % increase in EV penetration. The majority of electrical networks, in their existing configuration, can accommodate EVs in a 10 %–60 % penetration range under the current unregulated EV charging regime, according to research publications that are primarily focused on the impact of EVs and hosting capacity. Many of this research used a model-based approach, using a particular time-varying EV demand profile and a real-world or IEEE bus network model [6]. Although the influence is accurately captured by model-based approaches, their applicability is restricted to networks with similar features. Stochastic approaches, which account for EV charging uncertainty, offer the capacity to generalize these methods [7]. Research shows that with the right mitigation solutions, smart or regulated EV charging, which is claimed to be the most successful approach, network hosting capacity limitations can be removed and extended by up to 100 % [8]. Active EV and DG management comes next [9], with network orchestration being the most expensive option.

Due to EVs potential impact on energy distribution, load management, and grid stability, EV integration has garnered significant research interest. The increasing trend in scholarly papers on EV integration from 2000 to 2025 is depicted in Fig. 1, suggesting that the technological difficulties of widespread EV adoption are receiving more attention from academia and business. This research growth reflects increasing concern over EV charging's effects on peak load demand, grid voltage stability, distribution network hosting and thermal capacity which are the key determinants of network reliability and planning. Therefore, it has become necessary to attract attention of all EV stakeholders to address the issues of EV charging effect different factors of distribution network specially load demand which has adverse impact on distribution networks voltage stability, thermal capacity and hosting capacity. These concerns of EV charging on distribution network stability are the main motivation behind this review study to give all the stakeholders a summary of the effect modern distribution network is facing, and the measures should be taken to get rid of these issues. While it is also acknowledged that EV charging can also introduce power quality issues such as harmonics, flicker, and phase imbalance, these aspects have been comprehensively addressed in previous specialized review studies [10–12].

To systematically understand the broad spectrum of research addressing the impact of EV charging on electrical distribution networks, Table 1–4 presents a summary of key studies in the domain of network load management, voltage, hosting capacity and thermal capacity respectively. By examining these studies' limitations and focal points, insights into the prevailing research trends and gaps are gained, setting the stage for a deeper analysis of the impacts and mitigation strategies elaborated in subsequent sections.

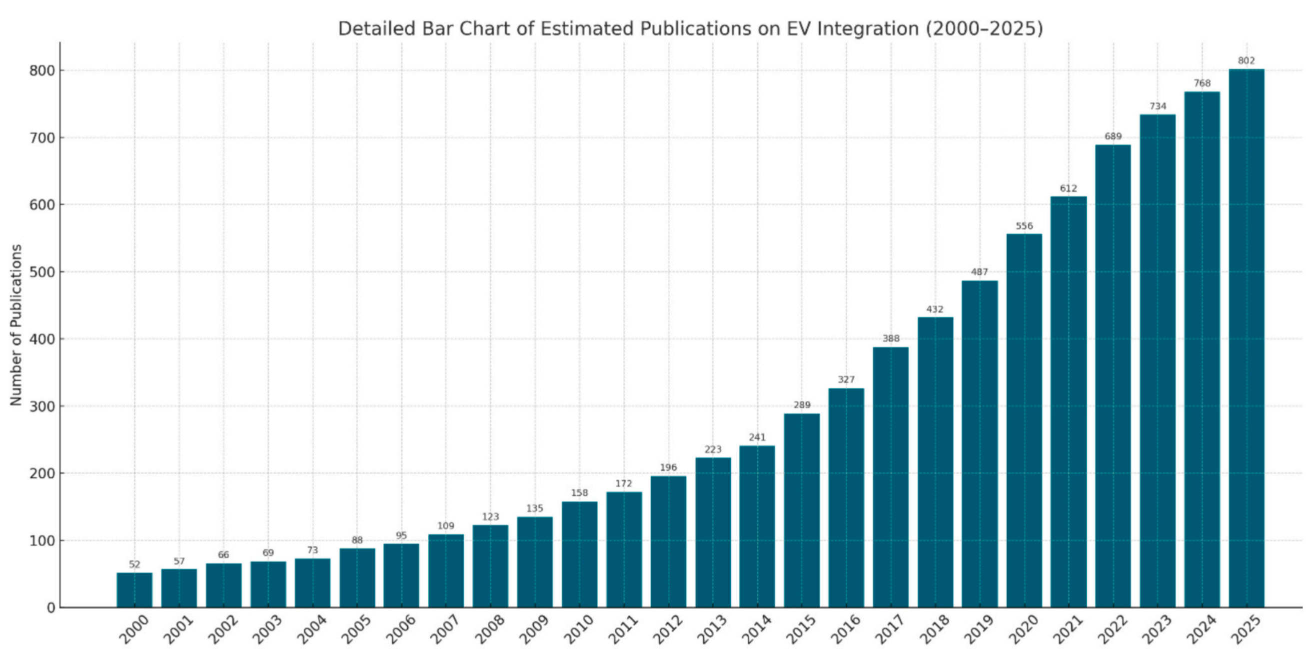

Fig. 1. Annual growth in research publications related to EV integration and grid impact studies.

Table 1
Summary of the existing literature on EVs charging impact on network load demand.

Refs.	Focused Area	Limitations
[13]	Impact of residential EV charging on peak load demand using real-world charging data in California	- Does not address voltage impact - Small sample size - 90 % of charging events under 9.1 kWh
[14]	Uncontrolled EV charging impact on load profile and peak demand using Monte Carlo simulation (South China)	- Only load increase studied - Does not assess voltage or thermal aspects - Simulation results may not reflect real-world behavior
[15]	Impact of 40 % EV penetration on load demand peaks using probabilistic modeling	- Limited to simulation context - Does not explore control methods or mitigation
[16]	Impact of EV's charging behavior on peak electricity demand and the lifespan of residential electricity network components, particularly distribution transformers	- All EV charging happens at residences - Only basic delayed-charging algorithms were studied
[17]	Investigates the impacts of fluctuating and random fast-charging EV loads on power grids	- Did not consider the impact of EV's charging on thermal and hosting capacity
[18]	Strategic grid integration of EVs in India using DSM, pricing models, renewable energy, and smart grid technologies	- Only focused on India's load modeling to accommodate the fluctuating EV charging
[19]	Reviews the impacts, contributions, and challenges of EV integration into smart grids	- Did not consider the impact of EV's charging on load demand, voltage stability, thermal and hosting capacity
[20]	Review on planning, optimization and grid integration strategies for fast-charging EV stations, emphasizing on renewable energy and grid interaction	- Only focused on losses and voltage stability, neglecting load demand, thermal and hosting capacity
[21]	Impact of uncontrolled EV charging on utility grid stability and their mitigation strategies	- Mitigation strategies do not consider artificial intelligence based methods
[22]	Reviews the impact of EV integration on power systems reliability	- Did not consider the impact of EV's charging on load demand, voltage stability, thermal and hosting capacity

Based on Table 1–4, the reviewed studies reveal key shortcomings that restrict their practicality. The majority depend on artificial or simplified network models (like IEEE feeders), which diminishes their external validity. Ignoring comprehensive evaluations considering thermal capacity and hosting restrictions, they frequently concentrate on discrete effect criteria like peak load or voltage. Several disregard user behavior, temporal dynamics, and spatial variety; they also presume static, uncoordinated charging and fail to consider smart charging or V2G mitigation techniques. Inconsistent EV penetration and hosting capacity definitions are the result of studies' habitual use of tiny or limited datasets, absence of seasonal or ambient variability analysis, and non-standardized methodology. Studies such as [13,14,26,36] produce conclusions that are not scalable because they rely on tiny datasets or limited simulation circumstances. Furthermore, as can be shown in [37,39], few studies examine seasonal, ambient, or behavioral variability, and others, such as [32,40,46], evaluate only one constraint (such as voltage or temperature stress), leaving out multidimensional evaluations. Overall, literature lacks practical, cohesive, and scalable strategies for efficient EV-grid integration.

There are also few review papers available which are enlisted in

Table 2
Summary of the existing literature on EVs charging impact on network voltage.

Refs.	Focused Area	Limitations
[23]	Voltage and thermal capacity impact of coordinated vs. uncoordinated EV charging on test networks (Egypt)	- Based on synthetic models (RBTS2, ShC-D8) - Limited to studied network types - Requires more realistic data for generalization
[24]	Impact of EV load on thermal limits and voltage drops in a Malaysian 11 kV distribution model	- Assumes heat loading is the primary constraint - Network-specific findings - No smart charging or vehicle to grid (V2G) analyzed
[25]	Voltage deviations from EV adoption	- Single test network studied - No mitigation or adaptive strategies examined
[26]	Voltage violation analysis during nighttime peak from EV charging	- Assumes uncontrolled charging - Ignores effects of smart coordination - No DG integration considered
[27]	Voltage limit impact of EV chargers on radial feeders	- Specific to Level 2 chargers - No study on adaptive or smart response - Context-specific constraints
[28]	Voltage sensitivity in suburban LV digital twin network due to EV load location	- Location-dependent results - Limited scalability to other feeder topologies
[29]	Voltage imbalance from single-phase home EV chargers on LV model	- Only considers phase imbalance - Limited voltage mitigation strategies tested
[30]	Transformer loading and voltage deviation in rural LV network under increased EV load	- Synthetic environment - No control/management schemes considered
[31]	Time-based voltage violations in residential vs. industrial networks	- Event timings not uniform - Need for broader temporal simulation
[32]	Voltage changes and imbalance in bus networks at 50 % EV adoption	- No dynamic management strategies - Limited to voltage profile only
[33]	Real-case EV impact with solar photovoltaic (PV) presence on LV/MV grids	- PV presence may offset general findings - Not adverse in this case, limiting relevance elsewhere
[19]	Reviews the impacts, contributions, and challenges of EV integration into smart grids	- Did not consider the impact of EV's charging on load demand, voltage stability, thermal and hosting capacity
[34]	Reviews the impact of fast EV charging stations on power quality and grid stability.	- Did not consider the impact of EV's charging on load demand, thermal and hosting capacity
[35]	Reviews strategies adopted for EVs' fast-charging station operation and their impact on power grids	- Only impact of EVs on load and voltage demand is considered

Table 3
Summary of the existing literature on EVs charging impact on network hosting capacity.

Refs.	Focused Area	Limitations
[36]	Effect of fast-charger penetration on LV distribution network hosting capacity	- High emphasis on fast chargers - Generalization limited by network structure - Coordination not considered
[37]	Seasonal effects on hosting capacity and voltage violations in MV feeder with 15 charging profiles	- High variability across seasons - Uncertainty in capacity planning - Generalizability limited
[38]	Feeder and node-level hosting capacity assessment using hybrid LV model	- Capacity bottleneck varies per asset - May not generalize beyond single networks
[39]	Urban hosting capacity sensitivity to user charging behavior using LV urban model	- High dependence on behavior patterns - Voltage profiles not studied
[40]	Voltage-based hosting capacity assessment	- Considers only voltage constraints - Ignores thermal and temporal dynamics
[41]	Influence of ambient temperature on LV/MV hosting capacity	- Environment-specific results - Needs seasonal calibration
[7]	Multi-factor hosting capacity evaluation based on location, SOC, arrival time, and charger type	- High complexity - Difficult to implement in real-time systems
[42]	Focuses on the effects of integrating EVs on the distributed networks hosting capacity	- Did not the enhancement method of hosting capacity using artificial intelligence
[18]	Reviews on EV hosting capacity evaluation and improvement methods	- Improvement methods for hosting capacity using artificial intelligence are not discussed
[20]	Application of hosting capacity on PV and EV	- Impact of EV on hosting capacity is not presented - Improvement methods for hosting capacity using artificial intelligence are not discussed
[43]	Impact of EV hosting capacity on distribution network and its mitigation strategies	- Improvement methods for hosting capacity using artificial intelligence are not discussed

Table 1–4 summarize different impact analysis methods of EVs on power distribution network. Most of the reviews are based on EVs impact on network load demand and voltage stability. Very few papers reviewed the methods that incorporate EVs impact on thermal and hosting capacity of distribution network. Furthermore, the existing reviews are not comprehensive enough to provide actual insight into the issues of EVs integration on distribution network. The most important part missing in the existing reviews is the incorporation of mitigation strategies to overcome EVs impact on distribution network. Finally, nowadays AI is widely applied to enhance power grids stability by mitigating the impact of EVs through accurate forecasting and prediction of load demand. AI based mitigation strategies of EVs impact on distribution networks are also not discussed in the existing reviews.

Although the current review articles and their synthesized findings provide valuable insights, a thorough review of the impact of EVs on distribution networks, encompassing data types, methodologies, trends, quantitative outcomes, associated mitigation strategies, and immediate future research directions and requirements, has not yet been comprehensively addressed. The purpose of this study is to discuss these drawbacks and particulars. This paper's main contributions are:

- A systematic and technically detailed review of EV's impacts on power distribution networks net load, voltage stability, thermal capacity, and hosting capacity is presented all at once—areas that were frequently discussed separately in previous works—to present a thorough and integrated examination of the effects of EV charging on distribution networks.
- Under various EV penetration scenarios, quantitative parameters like as energy requirement, thermal loading and the Voltage Deviation Index (VDI) are analyzed.
- Unlike earlier research, it evaluates a variety of mitigation measures in network management, EV/DG coordination, and controlled charging, and it carefully classifies existing research with an emphasis on methodologies, data kinds, and constraints.
- A comparative analysis of mitigating techniques is presented, encompassing EV–DG coordination methods, smart/controlled charging, and network management.
- AI techniques are reviewed for their role in predictive load management, voltage-aware scheduling, and EV behavioral modeling.
- Identifies persistent research gaps, including insufficient use of large-scale real-world EV charging data, lack of dynamic co-simulation environments, and minimal consideration of seasonal or ambient variability in hosting capacity assessments.
- Proposes future research directions, including the development of real-time Python–PowerFactory co-simulation framework, hybrid modeling architectures and techno-economic optimization of mitigation strategies.

The rest of the paper is structured as: Section 2 presented the overall methodology adopted to conduct the review. Section 3 includes the categorization of the articles on EVs impact analysis into 4 different

Table 4
Summary of the existing literature on EVs charging impact on network thermal capacity.

Refs.	Focused Area	Limitations
[44]	Thermal and voltage stress at high EV uptake (up to 100 %) using Monte Carlo simulation	- High stress scenario - Assumes no mitigation - Weather and temperature effects not deeply modeled
[45]	Transformer thermal aging due to EV charging stress (LV side)	- Focuses only on thermal lifespan - Broader network impacts unaddressed
[46]	Impact of EV load on transformer service life using Simulink model	- Applies only to LV/MV transformers - Broader grid impacts unstudied
[47]	Focuses on the EVs thermal management strategies for Li-ion batteries	- Limited to EVs thermal management methods
[48]	Reviews on challenges related to EVs thermal management system design	- Only discussed the challenges associated with EVs thermal management system design
[43]	Impact of EV on distribution network parameters is discussed	- Improvement methods for thermal capacity using artificial intelligence are not discussed

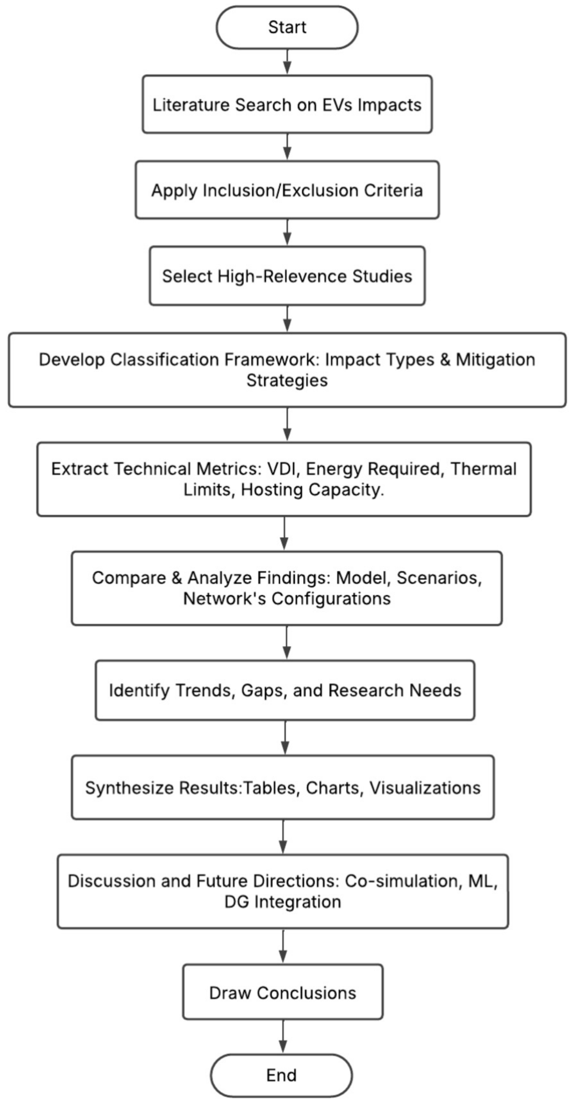

Fig. 2. Methodological flowchart for conducting the systematic review.

categories and presents their exact impact on distribution network. Section 4 presented the mitigation strategies of EVs impact on distribution network both conventional and artificial intelligence based approaches. Section 5 incorporates shortcomings of current research and its future direction. Finally, conclusion is drawn highlighting the major findings of the study.

2. Methodology

The methodology adopted in this review follows a structured and systematic approach to ensure comprehensive coverage, critical analysis, and meaningful synthesis of relevant literature concerning the impacts of EV charging on electrical distribution networks and the associated mitigation strategies, as illustrated in Fig. 2.

Table 5
Findings of the literature based on EVs impact on network load demand.

Refs.	Data source	Network/Model	Voltage	Key findings
[13]	Real	Charging load model	N/A	A 6 % rise in demand was the outcome of using a limited sample size, with 90 % of charging events falling below 9.1 kWh.
[14]	Hybrid	Monte -Carlo simulation	N/A	Network loading rises as a result of uncontrolled charging, usually during peak hours.
[15]	Hybrid	Monte-Carlo simulation	LV	An 82 % rise in peak demand occurred with 40 % EV adoption.
[52]	Real	LV distribution network model	LV	Uncontrolled EV charging increases peak loads, while simple rule-based charging limits can mitigate this without affecting EV use.
[16]	Synthetic	Agent-based network Model	LV	Delayed EV charging keeps transformer overloads low, with exceedance under 20 % at 40 % EV uptake
[53]	Real	LV distribution network	LV	In California, 50 % of the feeders by 2035 will be overloaded, and by 2045 this percentage will reach to 67 % by EV charging demand.
[54]	Real	LV distribution network	LV	Peak load reduced from 4.5 to 2.6 MW and minimum load increased from 0.5 to 1.2 MW

Abbreviations: LV - Low Voltage; MV - Medium Voltage.

The methodology adopted in this review follows a structured, technically focused process, as illustrated in Fig. 2. A focused literature search on the implications of EV charging on electrical distribution networks was conducted at the start of the review, with an emphasis on hosting capacity, net load effects, thermal restrictions, and voltage stability. Particular inclusion and exclusion criteria were used to find works that use deterministic, stochastic, or hybrid methodologies to give quantitative or model-based analysis.

A classification framework was developed to group studies by impact types and proposed solutions. Important technical parameters, including as the VDI, peak demand shifts, thermal stress levels on transformers and feeders, and EV hosting thresholds under different charging situations, were taken from each study. These parameters were compared with studies that used IEEE test feeds, simulated load profiles, or real-world data.

The absence of extensive data on EV charging, the underutilization of artificial intelligence for predictive load management, and the varied definitions of hosting capacity were among the trends, constraints, and research gaps that were subsequently found. To aid in cross-study analysis, the retrieved results were combined into comparative tables and figures.

The methodology concludes with a critical discussion of technical insights and future research directions, such as the creation of frameworks for real-time Python–PowerFactory co-simulation, the incorporation of scheduling techniques driven by artificial intelligence, and

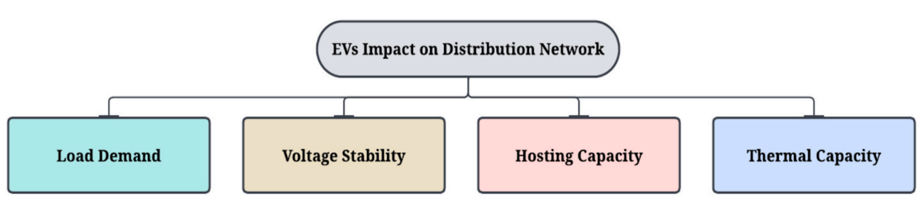

Fig. 3. The primary factors of EVs effects on distribution networks.

Table 6
Findings of the literature based on EVs impact on network voltage.

Refs.	Data source	Network/Model	Voltage	Key findings
[23]	Hybrid	RBTS-bus-2/ShC-D8 test systems	LV/MV	Uncoordinated EV charging caused a reduction in system voltage and overloading of network resources. Coordinated charging considerably mitigated these impacts.
[24]	Synthetic	11 kV distribution network model	MV	Under the majority of EV charging scenarios in Malaysia, the primary limiting issue is the heat loading of network assets.
[25]	Synthetic	IEEE-13 node test feeder	LV/MV	Voltage violations rise as EV adoption rises.
[26]	Synthetic	RBTS-bus 5	MV/ HV	Uncontrolled charging led to undervoltage.
[27]	Synthetic	IEEE-33 bus Radial distribution feeder	MV	Level 2 charging system adoption had a major effect on the network's capacity to maintain voltage within regulatory bounds.
[28]	Hybrid	Digital twin LV Sub-urban network	LV	Voltage effects are mostly determined by the feeder's location.
[29]	Hybrid	LV distribution network model	LV	A substantial voltage imbalance was caused by the single-phase nature of the majority of domestic EV charging loads.
[30]	Synthetic	Typical LV grid	LV	The main effects of increased EV adoption were transformer overloading and voltage deviations along the feeders in the majority of the network.
[31]	Real	IEEE-33 bus Radial distribution feeder	LV	Residential networks and industrial networks experience voltage breaches at different times.
[32]	Real	IEEE-123 bus	LV/MV	Voltage changes and violations were caused by increased EV uptake, and a notable degree of voltage imbalance was noted at 50 % EV uptake.
[33]	Real	LV/MV distribution grid	LV/MV	The network impact of EVs is not adverse, and solar PV systems can further lessen it.
[55]	Synthetic	IEEE-33 bus Radial distribution feeder	MV	Grid voltage is maintained by using conservation voltage reduction and SVC by meeting load and EV demand
[56]	Synthetic	IEEE 69-bus and 85-bus systems	MV	EVs total number and their load characteristics effect distribution network stability compare to number of charging stations.
[57]	Hybrid	Modified IEEE 33-bus radial distribution network	MV	Coordinated EV charging–discharging with renewable energy sources reduces voltage unbalance factor and improves voltage reliability & power loss index
[35]	Synthetic	IEEE-33 bus Radial distribution feeder	MV	EVs can recharge up to 80 % within 20–30 min in fast charging stations, however simultaneously introduces voltage instability, and transformer stress in distribution networks
[58]	Synthetic	IEEE 33-bus distribution network	MV	With the increase in projected EV loads with time the severity of impact of EV on distribution network increases.

Abbreviations: LV - Low Voltage; MV - Medium Voltage.

hybrid approaches that combine economic analysis, optimization, and simulation. For assessing the effects of EV charging and the efficacy of both established and new mitigation techniques, this methodical approach offers a technically sound basis.

3. Review of EVs impact on distribution Network

This section reviews the main effects of EVs on distribution networks, different factors that have been documented in the literature to date, as described in Fig. 3. The key findings of the literature on the EVs impact on distribution network's load, voltage, hosting capacity and thermal capacity are summarized in Table 5–8 respectively.

As shown in Fig. 3, the research articles have determined that the main issues limiting the network's ability to host EVs are its voltage stability, network load demand, hosting and thermal capacity. In [49], researchers have assessed how EVs affect grid economics and stability, concentrating on issues related to controlled and non-stationary loads. Although the article concentrates on EV operation techniques and charging infrastructure development, it does not quantify the impact. Other review publications, such as references [50, 51], have examined case studies that have already been done that particularly address distribution network voltage and peak demand, as well as the effects of current charger arrangement on power quantity. They have also briefly discussed ways to mitigate the impact of EVs.

Representing the focus areas of research on EV impact factors in distribution networks, Fig. 4 shows that the majority (37.7 %) of studies concentrate on Load Demand, followed by Voltage Stability (26.4 %), Hosting Capacity (22.6 %), and Thermal Capacity (13.2 %). Load Demand receives the most attention because EVs introduce significant and often unpredictable increases in electricity consumption, potentially straining local transformers and distribution lines. As EV adoption grows rapidly, traditional electrical infrastructure faces challenges in handling this added load, especially during peak hours. Additionally, EV charging alters established load patterns, requiring utilities to rethink demand forecasting and system design. Effectively managing EV-related load demand is crucial, as it directly influences other factors such as voltage stability and thermal limits, and enables grid operators to avoid costly infrastructure upgrades through strategies like smart charging and demand response. Thus, understanding and managing load demand forms the foundation of most research into EV impacts on power distribution networks.

3.1. Load demand

System load demand is predicted to rise proportionately as EV penetration increases. When all residential EVs are charged using the actual charging pattern from EV trial data [67], Fig. 5 illustrates this load demand increase for a medium density metropolitan network with 1264 households [68].

Numerous studies have documented how EVs affect the demand for distribution networks. The influence on California's distribution network was assessed by the authors in ref. [13] using actual charging data from 64 distinct EV kinds. According to the analysis, peak demand rises by 6 %, from 4300 MW to 4600 MW, with a moderate 30 % EV penetration rate. For the South Chinese distribution network, a comparable modest demand growth is also documented in ref. [14], where a probabilistic model of EV charging profiles is created using actual EV charging data from numerous mixed fleets. According to the research shown in references [23, 24], EV penetration has increased demand proportionately. For example, in reference [23], the authors describe a one-on-one increase in load demand due to EVs. The demand increase is quantified using the RBTS2 standard test model. Using a digital duplicate of an existing distribution network in Egypt, these findings have been verified.

3.1.1. Required energy calculation

To ensure an EV remains fully charged for the next day's trips, the energy needed to replenish its reduced State of Charge (SOC) can be

Table 7
Findings of the literature based on EVs impact on network hosting capacity.

Refs.	Data source	Network/Model	Voltage	Key findings
[36]	Synthetic	Network model distribution network (LV side)	LV	Uncoordinated charging conditions caused by fast-powered chargers have a substantial influence on hosting capacity.
[37]	Hybrid	MV residential feeder	MV	EV adoption is greatly impacted by seasonal demand fluctuations, which also allow for a wide range of hosting capacity throughout the year.
[38]	Hybrid	LV feeder model	LV	At the feeder and node level, hosting capacity is severely limited, and it frequently changes by a single asset throughout a distribution network.
[39]	Synthetic	Urban LV grid model	LV	Charging behavior in urban environments has a significant impact on hosting capacity.
[40]	Synthetic	IEEE 123 test feeder	MV	Proposed a voltage-based method for figuring out distribution networks' EV hosting capacity.
[41]	Synthetic	Monte-Carlo simulation, IEEE-33 node	LV/MV	EV hosting capacity is greatly impacted by ambient temperature because of seasonal fluctuations in usage and the effects of weather on feeders' thermal constraints.
[7]	Synthetic	Mathematical	LV/MV	Using a multifaceted approach to hosting capacity, taking into account many elements like location, arrival time, and state of charge.
[59]	Synthetic	Garver network and the IEEE 24-bus system	LV	Demand response did not impact the total energy consumed by EVs throughout the day, but it did reshape the time of EV charging, creating more opportunities for integration during periods of high demand.
[60]	Real, Hybrid, Synthetic	Monte-Carlo simulation	LV	Nodal voltage violation or line or transformer overload is the dominant attribute for EV hosting capacity.
[61]	Synthetic	IEEE-33 bus and real-life 108-bus	LV/MV	Hosting Capacity with V2G capability is higher.
[62]	Synthetic	Spatio-temporal modeling	MV	EV hosting capacity is found slightly lower on weekdays compared to weekends
[63]	Hybrid	Spatio-temporal modeling	LV	EV hosting capacity increased with higher PV generation.
[16,64]	Hybrid	IEEE 33-bus and 69-bus distribution networks	LV	Overall hosting capacity of distribution network is improved through the integration of V2G
[23,55]	Synthetic	IEEE 33-bus	MV	EV penetration and SVC levels needed to maintain grid voltage within operational limits.

Abbreviations: LV - Low Voltage; MV - Medium Voltage.

determined based on its Vehicle Miles Traveled (VMT). Eq. 1 calculates that energy requirement, expressed as,

$$\text{Energy required for EV to be fully charged} = \left(\frac{\text{VMT}}{\text{Driving range (miles)}}\right) \times \text{EV capacity (kWh)} \quad (1)$$

Energy expectation from EV users is expressed using Eq. 2,

$$\mathrm{Soc}_{j,end} = \mathrm{Soc}_{j,start+} \int_{t=start}^{end} P^{i}_{EV,j}\,di = E_{exp,j} \quad (2)$$

To assess how well EV integration impacts the feeder at various penetration levels, the following metrics are considered:

$$\text{Voltage Deviation Index (VDI)} = \sqrt{\frac{\sum_{t=1}^{T}\left(V_t - V_{nominal}\right)^2}{T}} \quad (3)$$

$$\text{Power losses ratio} = \frac{\text{Total active Power Losses}}{\text{Total Active Power}} \quad (4)$$

$$\text{Percentage change in peaks} = \frac{\text{Difference in Peak Load}}{\text{Base Peak Load}} \quad (5)$$

Authors in [9], presented an example of daily demand profile combining household and EV power consumption over a 24-h period which is shown in Fig. 6. The blue bars indicate average power demand at each hour, and the black error bars reflect the variability or uncertainty in those values, possibly due to differences across households or days. The profile shows a gradual increase in demand from early morning, with relatively low consumption during the night and early

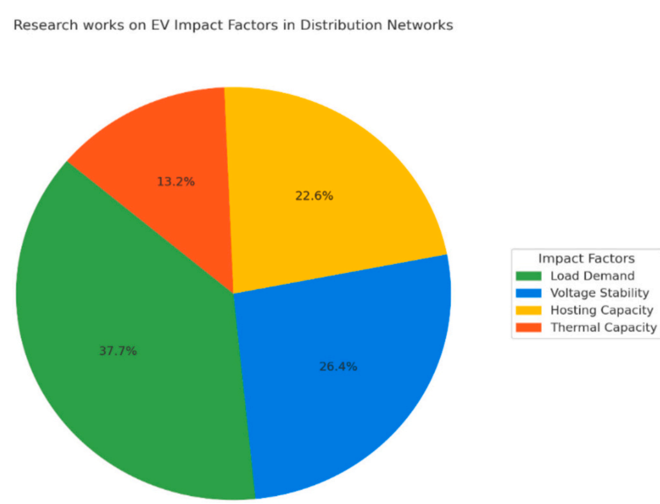

Fig. 4. Research works so far on EVs impact on different factors of distribution network since 2010.

Table 8
Findings of the literature based on EVs impact on network thermal capacity.

Refs.	Data source	Network/Model	Voltage	Key findings
[44]	Hybrid	Digital twin, Monte-Carlo simulation	LV	When EV penetration reaches 40 %, thermal restrictions are seen, and peak demand rises by 150 % at 100 % penetration rate.
[45]	Hybrid	Digital twin distribution network (LV side)	LV	Increased penetration rates cause transformers to age thermally more quickly.
[46]	Hybrid	Simulink model	LV/MV	A high EV adoption rate shortens the service life of transformers.
[65]	Real	LV feeder model	LV	Up to 50 % EV penetration levels has less impact on transformer functionality and above 50 % penetration transformer's loss of life index increases significantly.
[66]	Real	LV feeder model	LV	Different EV charging schemes and charging harmonics have significant impacts on transformer thermal capacity.

Abbreviations: LV - Low Voltage; MV - Medium Voltage.

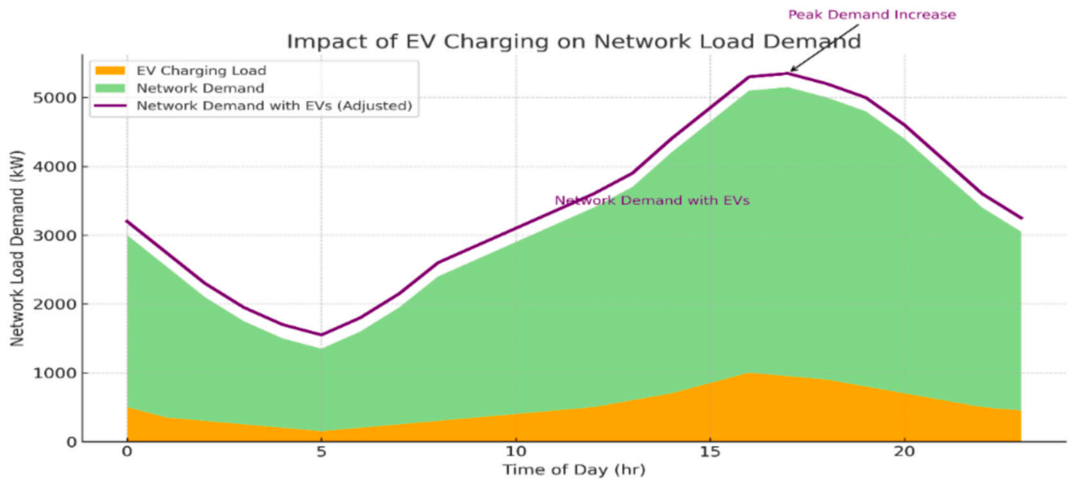

Fig. 5. Exemplary load demand profile for a medium density urban network comprising 1264 households [39,68] without EVs and with EVs charged using the charging profile from of EV trial [40,67].

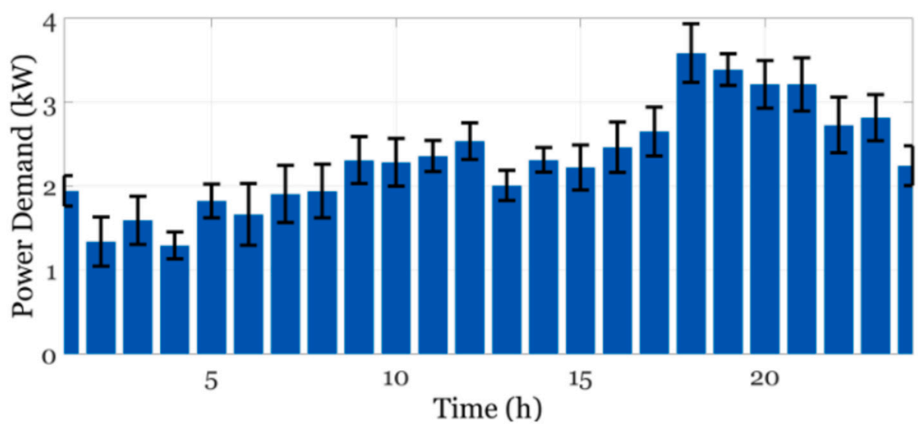

Fig. 6. Example demand profile (household and EV demand) [9].

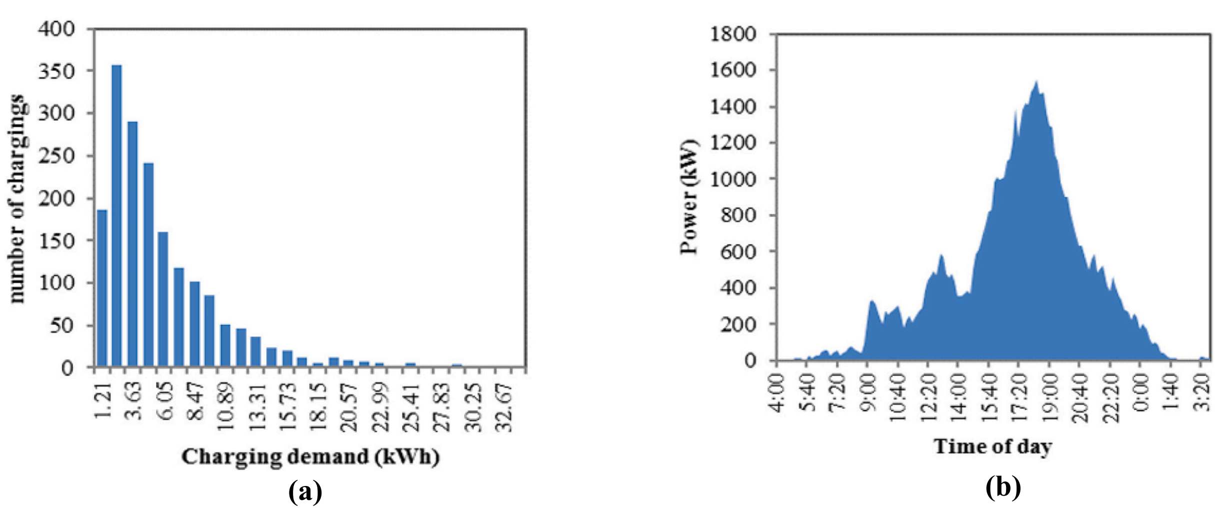

Fig. 7. EV charging profiles for 1262 EVs over 24 h for 7.44 kW charging only. (a) frequency distribution of charging demand, (b) timeseries EV charging demand profile assuming charging on return home [9].

hours, followed by a steady rise throughout the day. The demand peaks in the early evening hours (around 18:00–19:00), coinciding with typical household activities and EV charging after users return home from work. After the peak, the demand slightly decreases but remains elevated into the evening. This profile highlights the significant impact of EV charging on peak demand, emphasizing the need for effective demand management and smart charging strategies in distribution networks. Fig. 7 presents a detailed illustration of EV charging behavior,

Table 9
Detailed analysis on literature based on EVs impact on network load demand.

Refs.	Locality	Approach	Model/Analysis	EV Uptake (%)	Load Demand Increase (%)	Remarks
[13]	Inner City	D + H	Analytical/Statistical	30	6	
[14]	Inner City	S	Simulation/Load flow	15	5	Moderate rising
[16]	Inner City	S	Simulation	40	20	
[23]	Urban Egypt/BRTS-B2	D	Simulation/Load flow	100/100	86/100	
[24]	Urban	D	Simulation/Load flow	44	33	
[25]	Suburban-IEEE B13	D	Simulation/Load flow	50	47	
[69]	Urban	S	Simulation/Load flow	30	30	Proportionate increase
[6]	Urban and rural	D	Simulation/Load flow	160	100	
[70]	Urban	H	Trial/Measurement	100	125	
[52]	Inner City household	H + S	Analytical / Statistical	100	35	
[15]	Urban	S	Analytical/Probabilistic	40	82	
[26]	Suburban BRTS-B5	S	Simulation/Load flow	100	350	
[36]	Urban	S	Analytical/Probabilistic	100	500	Extreme increase
[53]	Inner City	S	Analytical / Statistical	67	725	
[54]	Urban	H + S	Simulation/Load flow	19	140	

Abbreviations: D - Deterministic; H - Heuristic; S - Stochastic.

broken into two parts: (a) the distribution of charging demand and (b) the aggregated power requirement over time. The histogram reveals a right-skewed distribution, where most EVs require low to moderate energy (1–10 kWh), indicating short or partial charging sessions, while fewer vehicles need higher energy levels. Subplot (b) illustrates the temporal distribution of power consumption throughout the day, with a noticeable peak occurring between 16:00 and 19:00, suggesting that the evening period experiences the highest cumulative charging load. This trend aligns with typical commuter behavior, where EVs are plugged in after work hours. Collectively, the figures highlight critical patterns useful for load forecasting, grid planning, and demand-side management strategies in smart grid applications.

According to estimates, the network load demand will quadruple when four EVs per household are assumed [26], and it will double when EV charging time is restricted to 20:30 to 22:00 of the day, which exactly corresponds with the peak load demand [15], and rise by a factor of four when all EVs are plugged in at once and the estimated base load is low in relation to EV charging power [36]. Due to the wide variations in the anticipated scenarios for base load, number of EVs per home, and charging regime, the results summarized in Table 9 demonstrate a significant variety in the predicted increase in demand, ranging from 6 % to 500 %.

Furthermore, the higher peak demand brought on by EVs might only happen occasionally [71] and could change depending on the local driving habits and environment. For instance, peak demand because consumers are more likely to take lengthy drives and need to charge their EVs more frequently on weekends and holidays. In order to handle a modest EV uptake, these peak demand scenarios are inevitable and will necessitate a modest EV uptake, these peak demand scenarios are inevitable and will necessitate substantial network reinforcement on LV networks unless addressed through a mitigation plan [72].

3.2. Voltage stability

The increase in load demand brought on by EVs directly and negatively affects distribution network voltage and its capacity to maintain voltage within acceptable bounds, such as within þ10 % to −6 % in accordance with the International Electrotechnical Commission IEC 60038 standard [73]. The network voltage limit is one of the main factors limiting the network's ability to host EVs, and the majority of previous research has concentrated on this aspect. The daily EV demand is dependent on daily travel profiles. Fig. 8 shows the VDI distribution for both 20 and 50 % EV penetration cases. The impact of 10 % EV integration is negligible because each node typically has 5 EVs linked to it. With shorter charging times, the overall energy needed to charge them can be reduced. The variance increases with increasing penetration scenarios. As anticipated, the 50 % EV penetration is associated with higher VDI values. The difference in VDI between a 50 % EV penetration and a 20 % penetration is 8.3 %.

Residential load demand begins to rise around 4 PM, reaching its

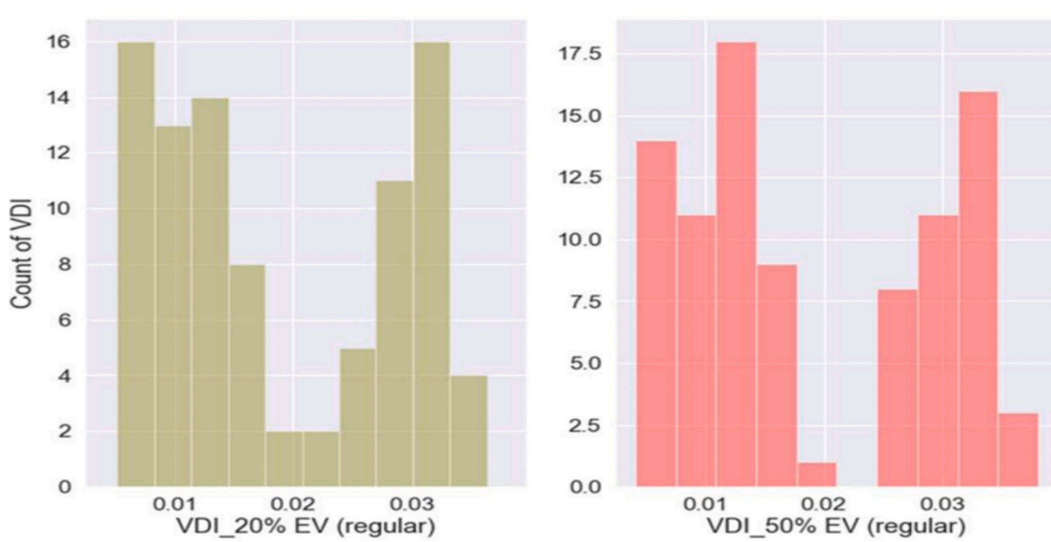

Fig. 8. VDI Distribution for 20 % and 50 % penetration Scenarios [32].

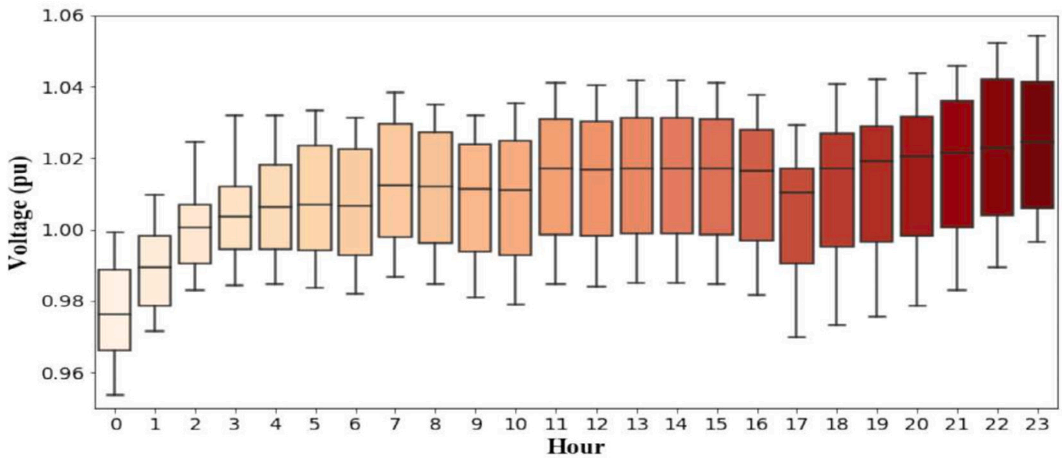

Fig. 9. Hourly Voltage Profile of test feeder across various buses without EV penetration [32].

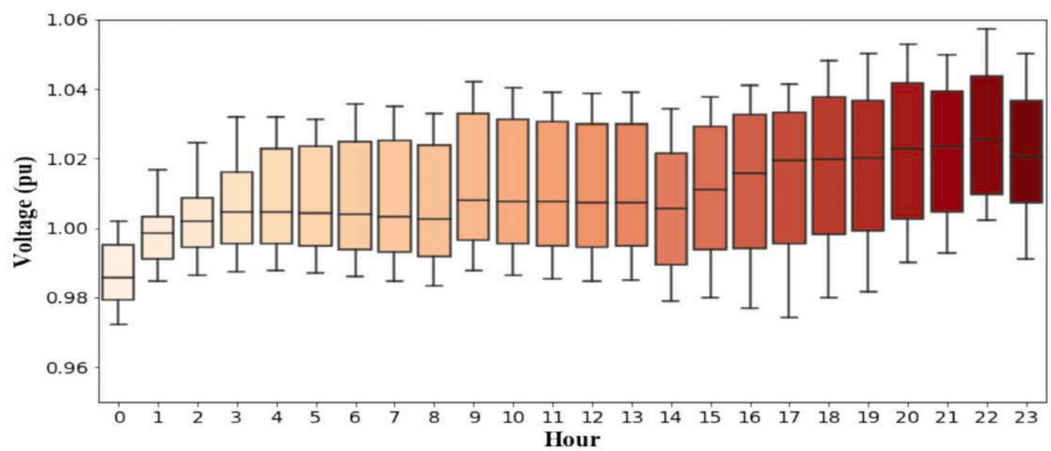

Fig. 10. Hourly Voltage Profile of test feeder across various buses with 50 % EV penetration [32].

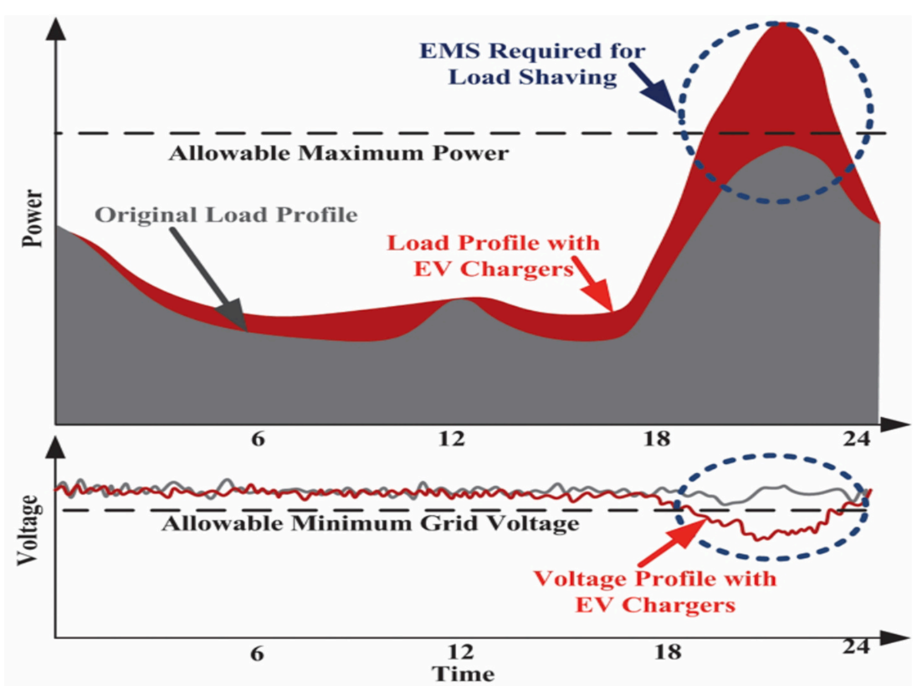

Fig. 11. Grid and Load Voltage Profiles without and with EV Charging [74].

peak at 7 PM, which leads to the most significant voltage drop of the day, as illustrated in Fig. 9. High-resolution simulations, like Quasi-Static Time Series simulation, can help analyze the impact of EV integration by capturing variations in customer load profiles. Fig. 10 illustrates the hourly voltage profile for a 50 % penetration scenario, where only the daily energy needs of EVs are fulfilled. Since EV charging load on the distribution grid is closely tied to home arrival times, significant voltage drops occur during these hours and persist until the end of the day.

In the study [74], the probable load and voltage profiles with and without EV charging are illustrated in Fig. 11. From Fig. 11, the impact of EV charging, especially serious power quality problems such as considerable voltage drop, on power grids can be visibly observed. In general, a centralized Energy Management Systems (EMS) can be used to control EV chargers and to mitigate the charging impact on power grids as shown in [74]. The upper graph shows that adding EV chargers significantly increases the evening peak load, pushing it beyond the allowable maximum power limit, which could overload the grid. The lower graph demonstrates how this elevated demand leads to voltage drops, with the voltage profile dipping below the minimum acceptable level during peak charging hours. These issues highlight the need for EMS to perform load shaving and maintain voltage stability by coordinating EV charging. Without such control, high EV penetration can result in infrastructure stress, reduced power quality, and potential service interruptions.

Voltage fluctuates during peak load hours, according to several studies that examined the effect of EV penetration load on network operating voltage. As an example, the writers in ref. [26] analyze how EVs affect residential and commercial feeders using the RBTS-5 test system, where lower voltage limit violations for residential feeders occur during the nighttime peak. This study also examines the effect of EV load on similarly sized road network voltage, taking into account various commutes and EV state-of-charge (SOC) situations where the network voltage limit is breached at the beginning of the workday for commercial feeders under moderate EV network uptake.

The study described in reference [23] reports the same voltage stress on the network in the evening using a computerized model of the Egyptian distribution network. Likewise, the findings demonstrated in ref. [37] employs 15 distinct probabilistic EV charging profiles from the transport survey data and assesses the voltage profile, confirming the earlier discovery that, at their moderate penetration level, EV-induced increases in load demand led to network voltage violations during the evening peak. Furthermore, a large number of research [24–32,36,49] have examined how EV load affects network operating voltage or operational voltage change, as shown in Table 10.

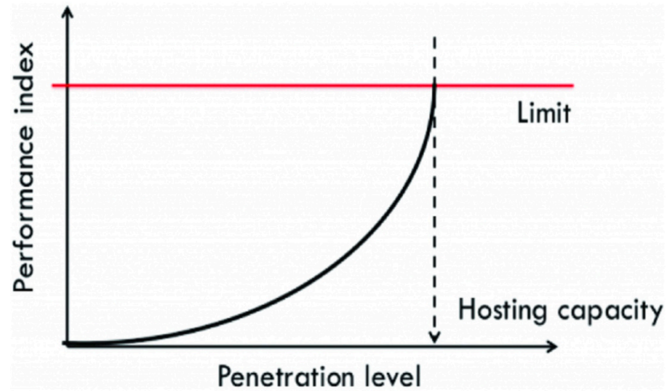

Fig. 12. The HC Concept [79].

Since every study is different and uses a different distribution network and EV profile, the results from these investigations varied widely. Furthermore, the concept of EV penetration level varies throughout different works. To facilitate understanding, the data have been categorized according to impact level and presented in ascending order of per-unit (P.U.) voltage variation induced by each 1 % EV penetration.

In conclusion, under normal circumstances, EVs at 100 % penetration can alter the MV networks voltage in the range of 0.02 PU to 0.05 PU and the LV networks voltage in the range of 0.1 PU to 0.15 PU, and in the worst-case scenario documented in refs. [26, 32, 37, 49], up to 0.25 PU to 0.3 PU. These findings apply to the most common condition of EVs at the moment, which is unregulated “dumb” charging regimes. Managing the effect of EVs on network voltage without taking any further mitigation measures is unavoidable, especially for the LV network, since EV penetration alone, at 10 % penetration, can derail network voltage by more than 10 %. Section 3 provides additional information on the current mitigating techniques and their effectiveness.

3.3. Hosting capacity

The maximum EV load that the current network can support without going over its operational voltage restrictions is known as the network EV hosting capacity. Hosting capacity (HC) as a concept in DG was first introduced by André Even in March 2004 during the integrated European EUDEEP project discussion to examine the effects of high DG integration in the distribution network [75–77]. This concept is

Table 10
Detailed analysis on the literature on EVs impact on the distribution network voltage.

Refs.	Locality	Approach	Model/Analysis	EV Uptake (%)	Volt. Level	Network Voltage (P·U)	ΔV/EV (P·U)	Violation (IEC)
[23]	Urban	D	Simulation/Load flow	30/100	MV	0.97/0.96	0.02	N/N
[24]	Urban	D	Simulation/Load flow	44	MV	0.97	0.05	N
[26]	Suburban	S	Simulation/Load flow	100	MV	0.93	0.04	Y
[27]	Urban	D	Simulation/Load flow	20/80	MV	0.94/0.93	0.02	N/Y
[28]	Urban	D	Simulation/Load flow	50/100	LV	0.9/0.88	0.04	Y
[25]	Urban	D	Simulation/Load flow	50	LV	0.85	0.16	Y
[26]	Urban	S	Analytical/Probabilistic	20	LV	0.95/0.86	0.1–0.2	N/Y
[29]	Suburban	D	Simulation/Load flow	23	LV	0.93	0.13	Y
[30]	Rural	S	Simulation/Load flow	60	LV	0.90	0.16	N
[31]	Suburban	D	Simulation/Load flow	20	LV	0.94	0.25	Y
[49]	Suburban	S	Simulation/Load flow	20	LV	0.90	0.25	Y
[37]	Urban	S	Simulation/Load flow	20/40	LV	0.96/0.9	0.3	N/Y
[32]	Urban	D + H	Simulation/Load flow	50	LV	0.97	–	N
[69]	Urban	S	Simulation/Load flow	20	LV	0.93	0.35	N
[55]	Urban	S	Simulation/Load flow	20	MV	0.96	0.04	N
[56]	Urban	D + H	Simulation/Load flow	100	MV	0.98	0.05	N
[57]	Urban	D + H	Simulation/Load flow	21	MV	0.97	0.01	N
[35]	Suburban	H	Analytical/Probabilistic	26	LV	0.94	0.02	N
[58]	Urban	D	Simulation/Load flow	55.55	MV	0.86	0.15	Y

Abbreviations: Y - Yes, N – No, D - Deterministic; H - Heuristic; S - Stochastic.

illustrated in Fig. 12. The theoretical application of the concept developed in [78] is now the widely adopted methodology by network operators, regulators, and researchers to determine HC.

Ambient temperature and weather conditions can have a substantial impact on the EV hosting capacity of residential distribution networks. In cold weather, the driving range of EVs decreases drastically —particularly when cabin heating is used—resulting in increased charging demand, altered charging schedules, and additional network stress, which may reduce EV hosting capacity [80]. Moreover, winter conditions are associated with higher heating demand, further limiting the available capacity for EV charging from distribution feeders. The simultaneous integration of EVs and heating loads can significantly influence thermal loading and voltage performance in distribution networks [81], thereby further constraining EV hosting capacity.

In ref. [40], the proposed voltage constrained-based approach to calculate the maximum hosting capacity of a distribution network to EVs follows an iterative method. The process begins by selecting nodes of the distribution network to host EVs. Then, the hourly extra available power (HEAP) at each of the selected nodes is estimated. After calculating the HEAP, initial number of EVs that can be accommodated at the selected nodes is estimated using the constructed load profile of EVs and the minimum HEAP of the respective nodes. Finally, the maximum hosting capacity of EVs in the distribution network is calculated under uncontrolled and fully controlled charging scenarios based on the following procedure. For uncontrolled charging the initial number of EVs at each node is calculated using Eq. 6 which is expressed as:

$$\min\left(P_{i,j,k}\right) = \max\left(\sum_{n=1}^{N_k^{u,min}} P^{ev}_{i,j,k,n}\right) \tag{6}$$

Here, i is the index for hours of a day; j is the index for days of a year; k is the index for number of buses of a distribution network; n is the index for number of EVs; $N^{u;min}$ is the minimum number of EVs under uncontrolled charging scenario for node k; $P^{i;j;k}$ is the extra available power at the i^{th} hour of j^{th} day for node k; and $P^{ev}_{i,j,k,n}$ is the demand to charge the n^{th} EV at the i^{th} hour of j^{th} day for node k.

And for controlled charging Eq. 7 is used, which is:

$$\min\left(W_j\right) = \max\left(\sum_{m=1}^{N^{e,min}} W^{ev}_{j,m}\right) \tag{7}$$

Here, $N^{c;min}$ is the minimum number of EVs under fully controlled charging scenario and $W_{j;m}{}^{ev}$ is the required energy to charge m^{th} EV on j^{th} day.

To evaluate the hosting capability of various residential distribution feeders, the researchers in ref. [36] considered 3.6 kW level 1 and 7.3 kW level-2 chargers, as well as 20 % to 100 % EV uptake. When no voltage is present at any node in the network, research indicates that the networks' hosting capacity with level-1 chargers is about 20 %. Similar to this, the study in reference [40] evaluates EV hosting capacity according to network voltage and takes into account level 1 and level 2 chargers for public and residential charging stations. The study reported in reference [39] demonstrates that charger compliance and charging behavior have a major influence on power quality and hosting capacity of the network supply.

The study described in references [41, 82] examines how seasonal temperature changes affect the capacity of northern European distribution networks to host, taking into account the fundamental needs for heating, ventilation, and air conditioning (HVAC), as well as the effect of temperature on the state-of-charge (SOC) of EV batteries. According to this research, because of the high demand for heating load during the winter, network EV hosting capacity can drop by as much as 30 %. In contrast, the same reason causes a 20 % reduction in network EV hosting capacity in Asia during the summer [37]. The authors of ref. [38] evaluated the network's overall and node-specific EV hosting capacity in order to identify network congestion sites. Furthermore, if level-1 chargers which are slower than level-2 chargers are utilized solely, network hosting capacity can be considerably higher, according to this study. By implementing an algorithm with multiple inputs, including the number of EVs, arrival time, state-of-charge (SOC), battery capacity, and charger type/rate, the authors in ref. [7] synthesized EV charging profiles for different nodes on the distribution network in a relatively detailed and unique manner. According to this analysis, the network can accommodate EV penetration of more than 30 %. Table 11 provides a summary of the studies on EV hosting capacity in networks and the limiting factor.

Table 11
EVs hosting capacity of distribution networks and primary constraining factor.

Refs.	Locality	Approach	Model/ Analysis	EV Hosting Capacity (%)	Constraint
[36]	Urban	S	Analytical/ Probabilistic	20	Undervoltage
[39]	Suburban	D	Simulation/ Load flow	50	Thermal (transformer)
[40]	Urban	S	Simulation/ Load flow	65	Undervoltage
[37]	Suburban	S	Simulation/ Load flow	60	Thermal (transformer)
[38]	Urban	D	Simulation/ Load flow	50	Thermal (feeder)
[41]	Suburban	D	Simulation/ Load flow	>100	N/A
[82]	Urban	S	Analytical/ Probabilistic	60	Thermal (transformer)
[7]	Uni Campus	H-S	Analytical/ Probabilistic	30	Undervoltage
[83]	Urban Rural	D	Simulation/ Load flow	5/10 2/10	Thermal/ Undervoltage Thermal/ Undervoltage
[6]	Urban-NSW Rural-NSW	D	Simulation/ Load flow	80 20/40	Thermal Thermal/ Undervoltage
[49]	Urban	H	Trial/ Measurement	40	Thermal (transformer)
[59]	Urban	S	Analytical/ Probabilistic	23	Thermal (transformer)
[60]	Urban	S	Analytical/ Probabilistic	35	Undervoltage
[61]	Urban	S	Simulation/ Load flow	30	Thermal (feeder)
[62]	Urban	H-S	Analytical/ Probabilistic	25	Thermal (transformer)
[63]	Urban	D-S	Analytical/ Probabilistic	62	Thermal (transformer)
[64]	Urban	D	Simulation/ Load flow	37	Thermal (feeder)
[55]	Urban	S	Simulation/ Load flow	32	Undervoltage

Abbreviations: D - Deterministic; H - Heuristic; S - Stochastic.

The impact of EVs and the hosting capacity of distribution networks have been evaluated using a variety of methodologies, analysis techniques, and data processing approaches, as discussed in this section. Deterministic and stochastic approaches are equally and extensively used among the three main approaches previously described in this study; however heuristic and hybrid approaches are only used in a small number of research. The deterministic technique is extensively used because it is simple to comprehend, apply, and analyze, despite its obvious limitations. However, because uncertainties and variabilities are not taken into account, they lack broad application and generalizability. On the other hand, the stochastic technique is the second most popular method utilized in research pertaining to EV impact and hosting capacity assessment, despite being rather difficult to apply and comprehend and requiring a large dataset. The majority of studies using a stochastic approach have either used fully synthetic data or EV trail data from a small number of EVs operating, most of which are in controlled environments, due to the lack of large-scale EV data. One of the major flaws in the current study is this. The hybrid approach has been rarely used for the same reasons, which presents an opportunity to be addressed in future research.

A wide range of EV integration, operational scenarios, and network types have also been explored in the aforementioned research. Nonetheless, there is room for evidence-based research on network dynamic hosting capacity [84] that makes use of actual EV charging data that precisely depicts user behavior under different benefit and price scenarios, which is discussed in section 5.

3.4. Thermal capacity

The thermal limits of current distribution networks, including the distribution transformer ratings, are exceeded at certain EV penetration levels because these networks were not designed to accommodate EV load requirements. The impact of EV load on the thermal aspects of distribution feeder operation and the relationship between thermal capacity restrictions and EV hosting capacity are examined using representative feeder models in the various studies reported in refs. [7, 15, 23, 30, 33, 49, 68, 85]. In the experiment described in ref. [49], for example, the CREST tool was used to construct typical home load profiles in order to examine the effect of EV load on LV distribution network thermal capacity.

Eq. 8 is used for calculating the energy balance in a battery, which is expressed as:

$$\frac{\mathrm{dE}}{\mathrm{dt}} = \mathrm{E_{gen}} - \mathrm{E_{loss}} + \mathrm{E_{in}} - \mathrm{E_{out}} \tag{8}$$

Here, $\frac{dE}{dt}$ is Energy Accumulation Rate, E_{gen} is Energy Generation Rate, E_{loss} is Energy Loss Rate, E_{in} is Input Energy Rate and E_{out} is Output Energy Rate.

Heat Transfer in a Battery is calculated using Eq. 9,

$$\mathrm{mC_p}\frac{\mathrm{dT_s}}{\mathrm{dt}} = \mathrm{Heat_{gen}} - \mathrm{hA}(\mathrm{T_s} - \mathrm{T_a}) - \mathrm{e}\delta\mathrm{A}\left(\mathrm{T_s^4} - \mathrm{T_a^4}\right) - \mathrm{Q_{Ext\_conduction}} \tag{9}$$

Here, $mC_p\frac{dT_s}{dt}$ is Rate of Temperature change, $Heat_{gen}$ is Rate of Internal Heat Generation, $hA(T_s - T_a)$ is Convection Heat Rate, $e\delta A\left(T_s^4 - T_a^4\right)$ is Radiation Heat Rate, and $Q_{Ext\_conduction}$ is Conduction Heat Rate.

When the load increases in steps, the top-oil temperature $\theta_o(t)$ and the winding hot-spot temperature θ_h rise to levels corresponding to the load factor K. The top-oil temperature $\theta_o(t)$ is expressed as,

$$\theta_o(t) = \Delta\theta_{o,i} + \left\{\Delta\theta_{o,r} \times \left[\frac{1 + R \times K^2}{1 + R}\right] - \Delta\theta_{o,i}\right\} \times \left(1 - e^{-\frac{t}{k_{11} \times \tau_o}}\right) \tag{10}$$

Lithium-ion battery (LIB) technology is anticipated to be the preferred energy storage solution for electric drive vehicles (EVs) in the near future [86]. Fig. 13 is a schematic that illustrates how temperature affects EV battery performance, power limits, and degradation rates. The horizontal axis represents temperature (T), while the vertical axis shows power limits. It identifies an optimal temperature operating range between approximately 15 °C and 35 °C, within which the battery delivers rated power. At temperatures below 15 °C, sluggish electrochemical activity restricts power, especially during charging and cold starts, limiting EV range and cranking power. At higher temperatures beyond 35 °C, the risk of thermal degradation increases, and power must be limited to prevent excessive temperature rise and capacity fade. The figure also includes arrows and annotations explaining how thermal conditions influence both design parameters (e.g., battery size) and operational constraints. Overall, it emphasizes that effective thermal management is critical to maintaining battery health, performance, and longevity in EVs. Temperature plays a crucial role in influencing the lifespan, performance, safety, and cost of LIBs [86]. Elevated temperatures accelerate battery degradation, whereas lower temperatures diminish power and energy output, leading to potential challenges in cost, reliability, safety, driving range, and overall vehicle performance.

The findings of this study indicate that feeder thermal limits are broken at about 50 % EV penetration and transformer thermal limits are broken at 30 % EV penetration. Studies that examine the effects of increased loading on network assets, the effects of overload operation on their lifespan, and the deterioration of end-user quality of service have taken a similar approach, as shown in ref. [15]. When a transformer is overloaded by up to 120 % for a few hours during the day, which could happen with 20 % EV penetration, the authors in refs. [46, 85] estimate that the transformer's life is reduced by 30 %. Since feeders are the main source of network hosting capacity constraints, the majority of studies concentrate on examining how EV penetration affects distribution transformers. These results are summarized in Table 12 and discussed in the following section.

4. Review of EVs impact mitigating solutions

Many strategies have been proposed to mitigate the impact of EVs on the network and, consequently, increase the hosting capacity. Fig. 14

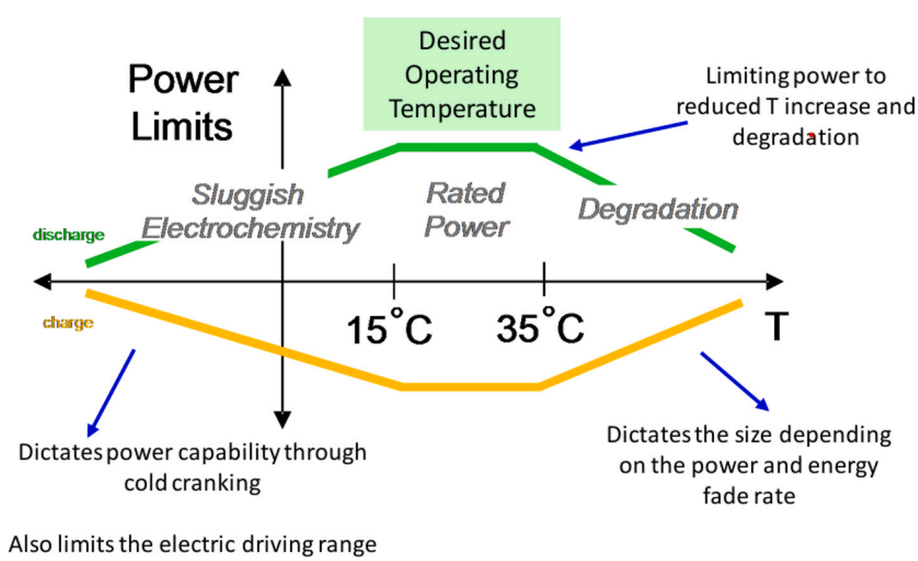

Fig. 13. Battery Temperature Impact in EVs [86].

Table 12
Detailed analysis on EVs impact on distribution network's thermal capacity.

Refs.	Locality	Approach	Model/Analysis	EV Uptake (%)	Feeder Overloaded	Transformer Overloaded
[23]	Urban	D	Simulation/Load flow	30/100	×/✓	×/✓
[15]	Urban	S	Analytical/Probabilistic	40	×	✓
[44]	Suburban	S	Simulation/Load flow	40	×	✓
[30]	Rural	S	Simulation/Load flow	60	✓	✓
[51]	Urban	D-H	Analytical/ Analytical	75	×	✓
[85]	Urban	D	Analytical/ Analytical	100	×	✓
[38]	Urban	D	Analytical/ Analytical	50	×	✓
[70]	Urban	H	Trial/Measurement	40	×	✓
[33]	Urban	D	Simulation/Load flow	50	✓	N/A
[68]	Suburban	D	Simulation/Load flow	80	×	×
[65]	Suburban	D	Analytical/Probabilistic	50	×	×
[66]	Suburban	S	Simulation/ Analytical	100	×	×

Abbreviations: D-Deterministic; H-Heuristic; S-Stochastic.

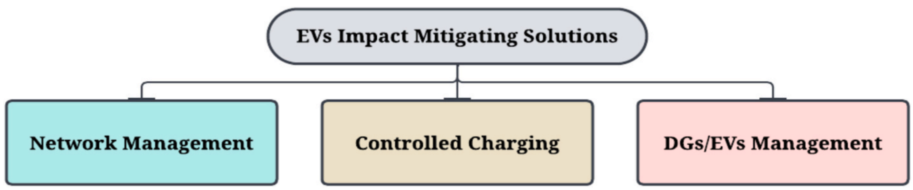

Fig. 14. Three Mitigation Strategies of EVs Impact.

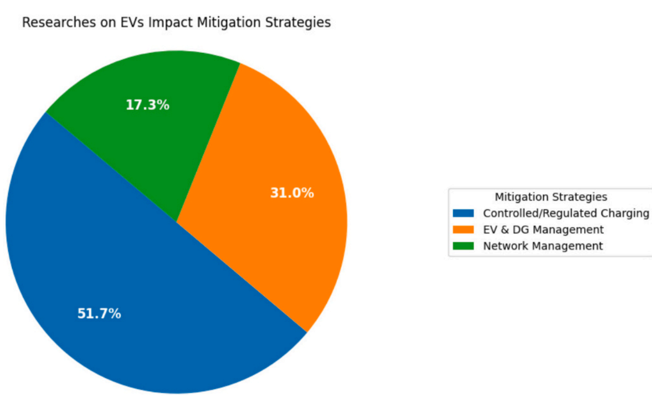

Fig. 15. Research works so far on EVs mitigation strategies since 2010.

shows that these tactics fall into three major categories: Network Management, EVs and DG Management, and Controlled/Regulated Charging.

The distribution of research efforts on various EV impact mitigation strategies is shown in Fig. 15. This visualization highlights that over half of the research since 2010 has been centered on controlled or regulated charging techniques, which involve timing and controlling EV charging to reduce grid stress. EV & DG Management, which includes the coordinated control of EVs and DG sources like solar PV, constitutes nearly a third of the research focus. Network Management, which may include infrastructure reinforcement, voltage regulation, and topology optimization, accounts for the smallest share. This distribution underscores the priority given to demand side solutions over network-level changes.

Different methods and model types are used to evaluate EV impact reduction solutions, like those employed in EV effect analysis studies. The majority of research employed a deterministic methodology utilizing analytical models and optimization techniques, as summarized in Table 13–16. Given its focus, accuracy, and usefulness in determining the relative efficacy of various impact mitigation techniques, this approach is undoubtedly logical. It should be noted that most research has a specific focus, such as controlling voltage or reducing load and peak load.

4.1. Network management

Network management strategies focus on grid-side reinforcement or optimization without directly controlling EV charging behavior. Examples include reinforcement through dynamic transformers and line rating [82], network reconfiguration [117], and demand response mechanisms [108,118]. Blockchain-enabled energy trading [107] provides a secure means of balancing supply and demand. Battery swapping [106] reduces charging peaks by decoupling charging and vehicle use, though it requires significant infrastructure investment. Renewable-powered EV stations [83] and optimized charging station placement [122] also help reduce congestion but are fundamentally planning-based solutions rather than active charging control. The mitigation strategies based on network management are summarized in Table 17.

4.2. Controlled/regulated charging

Controlled charging strategies directly manage the timing and rate of EV charging. Legacy solutions, such as time-of-use tariffs [87,88] and off-peak charging [89], shift demand away from peak hours. Dedicated controlled load schemes [89] also provide relief by aligning charging with available grid capacity.

To control the overall load of EVs, the authors in [90], a priority-based charging protocol is proposed that uses a distributed control structure for charging stations. By using fuzzy logic to identify the charging current that minimizes damage, the authors of [74] present a totally decentralized control technique that results in a minor reduction in the influence of voltage. Eq. 11 used in EV charging optimization, ensuring the proper state of charge (SoC) progression over time for each EV was presented in the study [92]. Eq. 11 ensures that the amount of energy charged during a time slot is at least enough to cover the drop in battery charge due to EV usage. It is expressed as,

$$r_t^i \cdot \Delta t \geq SoC_t^i - SoC_{t-1}^i + E_t^i \quad (11)$$

Here,
r_t^i: Charging rate of EV i at time slot t (in kW).
Δt: Duration of one time slot (in hours).
SoC_t^i: State of charge of EV i at the end of time slot t (in kWh).
SoC_{t-1}^i: State of charge of EV i at the end of the previous time slot t-1

Table 13
Comparative study of the mitigation strategies for EVs impact on network load.

Mitigation Strategy	Refs.	Type of Solution	Data Source	Network Model	Key Findings
	[87]	Load shift, Time of use	Hybrid	Mathematical	EV adoption rates of over 33 % can be achieved by off-peak charging without the need for additional energy infrastructure.
	[88]	Compensators Scheduled, Time of use	Real	IEEE-33	Tariff-based time of usage control offers users a financial incentive while significantly reducing the burden on the network.
	[89]	Load shift, Controlled charging	Hybrid	LV grid	An efficient legacy demand management technique that can greatly lessen the rise in peak demand brought on by EV adoption is load shifting.
	[90]	TOU, Controlled Scheduled	Hybrid	LV grid	Peak charging demand can be reduced by more than 80 % using distributed controlled charging.
	[91]	Controlled Charging	Synthetic	Mathematical	Distributed control can greatly lessen the effect that increased EV adoption has on transformer lifespan.
	[74]	Controlled Scheduling	Synthetic	LV grid	Decentralized control based on voltage greatly lessens the effect on network voltage.
Controlled Charging	[92]	Controlled Charging	Synthetic	LV grid	Collaborative scheduling solutions offer retailers and end users financial benefits in addition to a notable decrease in the impact of EVs.
	[93]	Forecasting	Hybrid	Mathematical	When smart scheduling and V2G technologies are used together, peak network demand can be somewhat but significantly reduced while end users' expected quantity of service (QoS) is maintained.
	[94]	Load Shift	Hybrid	IEEE-33	Flexible scheduling can greatly lessen the burden on the network during periods of high load by offering consumers and aggregators financial incentives to move non-time-critical loads.
	[95]	Load Shift, Time of Use	Synthetic	IEEE-33	EV charging timeslots can be efficiently optimized by smart scheduling, which reduces network impact and increases EV hosting capacity.
	[96]	Smart Charging	Real	LV grid	Smart charging reduces network losses by 35.5 % and EV charging costs by 61 %.
	[97]	Smart Charging	Real	Colorado LV grid	Smart charging significantly reduces transformer overloading.
	[98]	Coordinated Charging	Assumption	LV grid	Coordinated EV charging algorithm reduces peak charging demand by 40.8 %.
	[99]	Smart Charging	Assumption	LV grid	Implementation of smart charging and demand response program have effectively mitigated load demand significantly.
	[100]	DG	Hybrid	MATLAB	By absorbing excess power during off-peak hours and supplying additional localized generation during periods of high demand, smart charge/discharging optimization strategies can efficiently lessen the burden on the network.
	[101]	DG	Synthetic	Mathematical	Utilizing peak PV generation and clever scheduling based on underlying demand, PV-based smart planned charging is especially successful in office settings.
	[102]	DG, Controlled Scheduled	Hybrid	Monte-Carlo	When smart scheduling and real-time coordinated control are combined in microgrids, EVs can be implemented as virtual batteries that coordinate with intermittent power, such solar PV, to effectively limit network impact.
DGs/EVs Management	[9]	Load shift, DG	Hybrid	Mathematical	EV charging powered by surplus renewable electricity can successfully lessen the impact of EVs while also offering extra advantages such serving as a load sink to absorb excess generation.
	[103]	DG	Hybrid	LV grid	By changing the load from the network's point of view, energy storage systems at EV charging stations can drastically lower peak demand.
	[104]	DG	Real	33 bus	PV and battery storage units improve peak demand, reduce energy loss and voltage deviations
	[105]	DG	Real	LV grid	Through the integration of DGs, power losses and voltage fluctuations were reduced which were increased due to EVs inclusion.
	[106]	Battery Swap	Hybrid	Mathematical	The battery switching technique allows for quick refueling while managing network demand spikes brought on by the charging stations. But it needs a lot of infrastructure and battery standardization.
Network Management	[107]	Demand side management	Real	Decentralized LV network	Blockchain enables secure, transparent, and peer to peer energy trading for EVs
	[108]	Demand response management	Synthetic	IEEE-33	Peak demand can be reduced by 9–11 % through the adoption of demand response program.

(in kWh).

E_t^i: Energy consumed by EV i during time slot t (in kWh).

More advanced solutions fall under Intelligent Charging Coordination (ICC). ICC includes optimization-based charging coordination [93–99], voltage-based and distributed control methods [74,90,109,110], and user comfort or priority-driven scheduling [114,119,121]. These approaches align EV charging with grid stability while maintaining user convenience, reducing peaks, system losses, and operational costs. All legacy and ICC strategies are summarized in Table 18.

Fig. 16 illustrates uncontrolled charging, random charging, and the On-demand Automatic Control System (OACS) [83]. The OACS approach schedules charging during low-price periods while keeping transformer demand within safe limits, demonstrating the effectiveness of regulated charging strategies.

4.3. EVs and DGs management

EV impact can be managed to some extent by controlled or regulated EV charging techniques, although they might not be sufficient at high adoption levels. The active management of local DG and EV charging, including their operational modes, is another crucial strategy to mitigate EVs impact.

The authors of [71] presented a diagram of a modified IEEE 34-bus distribution network, operating at 14.7 kV with a total capacity of 268 kVA, as shown in Fig. 17. It models a **radial distribution network** typically used in suburban or semi-urban areas. The system begins with a HV source that steps down to MV via a transformer and distributes power across multiple buses (numbered 800 to 864). Several **distribution transformers (DTs)** are shown throughout the system, stepping down the MV to **415 V LV** for end-user consumption. Each LV feeder connects to a **local LV network** highlighted in the inset—serving multiple **residential households.** These households are modeled to account for varying levels of **EV penetration**, reflecting contemporary concerns

Table 14
Comparative study of the mitigation strategies for EVs impact on network voltage.

Mitigation Strategy	Refs.	Type of Solution	Data Source	Network Model	Key Findings
Controlled Charging	[88]	Compensators Scheduled, Time of use	Real	IEEE-33	Tariff-based time of usage control offers users a financial incentive while significantly reducing the burden on the network.
	[109]	Load shift, Time of use, Controlled Scheduled	Hybrid	IEEE-33	Under higher EV uptake rates, scheduled controlled charging techniques can successfully keep voltage within allowable bounds.
	[90]	TOU, Controlled Scheduled	Hybrid	LV grid	Peak charging demand can be reduced by more than 80 % using distributed controlled charging.
	[94]	Load Shift	Hybrid	IEEE-33	Flexible scheduling can greatly lessen the burden on the network during periods of high load by offering consumers and aggregators financial incentives to move non-time-critical loads.
	[95]	Load Shift, Time of Use	Synthetic	IEEE-34	EV charging timeslots can be efficiently optimized by smart scheduling, which reduces network impact and increases EV hosting capacity.
	[110]	Controlled Scheduled	Synthetic	IEEE-37	By employing scheduled charging and discharging strategy optimal voltage level was maintained.
DGs/EVs Management	[101]	DG	Synthetic	Mathematical	Utilizing peak PV generation and clever scheduling based on underlying demand, PV-based smart planned charging is especially successful in office settings.
	[111]	EV Charging station placement	Synthetic	IEEE-69	Optimal charging station placement with D-STATCOM and DG improves voltage stability.
	[112]	Reactive power management	Real	51-bus	Through efficient management of the reactive power of EV charging stations considerable power loss is achieved along with reduction in power loss.
Network Management	[113]	Virtual power plant	Hybrid	IEEE-33 and real-world 240-Bus	V2G with virtual power plant integration reduces power and improves voltage profile in larger systems.

Table 15
Comparative study of the mitigation strategies for EVs impact on network hosting capacity.

Mitigation Strategy	Refs.	Type of Solution	Data Source	Network Model	Key Findings
Controlled Charging	[74]	Controlled Scheduling	Synthetic	LV grid	Decentralized control based on voltage greatly lessens the effect on network voltage.
	[114]	Optimizing charging	Synthetic	LV grid	Maximizes the EVs hosting capacity of the LV network by optimizing EV charging.
DGs/EVs Management	[115]	DG	Hybrid	IEEE-33	DG sources and EVs utilizing V2G technology work together to coordinate, increasing the hosting capacity for both DG and EVs.
	[116]	Local storage, DG	Hybrid	MATLAB	Industrial plants that use localized combined heat and power (CHP) generation give their employees access to large amounts of EV charging capacity with little to no effect on the external distribution network.
	[47]	EV load forecasting	Synthetic	IEEE-9 and IEEE-30	Higher EV penetration was achieved through appropriate EV load forecasting along with maintaining environmental standards.
Network Management	[117]	Network optimization	Hybrid	IEEE-33	Reconfiguring the distribution network with sectionalization and tie-switches can greatly boost the network's hosting capacity.
	[106]	Battery Swap	Hybrid	Mathematical	The battery switching technique allows for quick refueling while managing network demand spikes brought on by the charging stations. But it needs a lot of infrastructure and battery standardization.
	[82]	Dynamic Trans/ Line rating	Hybrid	Mathematical	A feeder's hosting capacity can be significantly increased by using dynamic substation ratings based on the surrounding temperature.
	[118]	Demand response	Hybrid	IEEE 33 and Real Distributed Network of Cairo, Egypt	Synergistic enhancement approach significantly improved the DGs and EVs hosting capacity by almost 49.2 % and 61.2 %, respectively.

Table 16
Comparative study of the mitigation strategies for EVs impact on network thermal capacity.

Impact	Refs.	Type of Solution	Data Source	Network Model	Key Findings
Controlled Charging	[119]	DG	Synthetic	Mathematical	While maintaining high levels of service for the end user, transformer service life degradation can be significantly reduced using end-user comfort-based controlled charging.
	[114]	EVs charging management	Real	Mathematical	System load is prioritized, excluding EVs and excess load would be clipped to maintain transformer optimal loading, during evening peak hours.
	[119]	Smart Charging	Real	Mathematical	The proposed approach is pretty effective in mitigating the impact of EV high penetration on transformer life by increasing the number of times transformer is under low-risk failure from 87 % to 100 %.
DGs/EVs Management	[116]	Local storage, DG	Hybrid	MATLAB	Industrial plants that use localized combined heat and power (CHP) generation give their employees access to large amounts of EV charging capacity with little to no effect on the external distribution network.
Network Management	[82]	Dynamic Trans/ Line rating	Hybrid	Mathematical	A feeder's hosting capacity can be significantly increased by using dynamic substation ratings based on the surrounding temperature.
	[120]	Energy Management System	Real	Mathematical	Proposed EMS can handle intrinsic uncertainties related with EVs in real-time to minimize the expected apparent demand considering transformer's aging.

Table 17
EVs impact mitigation strategies based on network management.

Refs.	Mitigation Strategy	Type of Solution	Data Source	Network Model	Key Findings
[117]	Network optimization (tie-switch reconfiguration)	Reconfiguration	Hybrid	IEEE-33	Improves load balance and reduces peak loading. Keeps bus voltages within operating limits under EV penetration.
[108,118]	Demand response for voltage stability	Load shifting, DR programs	Hybrid	IEEE-33, Cairo grid	Reduces system peak demand and increases hosting capacity by 50–60 %. Helps maintain voltages within acceptable limits.
[106]	Battery Swap	Load transfer	Hybrid	Mathematical	Enables fast charging while avoiding simultaneous grid stress. Reduces coincident peak load, increases hosting capacity.
[82]	Dynamic Transformer/Line rating	Network reinforcement	Hybrid	Mathematical	Increases EV hosting capacity by adjusting ratings. Raises thermal hosting capacity.
[120]	Energy Management System	EMS optimization	Real	Mathematical	Reduces transformer aging by optimal energy management.

Table 18
EVs impact mitigation strategies based on regulated or controlled charging.

Refs.	Locality	Approach	Model/Analysis	Mitigation Strategy	Load Reduction
[87–89]	Urban	D/S	Analytical/Probabilistic	TOU, Off-peak, Tariff-based (Legacy Controlled Charging)	Low–High
[74,90–92,98]	Urban/Rural	D-H	Simulation/Optimization	ICC – Coordinated & Distributed Control	Medium–High
[93–97,99]	Urban/LV grids	D-S/H	Optimization/Load flow	ICC – Optimization-Based Charging	Medium–High
[109,110]	Urban/Typical LV	D	Optimization	ICC – Voltage-Based Scheduling	Medium–High
[114,119,121]	Urban/Typical LV	D	Simulation/Optimization	ICC – User Comfort/Priority Scheduling	Medium–High

Abbreviations: D - Deterministic; H - Heuristic; S - Stochastic. Low = 0–20 %; Medium = 20–50 %; High ≥50 %.

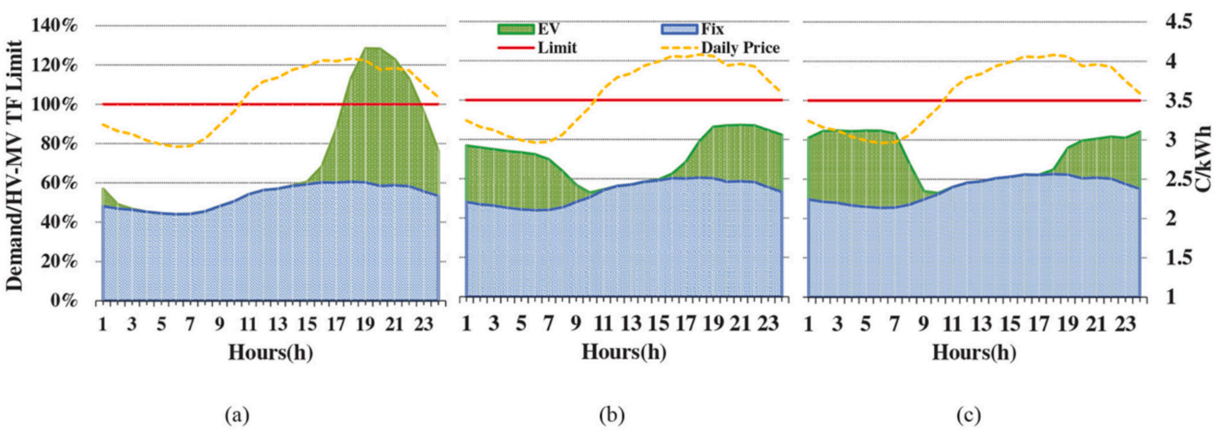

Fig. 16. EV charging coordination results of total power demand versus HV-MV transformer limit with 80 % EV penetration. (a) No schedule, (b) Random schedule and (c) OACS scheme [83].

about the impact of EV charging loads on grid performance. This configuration is often used for simulation studies involving **load flow, voltage stability, power losses**, and **demand-side management** under modern smart grid scenarios.

When flow optimization fails due to high EV demand, a charging maximization strategy is applied to ensure the highest possible battery charge for all newly connected EVs while adhering to Eq. 12,

$$\text{maximize} \sum_{n} \mathrm{DCTL}_{n}^{m'} \times t_{n}^{m'} \leq \mathrm{DT}^{m'}, \forall m \in \mathrm{EV}_{new} \tag{12}$$

Here,

$DCTL_n^{m'}$: Dynamic Charging Transfer Level of the n^{th} EV at transformer node m' (charging power level).

$t_n^{m'}$: Charging duration for the n^{th} EV at transformer m'.

$DT^{m'}$: Maximum energy capacity or available energy limit of the distribution transformer at node m'.

EV_{new}: Set of all newly connected EVs.

Eq. 12 ensures that the total energy drawn by all newly connected EVs at any distribution transformer does not exceed its energy capacity. The aim is to maximize the total charging (battery levels) within that capacity limit.

Integration of EVs with DG and energy storage provides additional flexibility and resilience. V2G operation [12,114] enables EVs to absorb renewable generation surpluses and discharge during peak demand. PV-based charging [100–102] allows EVs to function as mobile storage synchronized with solar production. Industrial CHP systems [115,116] support local charging without overloading the distribution network. Energy storage integration [103–105,111,112] helps reduce peaks and system losses.

Certain ICC approaches explicitly linked to DG are considered under ICC with DG Integration. For example, PV-based ICC [100–102] coordinates charging with solar production to minimize grid impact. A summary of the mitigation strategies based on EVs and DGs management is presented on Table 19.

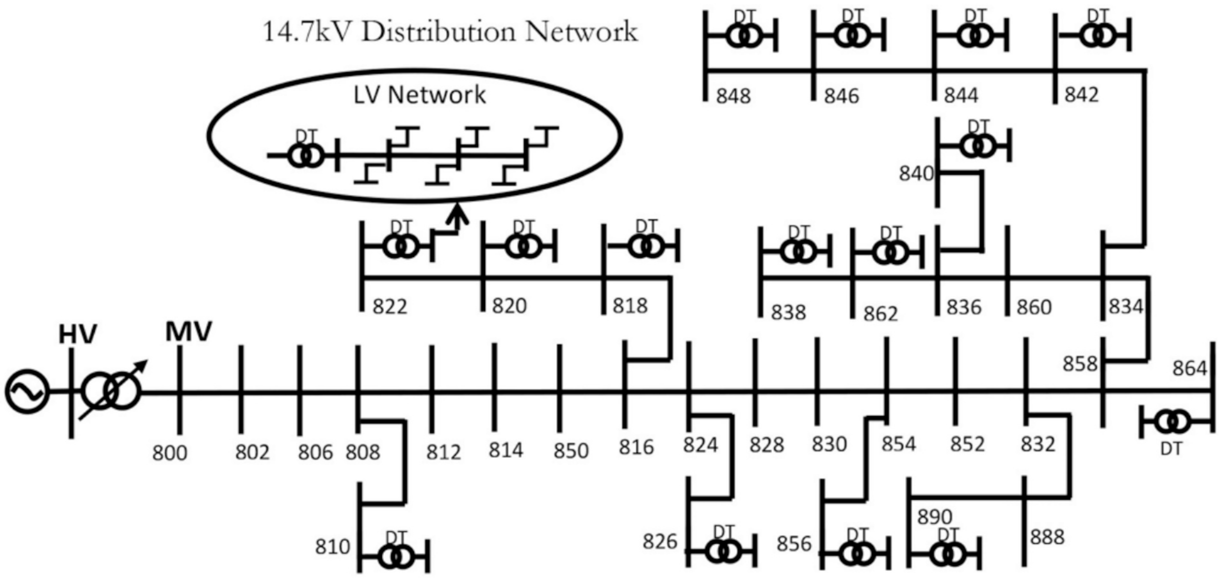

Fig. 17. Modified IEEE 34 14.7 kV 268kVA distribution network with several 415 V LV feeders. Each LV feeder connects to a LV network which consists of a number of residential households with varying penetration of EVs [71].

Table 19
Amount of load reduction with active management of EVs and DGs.

Refs.	Locality	Approach	Model/Analysis	Mitigation Method	Type	Load Reduction
[9,114,115]	Theoretical/Industrial	D	Analytical/Optimization	V2G operation	V2G	Medium–High
[100–102]	Theoretical/Urban	D	Analytical/Optimization	ICC with PV coordination	PV/V2G	Medium
[103–105]	Urban	D	Simulation/Load flow	Load shift with PV + Storage	PV-Energy Storage	Medium–High
[111,112]	Urban	D	Optimization/Simulation	Reactive power management with V2G	V2G	Low–Medium
[116]	Industrial	D	Simulation/Load flow	CHP-based EV charging	CHP	High

Abbreviations: D-Deterministic. Low = 0–20 %; Medium = 20–50 %; High ≥50 %.

4.4. Overview of artificial intelligence applications in EV impact mitigation

The growing complexity of EV integration and its effects on power distribution networks have made artificial intelligence techniques extremely effective tools for mitigating EVs impact on distribution network through efficient control and prediction. For user profiling, time-series demand forecasting, and schedule optimization, controlled charging schemes are increasingly relying on artificial intelligence. With the help of artificial intelligence, smart charging techniques can be customized and voltage-aware, greatly lowering peak load without compromising user happiness [74,119]. Moreover, artificial intelligence-driven forecast models efficiently automate load shifting protocols and assist predict charging surges [70,93].

Artificial intelligence can also be a proactive alternative to traditional network management, which relies on deterministic control of substations and switching configurations. For example, predictive reconfiguration to alleviate impending congestion or overloading is made possible by real-time algorithms that can forecast transformer and feeder load trends [91]. Additionally, substation output can be optimized based on predicted and ambient circumstances using artificial intelligence-driven dynamic transformer rating approaches [82].

The integration of DGs and EVs benefits from artificial intelligence through predictive coordination and optimization. In the context of DG and V2G operations, artificial intelligence models are used to manage bi-directional energy flow. Clustering methods group EV behavior to optimize local energy storage use [103], while supervised learning models forecast PV generation to synchronize V2G operations with surplus renewable supply [101,102]. This harmonization ensures stable voltage and maximizes hosting capacity without infrastructural

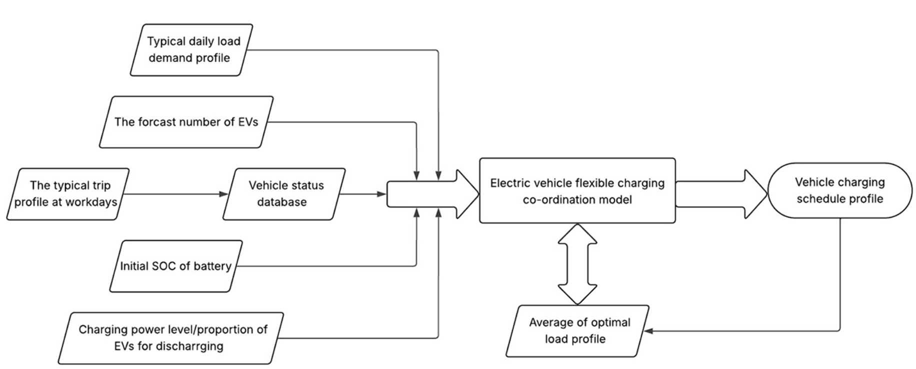

Fig. 18. The structure of EV flexible charging and discharging method using reinforcement learning.

Table 20
Summary of artificial intelligence Approaches Used in EV Integration Studies.

Refs.	Algorithms/Methods	Artificial Intelligence Techniques	Application Area/ Problem Addressed	Observations
[90]	Priority-based control	Fuzzy logic	Smart Charging / Load Optimization	Implements a smart charging mechanism considering user preference and voltage sensitivity.
[74]	Voltage-sensitive charging, Fuzzy-based dispatch	Fuzzy Logic	Controlled Charging / Network Stress	Allocates charging based on voltage levels and network conditions to reduce voltage violations
[119]	Heuristic machine learning (ML) scheduling, Fuzzy optimization	Hybrid ML-Heuristics	Predictive Charging / Load Forecasting	Combines fuzzy logic and ML to schedule EV charging while minimizing user discomfort and grid stress.
[93]	Neural networks, Reinforcement Learning	Supervised + Reinforcement	Forecasting & Real-time Scheduling	Predicts EV load patterns and learns optimal charging schedules based on reward-driven learning.
[91]	Transformer dispatch with predictive control	Neural Networks	Network Management / Asset Protection	Forecasts transformer stress due to EV charging and reconfigures dispatch accordingly.
[9]	K-means clustering	Unsupervised Learning	User Behavior Analysis / Charging Patterns	Identifies user groups and patterns for adaptive demand-side energy management.
[109]	Voltage-based fuzzy scheduling	Fuzzy Logic + Expert System	Voltage Violation Management	Uses voltage threshold rules to prevent violations during peak EV load times.
[70]	Neural network-based demand prediction	Supervised Learning	Load Forecasting / Demand Management	Learns from historical load data to forecast future EV charging demands.
[103]	User behavior clustering	Clustering (Unsupervised)	Demand Aggregation / DG Coordination	Segments EV users for tailored charging strategies integrated with distributed energy resources.
[92]	Pattern-based scheduling via user profile clusters	Clustering + Metaheuristics	Demand Response Management	Matches user patterns with optimal charging windows to reduce load impact.
[101,102]	PV forecasting with EV scheduling	Time-series Prediction + Reinforcement learning	Renewable Integration / V2G Management	Synchronizes EV charging/discharging with solar generation using learned temporal patterns.
[123]	Demand forecasting with price prediction and load balancing	Artificial intelligence + ML	Demand response	Optimization of real-time EV charging is conducted through AI driven demand forecasting and dynamic load distribution.
[124]	Energy load balancing and predictive cyber threat mitigation	Artificial intelligence smart grid framework	V2G Management	Ensures efficient EV charging infrastructure while securing the smart grid from cyber threat.
[125]	Prediction of SoC of EV batteries	Deep Learning Neural Network	Reactive power management	Voltage regulation and THD of the voltage source converters is improved.
[126]	Prediction of Charging duration	Feedforward fully connected artificial neural network	Optimal Charging	Optimal charging framework is designed to enable fast charging and by smoothing the “duck curve” grid stress is mitigated.
[127]	User demand is forecasted	Reinforcement Learning + Linear Programming	Optimize EV charging schedule	Peak transformer load is reduced by 31.5 %, solar utilization improved from 48 % to 66 % and voltage deviation is lessened from ±5.8 % to ±2.3 %.
[128]	Forecast user demand and optimize energy allocation	Random Forest, Support Vector Regression, Gradient Boosting Regressor, XGBoost, LightGBM, and Long Short-Term Memory (LSTM)	Smart charging for efficient energy distribution	Artificial intelligence framework enhances grid stability and charging station operations efficiently.
[129]	Load demand forecasting, charging station optimization, and energy management	Time-series forecasting models and neural networks	Optimizing charging schedules	Enhancing the accessibility, reliability and efficiency of EV charging systems in distribution network.
[130]	Predicts charging patterns, considering user preferences, grid demand and renewable energy availability	Whale-Optimized Neuro-Fuzzy	Smart charging schedule	Confirms optimal load balancing, grid performance and cost efficiency.
[131]	Forecasting charging demand and optimizing charging schedules	Reinforcement learning, genetic algorithms, and neural networks	Dynamic Charging	Grid stability, reliability and efficiency enhance.
[132]	Dynamic price forecasting	Decision tree regression and XGBoost	Energy consumption management and demand response	Energy costs minimizes and power system stability increases.
[133]	Charging power dynamic allocation	Support Vector Machines and reinforcement learning	Smart Load management	Enhance both load distribution and cybersecurity in EV charging networks.
[134]	Energy management through remote switching of tie line	Gaussian Process and Krill Herd Algorithm	Coordinated and smart charging	Operation cost during intelligent charging is found less compared to coordinated charging.
[135]	Optimal allocation of battery, EV charging stations, and DG units in grid	Real coded genetic algorithm	Peak load shaving	Improvement in voltage level and reduction in energy losses is achieved.
[136]	Optimize PV production and dynamic control of energy distribution	Adaptive neuro-fuzzy inference system + ML	Charging through DG	Reliance on grid power reduces for charging EV ensures grid stability.
[137]	Forecasting EV energy consumption	ML regression model	Time of charging	Through managing charging schedule grid stability can be improved.
[138]	Optimizes EV energy management, battery usage, and DG dispatch	Meerkat Optimization Algorithm	Smart charging	System efficiency, reliability, and sustainability through optimal EV energy management.
[139]	Predict future EV charging demands	Model Predictive Control + ML	Load management	Peak demand is reduced by 63 % through the adoption of MPC and ML based EV charging management.

(*continued on next page*)

Table 20 (*continued*)

Refs.	Algorithms/Methods	Artificial Intelligence Techniques	Application Area/ Problem Addressed	Observations
[140]	Predict EVs fast charging time	Random Forest, Decision Tree and XGBoost	Coordinated charging	Voltage fluctuation and power quality in grid is improved significantly.
[141]	Optimize charging patterns based on real-time data	Adaptive multi-agent reinforcement learning	EV charging network management	Effciency of EV charging network improves to meet growing charging demand.
[142]	Optimize the cost and manage the charging station load	Deep-Q reinforcement learning	Demand management strategy	Optimizes charging and discharging costs and manages charging station demand efficiently.
[143]	Analyzes system data and grid conditions	Golden Jackal Optimization and Attention Pyramid Convolutional Neural Network	Smart charging	The overall system cost was reduced while grid performance improved.
[144]	Short-term prediction of energy consumption	Deep learning and transformer models	Energy demand forecasting	Through accurate demand forecasting, grid stability and resilience enhanced by integrating EV charging infrastructure.

upgrades. Smart coordination between PV generation and EV storage, as seen in [102104], benefits from learning algorithms that anticipate generation variability and EV availability. AI enhances decision-making for dispatch and charging in microgrid environments, ensuring optimized energy balance and improved hosting capacity.

The authors in reference [49] presented a flexible framework clearly illustrating the structure of EV flexible charging and discharging networks, shown in Fig. 18. It depicts the interaction between EVs, charging stations, the power grid, and energy management systems to optimize energy flow. The diagram emphasizes the importance of coordinated scheduling to balance grid load, reduce energy costs, and enhance the integration of renewable energy sources. By implementing intelligent control strategies, such as deep reinforcement learning, the system aims to efficiently manage the timing and rate of EV charging and discharging, thereby contributing to grid stability and energy efficiency. This approach is particularly relevant in scenarios involving V2G technology, where EVs not only consume energy but also supply it back to the grid during peak demand periods. Table 20 highlights the approaches, strategies, and intended uses of important studies that used artificial intelligence to address different impact related problems EV on distribution network.

4.4.1. Advantages and disadvantages of AI methods used to mitigate EVs impact

Table 21 provides a comparative overview of various AI methods applied to mitigate the operational and environmental impacts of EVs on modern power grids. These approaches support accurate load forecasting, efficient charging control, and intelligent energy management through data-driven decision-making. Supervised learning algorithms such as Random Forest, Gradient Boosting, XGBoost, LightGBM and Artificial Neural Networks are widely applied for EV load forecasting, charging demand estimation, and battery health prediction [145]. They effectively capture complex nonlinear relationships and handle large datasets, but require substantial labeled data, high computational resources and careful tuning to prevent overfitting and improve adaptability under changing grid conditions.

In contrast, unsupervised learning approaches like K-means clustering, Gaussian processes or metaheuristic-assisted clustering are suitable for pattern recognition, EV user segmentation and fault or anomaly detection [146]. They can uncover hidden behavioral trends without labeled data. However, their interpretability is limited, and they often face convergence issues, reducing their efficiency in real-time control. Classifier-based algorithms, including Decision Tree Regression with XGBoost, Support Vector Regression and hybrid models such as Random Forest–LSTM are effective for decision-making and control applications [128]. They support grid state classification, charging prioritization and dynamic energy balancing, though they demand extensive tuning and computational power for real-time operation.

Reinforcement learning methods, such as Deep-Q Learning, Multi-Agent reinforcement learning and hybrid reinforcement learning frameworks, are particularly useful for adaptive energy management and V2G optimization [147]. By learning optimal control policies through interaction with the environment, reinforcement learning enables dynamic and autonomous decision-making but requires intensive training and careful stability management. Finally, fuzzy logic and hybrid AI systems, including ANFIS, Neuro-Fuzzy models and heuristic-optimized hybrids offer superior adaptability and interpretability for multi-objective optimization problems involving cost, energy and emissions [130]. Although effective in handling uncertainty and real-time adaptation, their performance depends heavily on expert-defined rules and optimization efficiency.

5. Discussions & Future Scopes for research

5.1. Discussion and identified shortcomings

- ***Consumer behavior modeling and practical aspects:*** The majority of studies on how EVs affect the distribution network have concentrated on predicting the extra load demand of EVs and evaluating its effects on stability, operating voltage, and thermal capacity. These studies address a broad spectrum of network topologies, including their operational scenarios and design. However, most of these studies' EV demand profiles are projected or derived from small-scale trials, which limit their usefulness and take consumer behavior into account. A major limitation in the development of deterministic and probabilistic EV load models is the lack of abundant EV charging data needed for model validation and development.

- ***The significance of detailed impact analysis and generalization:*** Numerous research provide results in absolute values, and deterministic or stochastic approaches are frequently used to establish violations of network voltage limitations caused by EV charging load using synthetic data. Furthermore, at certain levels of EV penetration, the majority of studies base network hosting capacity on one or a small number of voltage violations. Information from this method can be inaccurate or lacking. As a result, the results of each study's hosting capacity vary greatly, in addition to taking into account various network architectures and operational conditions. While previous research identifies the main network and EV hosting capacity bottlenecks, there is still a significant opportunity to more precisely measure this impact and extrapolate the results.

- ***The necessity of defining precise guidelines and rules for Network Managers and Research Using Actual EV Data about Charging:*** Research on EVs' impact on distribution networks has focused on controlled charging strategies, smart charging based on network conditions, and active management of EVs and DG, including V2G operations. Most studies explore time-based or scheduled charging, but there's a need for comprehensive solutions to address network capacity issues and establish regulations. Understanding financial implications, regulatory challenges, and consumer behavior is

Table 21
Advantages and disadvantages of AI methods in EVs impact mitigation application.

Classification of AI Methods	Name of the AI Methods	Advantages	Disadvantages
Supervised Learning	Random Forest Decision Tree Support Vector Machines (SVM) Gradient Boosting Regressor XGBoost LightGBM Neural Networks Feedforward Fully Connected ANN ML Regression Models Deep Learning Neural Network Deep Learning + Transformer Models	• High prediction accuracy for load demand and charging patterns • Handles nonlinear relationships effectively • Useful for time-series forecasting of EV charging load • Can be integrated with control algorithms for smart charging • Scalable for large datasets	• Requires large labeled datasets • Training can be computationally expensive • Risk of overfitting if not tuned properly • Limited adaptability to unseen grid or EV behaviors
Unsupervised Learning	Clustering (e.g., K-means) Clustering + Metaheuristics Gaussian Process + Krill Herd Algorithm Time-series Forecasting Models + Neural Networks Artificial Intelligence + ML Frameworks	• Identifies hidden patterns in EV consumption and behavior • Useful for segmenting EV users and charging profiles • Helps detect anomalies or faults in grid-vehicle interactions • Reduces dependency on labeled data • Can discover complex patterns from large datasets	• Clusters may be difficult to interpret meaningfully for decision-making • Model evaluation can be subjective • May converge to local minima • Less accurate for real-time grid control without supervision • Lack of labeled outputs makes prediction and control challenging
Classifier Based	Decision Tree Regression + XGBoost Random Forest + Decision Tree Support Vector Regression (SVR) Random Forest, SVR, Gradient Boosting, XGBoost, LightGBM, LSTM	• Effective for decision-making and control strategies • Can balance energy between EVs and grid dynamically • Learns optimal charging/discharging policies • Handles nonlinear and dynamic environments • Adaptive to changing grid and traffic patterns	• Requires extensive training and tuning • Stability and convergence issues • Computationally intensive • Real-time deployment can be challenging
Reinforcement Learning	Reinforcement Learning + Linear Programming Supervised + Reinforcement Adaptive Multi-Agent Reinforcement Learning Deep-Q Reinforcement Learning Reinforcement Learning, Genetic Algorithms, Neural Networks	• Learns optimal charging/discharging strategies through interaction with the environment • Effective for dynamic, uncertain EV–grid systems • Can optimize long-term rewards such as energy cost, grid stability, and user comfort • Supports adaptive and autonomous decision-making without explicit supervision • Scalable to multi-agent systems and decentralized control • Capable of integrating with optimization (e.g., LP) and deep learning for improved performance	• Requires extensive training and simulation environments High • computational cost and long convergence time • Sensitive to reward design and hyperparameters • Stability and safety issues in real-time deployment • Limited interpretability of learned policies • Difficult to generalize to unseen grid or behavioral scenarios
Fuzzy and Hybrid AI Systems	Fuzzy Logic Fuzzy Logic + Expert System Hybrid ML-Heuristics Whale-Optimized Neuro-Fuzzy Adaptive Neuro-Fuzzy Inference System (ANFIS) + ML Real-Coded Genetic Algorithm Meerkat Optimization Algorithm Golden Jackal Optimization + Attention Pyramid CNN Artificial Intelligence Smart Grid Framework Model Predictive Control + ML	• Handles uncertainty and imprecise EV-grid parameters • Flexible for multi-objective optimization (cost, energy, emissions) • Can combine human expertise with data-driven methods • Efficient for real-time adaptive control of charging stations • High interpretability compared to deep networks	• Complex design and parameter tuning • May require expert knowledge to define rules • Limited scalability for very large datasets • Performance depends on optimization algorithm efficiency

crucial. Large-scale, real-world studies using diverse EV fleet data are essential for practical and conclusive insights.

- ***Multiple-purpose Solutions and a Hybrid Approach:*** The majority of research has primarily used deterministic or stochastic techniques with real, synthetic, or hybrid data, focusing on specific elements like heat loading or voltage stability issues caused by EVs, or investigating isolated methods to mitigate EV charging demand. Because of the small scope of each research paper, the complexity involved, and the lack of large-scale EV data, a more holistic and hybrid strategy that could yield more robust conclusions relevant to various contexts has rarely been adopted. Future research must therefore use more hybrid and comprehensive techniques. A combination of methods can also provide greater adaptability and flexibility to various situations and settings, assisting in determining the best trade-offs and answers. Additionally, the effects of various mitigation strategies on different aspects of the network have not been the main focus and must therefore be addressed.

5.2. Future research scopes & recommendations

A few suggestions for further study are offered based on the shortcomings:

- ***Co-simulation for Voltage Barrier Based EV Hosting Capacity:*** Previously, researchers have studied voltage barrier-based changes in the characteristics of distribution networks due to EV penetration. But a real time simulation has not been studied yet in the operational stage. For future research, a real-time Python–PowerFactory co-simulation framework can be developed for operational scenarios. This would provide a one-stop solution where, when multiple EVs are connected in a specific region, the interface simulates the network in PowerFactory, updates the network status, and then Python determines which EVs should be connected or disconnected at that moment based on voltage barriers.
- ***Realistic EV Load Model and Profiles:*** Future research should create realistic EV load models and usage profiles based on the growing amount of consumer data on EV usage and charging behavior.

Energy demand, driving trends, and customer behavior in relation to various retailer incentives should all be taken into consideration by these models. As a result, it is essential to employ the deterministic and probabilistic EV and load models and profiles using the charger types and usage of actual EV fleets. Commercial charging stations and commercial electrical cars, including heavy vehicles, in particular, are anticipated to have a major impact on the distribution networks. This has been largely disregarded in previous studies and hence requires careful consideration.

- ***Techno-economic Analysis of Solutions:*** Although regulated or controlled charging has proven successful, there is limited comprehensive research on its financial and legal implications for various stakeholders, such as market participants, network operators, and owners of EVs or charging stations. Techno-economic analyses of various solutions and their real-world applications, like regulatory concerns, should be the focus of future research.

- ***Role of Distribution Generation and Storage:*** Several studies have shown that the best ways to manage EV charging and its effects are through DG and storage, which come after regulated or controlled EV charging. To handle the unique demand of EV charging, more research is required to ascertain the degree of penetration of DGs and electricity storage systems as well as their operating regime. Further research is also necessary to fully understand the economic effects of the additional DGs (such as solar PV) and storage systems required to manage EV demand.

- ***Holistic and Hybrid Approach:*** Distribution networks' ability to host EVs is dependent on a number of variables, including load demand, charging patterns, network architecture, and restrictions. Numerous of these variables and uncertainties may impact several goals for solution development, including network performance and the cost-effectiveness of EV mitigation measures. The problem's complexity and diversity may be better captured by a more hybrid and holistic approach that combines two or more methodologies and produces more workable solutions. Additionally, as previously mentioned, combining multiple objective criteria when developing solutions can yield more reliable and broadly applicable outcomes. Furthermore, certain areas of network design and operation that have not yet received much attention require a detailed evaluation of the effects of potential mitigation strategies.

Additionally, it is necessary to thoroughly evaluate the effects of different mitigation strategies on various network design and operational factors, which have not been widely studied to date.

6. Conclusions

The impact of EV charging on the distribution network and the associated mitigation techniques and solutions have been thoroughly reviewed in this study. The goal of this review paper is to present a qualitative and quantitative analysis of the literature that has been published in this field. Additionally, this paper highlights the main research gaps and offers insight into potential future approaches for this field of study. The assessment of the literature indicates the following findings.

- EV charging will have a major impact on the network's operational voltage, load demand, hosting capacity and thermal capacity, which needs to be effectively managed.
- Although regulated or controlled EV charging has been shown to be a successful approach, it might not be sufficient on its own. To fully overcome their impact on the network, DGs and storage systems, including EVs themselves, can be actively controlled. This is another efficient method that doesn't require a major revamp of the infrastructure.
- Research on EVs impact on transformer loading and lifetime need to be increased to reduce transformer loss of life percentage.
- More RES integrated DG management approach should be introduced to reduce EVs impact on grid.

Despite significant progress in this area, the research indicates that more study is still needed. In summary:

- Researchers are encouraged to investigate the complex relationship between EVs and distribution networks in greater detail, considering the networks' dynamic capabilities, real-world data, varied operating circumstances, and sophisticated and thorough impact measurement techniques. The research stresses the necessity of a comprehensive and hybrid strategy that combines deterministic, stochastic, and heuristic methodologies in order to produce reliable and broadly applicable results as well as the best solutions based on multi-objective criteria for EV impact reduction.
- The study gives utilities and policymakers a clear roadmap for creating regulations that actively monitor networks and encourage controlled charging procedures for the best possible network efficiency. However, concerted and cooperative research efforts to create a workable and efficient implementation plan may be essential to successful implementation.
- Although this sector has seen significant progress, the research indicates that further study is urgently needed. Specifically, in the application of artificial intelligence models to mitigate the impact of EV on power distribution network.

This review paper also provides critical insights for power utilities, policymakers, researchers, and energy solution providers. Power utilities can apply the findings to improve voltage stability, load planning, grid planning and EVs hosting capacity; policymakers gain guidance for regulatory support of smart charging and DG. Researchers are directed toward key data and modeling gaps, while charging operators and energy solution providers can use the strategies discussed to optimize load management and integrate intelligent control systems.

CRediT authorship contribution statement

Fahim Ahmed: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Shameem Ahmad:** Writing – original draft, Writing – review & editing, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mir Toufikur Rahman:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Investigation. **Md. Rifat Hazari:** Writing – review & editing, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rethwan Faiz:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis. **Tofael Ahmed:** Writing – review & editing, Validation, Investigation, Data curation, Conceptualization. **Mazaher Karimi:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition.

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.

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Data availability

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References

[1] Abedin MR, Das HS. Electricity from rice husk: a potential way to electrify rural Bangladesh. International Journal of Renewable Energy Resources 2014;4(3): 604–9.
[2] International Energy Agency, Tracking Transport 2020, IEA Reports, 2022. [Online]. Available, https://www.iea.org/reports/transport. Accessed: Feb. 20, 2023.
[3] Engel H, et al. The Potential Impact of Electric Vehicles on Global Energy Systems, McKinsey & Company [Online]. Available, https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/the-potential-impact-of-electric-vehicles-on-global-energy-systems/; 2021. Accessed: Feb. 20, 2023.
[4] International Energy Agency, Global EV Outlook 2021: Accelerating Ambitions Despite the Pandemic, IEA Reports, 2021. [Online]. Available, https://www.iea.org/reports/global-ev-outlook-2021/. Accessed: Feb. 20, 2023.
[5] Mai T, et al. Electrification futures study: Scenarios of electric technology adoption. Golden: National Renewable Energy Laboratory; 2018.
[6] Nacmanson WJ, Zhu J, Ochoa LF. "Assessing the unmanaged EV hosting capacity of Australian rural and urban distribution networks," in CIRED Porto Workshop. E-Mobility and Power Distribution Systems, Hybrid Conference, pp 2022; 681–685:2022.
[7] Kim T-H, Kim D, Moon S-I. "evaluation of electric vehicles hosting capacity based on interval undervoltage probability in a distribution network," IEEE. Access 2021;9:140147–55. https://doi.org/10.1109/access.2021.3116465 [Online]. Available:.
[8] Deb S, Pihlatie M, Al-Saadi M. "smart charging: a comprehensive review," IEEE. Access 2022;10:134690–703. https://doi.org/10.1109/access.2022.3227630 [Online]. Available:.
[9] Huang DS, Infield A, Cruden D. Plug-in electric vehicles as demand response to absorb local wind generation in power distribution network. In: in 2013 world electric vehicle symposium and exhibition. Barcelona, Spain; 2013. p. 1–5.
[10] Rana MM, Alam SM, Rafi FA, Deb SB, Agili B, He M, et al. Comprehensive review on the charging technologies of electric vehicles (EV) and their impact on power grid. IEEE Access; 2025.
[11] Srivastava A, Manas M, Dubey RK. Electric vehicle integration's impacts on power quality in distribution network and associated mitigation measures: a review. Journal of Engineering and Applied Science 2023;70(1):32.
[12] Narasimhulu N, Awasthy M, Pérez de Prado R, Divakarachari PB, Himabindu N. Analysis and impacts of grid integrated photo-voltaic and electric vehicle on power quality issues. Energies 2023;16(2):714.
[13] Jiang H. Analysis of electric vehicle charging impact on the electric power grid: based on smart grid regional demonstration project — Los Angeles. In: in 2016 IEEE PES Transmission & Distribution Conference and exposition-Latin America (PES T&D-LA). Morelia, Mexico; 2016. p. 1–5.
[14] Feng K, et al. The impact of plug-in electric vehicles on distribution network. In: in 2020 IEEE international smart cities conference (ISC2). Piscataway, NJ, USA; 2020. p. 1–7.
[15] Silva GM, et al. Recharging electric vehicles: impact on the load curve of a low-voltage distribution network. In: in 2019 IEEE PES innovative smart grid technologies conference - Latin America (ISGT Latin America). Gramado, Brazil; 2019. p. 1–6.
[16] Kamana-Williams B, Hooper Daniel Bishop G, Chase JG. Driving change: electric vehicle charging behavior and peak loading. Renew Sustain Energy Rev 2024; 189:113953.
[17] Muttaqi Kashem M, et al. Fast and random charging of electric vehicles and its impacts: state-of-the-art technologies and case studies. Electr Pow Syst Res 2024; 226:109899.
[18] Saklani M, Saini DK, Yadav M, Gupta YC. Navigating the challenges of EV integration and demand-side management for India's sustainable EV growth,IEEE Access 2024;12:143767–96. https://doi.org/10.1109/ACCESS.2024.3470218.
[19] Inci Mustafa, et al. Power system integration of electric vehicles: a review on impacts and contributions to the smart grid. Applied Sciences 2024;14(6):2246.
[20] Mohammed Abdallah, et al. Strategies and sustainability in fast charging station deployment for electric vehicles. Sci Rep 2024;14(1):283.
[21] Ibrahim Rania A, Gaber Ibrahim M, Zakzouk Nahla E. Analysis of multidimensional impacts of electric vehicles penetration in distribution networks. Sci Rep 2024;14(1):27854.
[22] Sun Lijie, et al. Impact of electric vehicles on power system reliability and related improvements: a review. Electr Pow Syst Res 2025;247:111838.
[23] Abul'Wafa AR, El'Garably A, Mohamed WAF. Impacts of uncoordinated and coordinated integration of electric vehicles on distribution systems performance. In: in 2017 nineteenth international Middle East Power systems conference (MEPCON). Cairo; 2017. p. 337–64.
[24] Hashim MS, et al. Assessment of technical impacts of EV charging to Malaysian distribution grid. In: in 2021 IEEE international conference on Automatic Control & Intelligent Systems (I2CACIS). Malaysia: Shah Alam; 2021. p. 337–64.
[25] Jain A, Jariwala HR, Mhaskar U. "Impact on the transmission and distribution grid by the deployment of electric vehicles charging," in 2019 International Conference on Computing, Power and Communication Technologies (GUCON), pp. 250–256. 2019.
[26] Shrestha S, Hansen TM. Distribution feeder impacts of electric vehicles charging in an integrated traffic and power network. In: in 2016 north American Power symposium (NAPS). Denver; 2016. p. 1–6.
[27] Antoun J, et al. "Impact analysis of level 2 EV chargers on residential power distribution grids," in 2020 IEEE 14th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG), pp. 523–529. 2020.
[28] Prakash P, et al. Impact of electric vehicles in three-phase distribution grids. In: CIRED 2021 - the 26th international conference and exhibition on electricity distribution. Virtual; 2021. p. 2084–8.
[29] Helm S, et al. Impact of unbalanced electric vehicle charging on low voltage grid. In: in 2020 IEEE PES innovative smart grid technologies Europe (ISGT-Europe). Virtual; 2020. p. 665–9.
[30] Venegas FG, et al. Impact of distributed energy resources and electric vehicle smart charging on low voltage grid stability. In: CIRED 2021 - the 26th international conference and exhibition. Virtual; 2021. p. 1905–9.
[31] Hasan KN, et al. Measurement-based electric vehicle load profile and its impact on power system operation. In: in 2019 9th international conference on Power and Energy systems (ICPES). Perth; 2019. p. 1–6.
[32] Yusuf J, Hasan ASMJ, Ula S. Impacts analysis of electric vehicles integration to the residential distribution grid. In: in 2021 IEEE Kansas Power and Energy conference (KPEC). Kansas, USA; 2021. p. 1–6.
[33] Wagh S, et al. Aggregated impact of EV charger type and EV penetration level in improving PV integration in distribution grids. In: in 2021 IEEE Transportation Electrification Conference & Expo (ITEC). Chicago; 2021. p. 595–600.
[34] Bishla Sandeep, Khosla Anita. Review of power quality and stability of EV charging with grid and PV solar. Energ Technol 2024;12(2):2300744.
[35] Babar R, Muhammad A, Khan RS, et al. Operational strategies for EV fast-charging and their impact on power grid and renewable integration. Energy Exploration & Exploitation 2025;0(0):1–41. https://doi.org/10.1177/01445987251352551.
[36] Cundeva S, Mateska AK, Bollen MHJ. Hosting capacity of LV residential grid for uncoordinated EV charging. In: in 2018 18th international conference on harmonics and quality of Power (ICHQP). Ljubljana; 2018. p. 1–5.
[37] Abid MS, et al. Impact assessment of charging of electric vehicle. In: in 2021 56th international universities Power engineering conference (UPEC). Middlesbrough, United Kingdom; 2021. p. 1–6.
[38] Paudyal P, et al. EV hosting capacity analysis on distribution grids. In: in 2021 IEEE Power & Energy Society General Meeting (PESGM). Washington; 2021. p. 1–5.
[39] Draz M, Voß DFM, Albayrak S. "The impact of electric vehicles on low voltage grids: A case study of Berlin," in 2018 Power systems computation conference (PSCC), Dublin, Ireland. 2018. p. 1–7.
[40] Kamruzzaman M, Bhusal N, Benidris M. "Determining maximum hosting capacity of electric distribution systems to electric vehicles," in 2019 IEEE industry applications society annual meeting, Baltimore, MD, USA. 2019. p. 1–7.
[41] Letha SS, Bollen M. "Estimation of electric vehicle hosting capacity of a distribution network including ambient temperature," in CIRED 2021 - The 26th international conference and exhibition on electricity distribution, Online Conference. 2021. p. 2350–5.
[42] Zenhom M, et al. "a comprehensive review of renewables and electric vehicles hosting capacity in active distribution networks." IEEE. Access 2024;12:3672–99.
[43] Nutkani Inam, et al. Impact of EV charging on electrical distribution network and mitigating solutions–a review. IET Smart Grid 2024;7(5):485–502.
[44] Quirós-Tortós J, et al. Control of EV charging points for thermal and voltage management of LV networks. IEEE Trans Power Syst 2016;31(4):3028–39. https://doi.org/10.1109/tpwrs.2015.2468062 [Online]. Available:.
[45] Godina R, et al. Weekend charging impact of EVs on a residential distribution transformer in a Portuguese Island. In: in 2016 51st international universities Power engineering conference (UPEC). Coimbra, Portugal; 2016. p. 1–6.
[46] Utakrue M, Hongesombut K. Impact analysis of electric vehicle quick charging to power transformer lifetime in distribution system. In: in 2018 IEEE transportation electrification conference and expo, Asia-Pacific. Bangkok, Thailand; 2018. p. 1–5.
[47] Tai Le Duc, et al. A review on advanced battery thermal management systems for fast charging in electric vehicles. Batteries 2024;10(10):372.
[48] Leoncini Gabriele, et al. A review on challenges concerning thermal management system design for medium duty electric vehicles. Appl Therm Eng 2024;236: 121464.
[49] Song Bingkun, Madawala Udaya, Baguley Craig. A review of grid impacts, demand side issues and planning related to electric vehicle charging. In: 2021 IEEE southern Power electronics conference (SPEC). IEEE; 2021.
[50] Rahman S, et al. Comprehensive review & impact analysis of integrating projected electric vehicle charging load to the existing low voltage distribution system. Renew Sustain Energy Rev 2022;153.
[51] Rahman S, Khan IA, Amini MH. "A review on impact analysis of electric vehicle charging on power distribution systems," in 2020 2nd International Conference on Smart Power & Internet Energy Systems (SPIES), pp. 420–425. 2020.

[52] Wang Han, Guo Fangce, Sivakumar Aruna. Analysing the impact of electric vehicle charging on households: An interrelated load profile generation approach. Energ Buildings 2025;335:115558.
[53] Li Yanning, Jenn Alan. Impact of electric vehicle charging demand on power distribution grid congestion. Proc Natl Acad Sci 2024;121(18):e2317599121.
[54] Kumar Manoj, Chokkalingam Bharatiraja. Demand side management using optimization strategies for efficient electric vehicle load management in modern power grids. PloS One 2024;19(3):e0300803.
[55] Permal Navinesshani, et al. EV and PV penetration impact on grid with conservative voltage regulation and reactive voltage compensation. ISA Trans 2025;158:477–87.
[56] Shaheen Abdullah M, et al. Performance assessment of modern distribution networks conjoined with electric vehicles in normal and faulty conditions. Scientific African 2025;28:e02630.
[57] KK, Nandini, Jayalakshmi N. Sabhahit, and Vinay Kumar Jadoun.. Voltage unbalance assessment in a distribution system incorporated with renewable-based sources and electric vehicles in an uncertain environment. IET Renewable Power Generation 2024;18:4288–307.
[58] Abiassaf Gerard Albadawi, Arkadan Abd A. "impact of EV charging, charging speed, and strategy on the distribution grid: a case study." IEEE journal of emerging and selected topics in industrial. Electronics 2024;5(2):531–42.
[59] Almutairi Sulaiman Z, et al. A hierarchical optimization approach to maximize hosting capacity for electric vehicles and renewable energy sources through demand response and transmission expansion planning. Sci Rep 2024;14(1): 15765.
[60] Fani Hossein, Hashmi Md Umar, Deconinck Geert. Impact of electric vehicle charging simultaneity factor on the hosting capacity of LV feeder. Sustainable Energy, Grids and Networks 2024;40:101581.
[61] Rawat Tanuj, et al. Planning renewables in distribution system with electric vehicles to improve hosting capacity and energy losses: two-stage stochastic optimization framework. Sustainable Energy, Grids and Networks 2024;39: 101445.
[62] Wanninayaka Mudiyanselage Chathuranga DW, et al. Spatio-temporal and correlation modeling of EV charging data for hosting capacity analysis. IEEE Transactions on Industry Applications 2025;61(6):8722–35. https://doi.org/10.1109/TIA.2025.3576744.
[63] Wanninayaka Mudiyanselage Chathuranga DW, et al. Probabilistic coupled EV-PV hosting capacity analysis in LV networks with spatio-temporal modelling and copula theory. IET Smart Grid 2024;7(6):917–28.
[64] Hassan S Jarjees, Ul, et al. An efficient modelling and hosting capacity analysis of a distribution system integrating PVs supported by the V2G technology. Electr Pow Syst Res 2024;236:110959.
[65] Diahovchenko Illia. Analyzing the influence of electric vehicle charging scheduling on distribution transformer lifespan. Heliyon 2024;10:21.
[66] McCann Justin, Liao Yuan. Development and application approach of EV impact and mitigation analysis methods for use in traditional rural electric utility planning practices. In: 2024 IEEE rural electric Power conference (REPC). IEEE; 2024.
[67] UK Power Network. Low carbon London electric vehicle load profiles [Online]. Available, https://data.london.gov.uk/dataset/low-carbon-london-electric-vehicle-load-profiles; 2021. Accessed: Dec. 18, 2023.
[68] Adam B., et al. Representative Australian electricity feeders with load and solar generation profiles. v1.CSIRO. Data Collection 2015. [Online]. Available: Accessed: Dec. 18, 2024. doi. https://doi.org/10.4225/08/5631B1DF6F1A0.
[69] Abid MS, et al. Mitigating the effect of electric vehicle integration in distribution grid using slime mould algorithm. Alex Eng J 2023;64:785–800. https://doi.org/10.1016/j.aej.2022.09.022 [Online]. Available:.
[70] Quiros-Tortos J, Ochoa L, Butler T. How electric vehicles and the grid work together: lessons learned from one of the largest electric vehicle trials in the world. IEEE Power and Energy Magazine 2023;21(2):64–76. https://doi.org/10.1109/mpe.2018.2863060 [Online]. Available:.
[71] Energy Velocity. Velocity Energy [Online]. Available: http://www.velocityenergy.com.au/peak-demand-management; 2016. Accessed: Feb. 20, 2023.
[72] Collins ME, et al. Understanding the network impact of EV growth: Long-term planning approaches developed in the charge project. In: CIRED 2020 Berlin workshop. Berlin; 2020. p. 147–50.
[73] International Electrotechnical commission (IEC), IEC 60038. International Standard Voltages; 2003.
[74] Teng J, Liao S, Wen C. Design of a fully decentralized controlled electric vehicle charger for mitigating charging impact on power grids. IEEE Transactions on Industry Applications 2017;53(2):1497–505. https://doi.org/10.1109/TIA.2016.2622221.
[75] Ismael SM, Aleem SHEA, Abdelaziz AY, Zobaa AF. State-of-the-art of hosting capacity in modern power systems with distributed generation. Renew Energy 2019;130:1002–20.
[76] Hatziargyriou N, Karfopoulos E, Tsitsimelis A, Koukoula D, Rossi M, Giacomo V. "On the DER hosting capacity of distribution feeders," in Proc. CIRED 23rd Int. Conf. Electricity Distribution, Lyon, France, Jun. 15–18. 2015.
[77] Deuse J, Benintendi D, Agrell P, Bogetoft P. "Power system and market integration of DER, the EU-DEEP approach," in proc. CIRED 2005–18th Int. Conf. Exhib. Electricity distribution, Turin, Italy, Jun. 6–9. 2005. pp. 1–4, IET, Stevenage, UK.
[78] Bollen M, Yang Y, Hassan F. "Integration of distributed generation in the power system—a power quality approach," in proc. 2008 13th Int. Conf. Harmonics quality Power, Wollongong, NSW, Australia, Sep. 28–Oct. 1. 2008. pp. 1–8, IEEE, Piscataway, NJ, USA.
[79] Umoh V, Davidson I, Adebiyi A, Ekpe U. Methods and tools for PV and EV hosting capacity determination in low voltage distribution networks—a review. Energies 2023;16(8):3609.
[80] Bayram I Safak. Impacts of electric vehicle charging under cold weather on power networks. In: In 2021 56th international universities Power engineering conference (UPEC). IEEE; 2021. p. 1–6.
[81] Edmunds Calum, Galloway Stuart, Dixon James, Bukhsh Waqquas, Elders Ian. Hosting capacity assessment of heat pumps and optimised electric vehicle charging on low voltage networks. Appl Energy 2021;298:117093.
[82] Hajeforosh SF, Bollen MHJ. "Increasing the grid capacity for electric vehicle charging using dynamic rating," in CIRED 2021 - The 26th international conference and exhibition on electricity distribution, Virtual Conference. 2021. p. 1777–81.
[83] Nutkani IU, Lee JC. "evaluation of electric vehicles (EVs) impact on electric grid," in international Power electronics conference (IPEC). Himeji: Japan; 2022. p. 239–46.
[84] Dippenaar J, Bekker B. "Towards locally appropriate electric vehicle hosting capacity regulations," in CIRED Porto Workshop 2022: E-mobility and Power distribution systems. Hybrid Conference, Porto, Portugal 2022:611–5.
[85] Jain A, Karimi-Ghartemani M. Mitigating adverse impacts of increased electric vehicle charging on distribution transformers. Energies 2022;15(23):9023. https://doi.org/10.3390/en15239023 [Online]. Available:.
[86] Bollen M, Rönnberg S. Hosting capacity of the power grid for renewable electricity production and new large consumption equipment. Energies 2017;10 (9):1325.
[87] Roth H, Kuhn P, Gohla-Neudecker B. "sustainable mobility - cost-effective and zero emission integration of Germany's EV fleet," in 2009 international conference on clean electrical Power. Italy: Capri; 2009. p. 207–11.
[88] Dang Q. "Electric vehicle (EV) charging management and relieve impacts in grids," in 2018 9th IEEE international symposium on Power electronics for distributed generation systems (PEDG), Charlotte. 2018. p. 1–5.
[89] Badugu J, Obulesu YP, Babu CS. "Development of demand side management strategy for smart residential distribution system embedded with EV Load," in TENCON 2019–2019 IEEE Region 10 Conference. India: Kochi; 2019. p. 1655–60.
[90] Reiner U, Elsinger C, Leibfried T. "Distributed self-organizing electric vehicle charge controller system: Peak power demand and grid load reduction with adaptive EV charging stations," in 2012 IEEE international electric vehicle conference, Greenville, SC, USA. 2012. p. 1–6.
[91] Beaude O, et al. Reducing the impact of EV charging operations on the distribution network. IEEE Transactions on Smart Grid 2016;7(6):2666–79. https://doi.org/10.1109/TSG.2015.2489564.
[92] Gupta V, et al. "EV benefit evaluation in a collaborative scheduling environment with penalties for unscheduled EVs," in 2018 8th IEEE India international conference on Power electronics (IICPE). India: Jaipur; 2018. p. 1–6.
[93] Gautam A, Verma AK, Srivastava AM. "A novel algorithm for scheduling of electric vehicle using adaptive load forecasting with vehicle-to-grid integration," in 8th international conference on Power systems (ICPS). India: Jaipur; 2019. p. 1–6.
[94] Wang X, et al. Tri-level scheduling model considering residential demand flexibility of aggregated HVACs and EVs under distribution LMP. IEEE Transactions on Smart Grid 2021;12(5):3990–4002. https://doi.org/10.1109/TSG.2021.3075386.
[95] Hua L, Wang J, Zhou C. Adaptive electric vehicle charging coordination on distribution network. IEEE Transactions on Smart Grid 2014;5(6):2666–75. https://doi.org/10.1109/TSG.2014.2336623.
[96] Khalid Mutayab, et al. Impact of public and residential smart EV charging on distribution power grid equipped with storage. Sustain Cities Soc 2024;104: 105272.
[97] Cesar Diaz-Londono, et al. Comparison and analysis of algorithms for coordinated EV charging to reduce power grid impact. IEEE Open Journal of Vehicular Technology 2024;5:990–1003. https://doi.org/10.1109/OJVT.2024.3435489.
[98] Aoun Alain, et al. Dynamic charging optimization algorithm for electric vehicles to mitigate grid power peaks. World Electric Vehicle Journal 2024;15:7.
[99] Acharige Sithara SG, et al. Grid integration of electric vehicles-impact assessment and remedial measures. J Power Sources 2025;650:236697.
[100] Suman S, et al. "Electric vehicle owner preferred smart charge scheduling of EV aggregator using PV generation," in 2018 20th National Power Systems Conference (NPSC), Tiruchirappalli, India. 2018. p. 1–6.
[101] Du G, et al. "An optimization model of EVs charging and discharging for power system demand leveling," in. IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC) 2016;2016:835–42.
[102] Rezaeumozafar M, Eskandari M, Savkin AV. A self-optimizing scheduling model for large-scale EV fleets in microgrids. IEEE Trans Industr Inform 2021;17(12): 8177–88. https://doi.org/10.1109/TII.2021.3064368.
[103] Kornsiriluk V. "Study of energy storage system: concept of using ESS in EV charging stations in MEA," in 2019 IEEE PES GTD grand international conference and exposition Asia (GTD Asia), Bangkok. 2019. p. 697–700.
[104] Thunuguntla Vinod Kumar, et al. A TOPSIS based multi-objective optimal deployment of solar PV and BESS units in power distribution system electric vehicles load demand. Sci Rep 2024;14(1):29688.
[105] Aggarwal Surbhi, et al. Revolutionizing load management: a novel technique to diminish the impact of electric vehicle charging stations on the electricity grid. Sustain Energy Technol Assess 2024;65:103784.
[106] Sindha J. "Impact of battery swapping stations on EV adoption and its contribution to peak load management," in 2020 17th International Conference on the European Energy Market (EEM), Stockholm. 2020. pp. 1–4.

[107] Alireza Zabihi. Parhamfar Mohammad Decentralized energy solutions: the impact of smart grid-enabled EV charging stations. Heliyon 2025;11(13):e41815. https://doi.org/10.1016/j.heliyon.2025.e41815.

[108] Barnabé Guilherme Pinheiro, et al. Non-intrusive demand response management strategy to mitigate the impacts of residential electric vehicle charging on distribution systems. Electr Pow Syst Res 2024;235:110849.

[109] Mao T, et al. "A new schedule-controlled strategy for charging a large number of EVs with load shifting and voltage regulation," in 2015 IEEE PES Asia-Pacific Power and Energy engineering conference (APPEEC), Brisbane. 2014. p. 1–5.

[110] Kim Ho-Young, et al. "voltage stability index (VSI)-based optimal vehicle-to-grid (V2G) charging/discharging strategy in radial distribution system." journal of electrical. Engineering & Technology 2024;19(7):3885–90.

[111] Yuvaraj T, et al. Minimizing the impact of electric vehicle charging station with distributed generation and distribution static synchronous compensator using PSR index and spotted hyena optimizer algorithm on the radial distribution system. e-Prime-Advances in Electrical Engineering, Electronics and Energy 2024;8:100587.

[112] Gholami Khalil, et al. Voltage stability improvement of distribution networks using reactive power capability of electric vehicle charging stations. Computers and Electrical Engineering 2024;116:109160.

[113] Türkoğlu A Selim, et al. Maximizing EV profit and grid stability through virtual power plant considering V2G. Energy Rep 2024;11:3509–20.

[114] Energy-Based Approach. Sustainability 2024;16(14):6149. https://doi.org/10.3390/su16146149.

[115] Da EC, et al. "assessment of distributed generation hosting capacity in electric distribution systems by increasing the electric vehicle penetration," in 2021 IEEE PES innovative smart grid technologies Europe (ISGT Europe). Finland: Espoo; 2021. p. 01–5.

[116] Alatise O, et al. "Expanding EV charging capacity in distribution networks: a case study for charging EVs at work," in CIRED 2021 – the 26th international conference and exhibition on electricity distribution, Virtual. 2021. p. 2945–9.

[117] Kamruzzaman M, et al. "A method for maximizing the hosting capacity to electric vehicles using feeder reconfiguration," in 2020 IEEE Power & Energy Society General Meeting (PESGM), Montreal, Canada. 2020. p. 1–5.

[118] Al-Dhaifallah Mujahed, et al. Enhancing hosting capacity for electric vehicles in modern power networks using improved hybrid optimization approaches with environmental sustainability considerations. Sci Rep 2024;14(1):25607.

[119] Soleimani M, Kezunovic M. Mitigating transformer loss of life and reducing the hazard of failure by smart EV charging. IEEE Transactions on Industry Applications 2020;56(5):5974–83. https://doi.org/10.1109/TIA.2020.2986990.

[120] Raghuveer Rayaprolu M, Bhalja Bhavesh, Agarwal Pramod. Energy management system for a workplace PV-EV charging station with active and reactive power dispatch of EVs considering transformer aging and uncertainties. Electr Pow Syst Res 2025;238:111062.

[121] An Y, et al. Optimal scheduling of electric vehicle charging operations considering real-time traffic condition and travel distance. Expert Syst Appl 2023;213:118941. https://doi.org/10.1016/j.eswa.2022.118941.

[122] Ahmad F, et al. "EV charging station placement using nature-inspired optimization algorithms," in 2023 international conference on Power. Energy and Control (PIECON), Aligarh, India: Instrumentation; 2023. p. 1–6.

[123] Singh Arvind R, et al. Optimizing demand response and load balancing in smart EV charging networks using AI integrated blockchain framework. Sci Rep 2024;14(1):31768.

[124] Sharma Ankita, Rani Shalli, Shabaz Mohammad. Artificial intelligence-augmented smart grid architecture for cyber intrusion detection and mitigation in electric vehicle charging infrastructure. Sci Rep 2025;15(1):21653.

[125] Karthikeyan M, Manimegalai D. Enhancing voltage control and regulation in smart micro-grids through deep learning-optimized EV reactive power management. Energy Rep 2025;13:1095–107.

[126] Jamil Umar, et al. Artificial intelligence-driven optimal charging strategy for electric vehicles and impacts on electric power grid. Electronics 2025;14(7):1471.

[127] Tanjil Sarker, Md, et al. AI-driven optimization framework for smart EV charging systems integrated with solar PV and BESS in high-density residential environments. World Electric Vehicle Journal 2025;16(7):385.

[128] Shern Siow Jat, et al. Artificial intelligence optimization for user prediction and efficient energy distribution in electric vehicle smart charging systems. Energies 2024;17(22):5772.

[129] Gudekota Sowmya, et al. Developing AI-based predictive analytics for electric vehicle charging infrastructure: utilizing machine learning models for demand forecasting, Charging Station optimization, and Energy management. Artificial Intelligence, Machine Learning, and Autonomous Systems 2025;9:137–75.

[130] Senthilkumar T, et al. An intelligent electric vehicle charging system in a smart grid using artificial intelligence. Optimal Control Applications and Methods 2025;46(3):1180–92.

[131] Mishra Debani Prasad, et al. AI-driven optimization techniques for electric vehicle charging infrastructure. In: Artificial intelligence for integrated smart Energy Systems in Electric Vehicles. Cham: Springer Nature Switzerland; 2025. p. 283–308.

[132] Palaniyappan Balakumar, Vinopraba T. Dynamic pricing for load shifting: reducing electric vehicle charging impacts on the grid through machine learning-based demand response. Sustain Cities Soc 2024;103:105256.

[133] Sabbir Hossen, Md, et al. AI-driven framework for secure and efficient load Management in Multi-Station EV charging networks. World Electric Vehicle Journal 2025;16(7):370.

[134] Hassan Marwa. Machine learning optimization for hybrid electric vehicle charging in renewable microgrids. Sci Rep 2024;14(1):13973.

[135] Saldanha John JA, et al. AI-based optimal allocation of BESS, EV charging station and DG in distribution network for losses reduction and peak load shaving. Electr Pow Syst Res 2024;234:110554.

[136] Alkahtani Ammar Ahmed, et al. Hybrid renewable Energy and smart app-based Management for Efficient and Sustainable EV charging infrastructure. International Journal of Energy Research 2025;2025(1):5872792.

[137] Kene Raymond O, Olwal Thomas O. Data-driven modeling of electric vehicle charging sessions based on machine learning techniques. World Electric Vehicle Journal 2025;16(2):107.

[138] Kashki Alireza, et al. Optimal charging of electric vehicles in smart stations and its effects on the distribution network using meerkat optimization algorithm. Energy Rep 2024;12:1936–46.

[139] Mejdi Lazher, Kardous Faten, Grayaa Khaled. Machine learning-based online MPC for large-scale charging infrastructure management. IEEE Access 2024;12:36896–907.

[140] Sharma Purnima K, Sathiyanarayanan Mithileysh, Zurek-Mortka Marta. Optimizing electric vehicle charging: An investigation into effective machine learning techniques for charging management. 2024.

[141] Jamjuntr Pitchaya, Techawatcharapaikul Chanchai, Suanpang Pannee. Adaptive multi-agent reinforcement learning for optimizing dynamic electric vehicle charging networks in Thailand. World Electric Vehicle Journal 2024;15(10):453.

[142] Choudhary Durgesh, Mahanty Rabindra Nath, Kumar Niranjan. Demand management of plug-in electric vehicle charging station considering bidirectional power flow using deep reinforcement learning. Eng Appl Artif Intel 2025;139:109585.

[143] Gunapriya B, et al. Performance enhancement of EV charging stations and distribution system: a GJO–APCNN technique. Electrical Engineering 2025;107(1):883–97.

[144] Makaremi Saeed. A multi-output deep learning model for energy demand and port availability forecasting in EV charging infrastructure. Energy 2025;317:134582.

[145] Gowda SN, Nath K, Zhang C, Gowda R, Gadh R. Short-term aggregate electric vehicle charging load forecasting in diverse conditions with minimal data using transfer and meta-learning. Energy Systems. 2024.

[146] Shang R, Ma Y. Electric vehicle charging load forecasting based on K-means++-GRU-KSVR. World Electric Vehicle Journal 2024;15(12):582.

[147] He C, Peng J, Jiang W, Wang J, Du L, Zhang J. Vehicle-To-Grid (V2G) Charging and Discharging Strategies of an Integrated Supply–Demand Mechanism and User Behavior: A Recurrent Proximal Policy Optimization Approach. World Electric Vehicle Journal 2024;15(11):514. https://doi.org/10.3390/wevj15110514.