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Review

Multi-stakeholder perspectives for transport electrification: A review on placement and scheduling of electric vehicle charging infrastructure

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ABSTRACT

In promoting transport electrification, addressing diverse stakeholder needs is vital for a balanced approach to placing and scheduling Electric Vehicle Charging Stations (EVCS). This paper highlights stakeholder-centric challenges for implementing and scheduling public charging infrastructures. To account for stakeholders' perspectives, it investigates the significance of assigning variable weightage to different stakeholders in optimizing the placement and scheduling of charging stations. This paper examines stakeholder priorities by selecting various features and assessing each stakeholder's contribution to those features in the context of placement and scheduling challenges. By analyzing relevant case studies focusing on stakeholder engagement, charger types, studied networks, and installation locations, this study presents multi-stakeholder-driven optimal allocation and scheduling strategies for charging infrastructures and practical implications. The findings reveal a predominant focus on distribution networks and EVCS owners in placement and scheduling strategies, with limited attention to other stakeholders. Also, around 80 percent of recent studies emphasize urban and highway networks, often validated in test networks, highlighting the need for real network validation, particularly in suburban and remote areas. Furthermore, the paper explores future perspectives on EVCS placement and scheduling, offering valuable insights to policymakers, industry professionals, and researchers addressing emerging research issues in transport decarbonization.

1. Introduction

Transport electrification is crucial in reaching net-zero emission goals, as the transportation sector contributes to around 15 percent of global greenhouse gas emissions (Victor-Gallardo et al., 2022). There has been a notable surge in global electric vehicle (EV) usage owing to techno-economic and environmental advantages compared to conventional gasoline vehicles (Ghasemi-Marzbali, 2022). At the end of 2022, global sales, encompassing battery and plug-in hybrid EVs, attained a 13 percent market share, resulting in a cumulative total of approximately 10.52 million EVs in operation worldwide, as shown in Fig. 1(a) (EV Volumes, 2023; International Energy Agency, 2023). In response to the swiftly evolving EV demand, policymakers are strategizing and establishing charging infrastructures, including fast and slow charging options for users (Jayapalan et al., 2022).

Presently, residential and workplace chargers meet a significant portion of charging needs, while the requirement for publicly accessible chargers is rising, particularly due to range anxiety concerns (Suhail et al., 2021). Also, in densely populated urban areas with limited access to residential and workplace charging, public charging infrastructure helps to build confidence among floating EV users. In 2022, the global public charging points reached 2.7 million, exhibiting a 55 percent rise compared to 2021 and totalling over 900,000 charging points (International Energy Agency, 2023). Fig. 1(b) illustrates the ratio of EVs to charging points across various countries, reflecting transport electrification efforts. Despite early adoption and limited charger installations, a strategic plan includes placing and scheduling charging facilities for widespread usage (Mastoi et al., 2022). During the initial stages of transport electrification, strategic placement of charging stations alleviates range anxiety, improves user convenience, and accelerates EV adoption (Gupta et al., 2021). Simultaneously, well-designed scheduling schemes are essential for balancing energy demand amid extensive EV uptake (Das et al., 2021). Addressing stakeholders' engagement is needed for a seamless EV transition in both placement and scheduling

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strategies.

The stakeholders involved in placement and scheduling tasks can be categorized into two groups - primary and secondary. Primary stakeholders are directly impacted entities, including local governments, distribution network operators, EVCS owners, transportation networks, and EV users. While indirectly influenced, secondary stakeholders include auto industries, community groups, and environmental and research institutions. Studies reported disparate outcomes in an energy transition process influenced by local contexts and stakeholder dynamics (Lopolito et al., 2022; Falcone et al., 2021). Another study underscores the importance of emphasizing stakeholder's perceptions and contexts in crafting effective and balanced policy interventions (Falcone, 2018).

Largs-scale EV integration with randomly installed chargers into distribution networks provides detrimental impacts, causing voltage violation, power loss, overloading, and voltage imbalances (Nour et al., 2020; Karmaker et al., 2019). Studies claimed that random charger placement impacts transport networks through traffic congestion, limited EV user accessibility, and reduced system efficiency (Ahmad et al., 2022; Bilal and Rizwan, 2020). Several studies have focused on charging station placement within distribution networks, often overlooking the integration of transport networks and EV users (Cadena Zarate et al., 2022; Datta and Sengupta, 2021). The government sets large-scale targets and initiatives, yet their role as key stakeholders in planning is overlooked in current studies (Torkey and Abdelgawad, 2022). EVCS owners manage EV fleets, necessitating their inclusion in deployment and scheduling phases (Suhail et al., 2021). Optimal placement and scheduling involve optimization techniques and stakeholder interaction, each with pros and cons dependent on data prerequisites, parameter calibration, computational efficiency, and the feasibility of attaining optimal solutions (Suhail et al., 2021; Islam et al., 2015). Some studies have incorporated deployment and scheduling strategies in test networks; however, the feasibility of these strategies in real networks requires validation integrating stakeholder interaction (Cadena Zarate et al., 2022; Bilal et al., 2021; Pal et al., 2021). Also, users' demographic profiles and acceptance vary across regions, necessitating region-specific planning approaches (Luo et al., 2015). Prioritizing stakeholder concerns is essential as it guarantees an adapted and user-centric approach for EVCS deployment and scheduling, resulting in a more integrated and effective system.

Once a widespread charging infrastructure is in place, scheduling becomes pivotal to effectively handle surging demand, alleviate grid congestion, and secure equitable stakeholder benefits. Existing studies on scheduling primarily deal with distribution networks where other stakeholder benefits and uncertainties are less prioritized (Wang et al., 2019a; Lee et al., 2021a, 2021b). Several studies predominantly explored profit maximization and minimizing the detrimental impacts of distribution networks while developing day-ahead charging/discharging schedules (Javor et al., 2019; Wang et al., 2019b; Rabiee et al., 2018). Other studies have employed dynamic pricing schemes to address scheduling challenges by reducing charging costs; however, these schemes can inadvertently elevate the probability of traffic congestion, impacting stakeholder convenience during off-peak hours, as highlighted in (Wang et al., 2019b; Amin et al., 2020). The stakeholder convenience can be improved by addressing stakeholder benefits linked with load profile, capacity constraints, traffic flow, and the availability of charging ports (Sah and Kumar, 2022). A study illustrates the necessity of demand-side management, including vehicle-to-grid (V2G) services and intermittent renewable integration in EVCS scheduling (Al-Ogaili et al., 2019). Unregulated power exports from prosumers to grids through solar photovoltaics (PV) and V2G systems reduce EV hosting capacity in distribution networks (Milford and Krause, 2021). As a result, distribution network operators are considering export limit restrictions, which could potentially limit customer advantages. Therefore, integrating and prioritizing stakeholder benefits is essential to improve performance in large-scale EV scheduling.

This paper delves into the current research on EVCS placement and scheduling approaches, shedding light on stakeholder engagement. Also, stakeholder priorities are evaluated and ranked according to their impacts and benefits concerning charging station deployment and scheduling. Furthermore, this paper examines the effects of EV scheduling strategies, proposing an integrated platform for monitoring and measuring the performance of the charging stations. Table 1 compares the present paper, and previous review works emphasizing stakeholder engagement, including topics, optimization methods, objective functions, constraints, and impact analysis in EVCS placement and scheduling.

The main focuses of this paper are as follows.

a. Outline challenges and solutions for EVCS placement and scheduling strategies, considering diverse stakeholder benefits.
b. Analyze recent studies depending on charger types, network studied, installation sites, and stakeholder engagement.
c. Determine stakeholder priorities in EVCS deployment and scheduling based on necessities extracted from relevant studies.
d. Propose multi-stakeholder-driven EVCS deployment and scheduling strategies and practical implications for large-scale penetration.
e. Suggest future research directions for optimal EVCS placement and scheduling.

The remaining content of this paper is divided into three sections. Section 2 describes methods, including overall research steps and the literature review process. Section 3 includes a detailed review of EVCS placement, focusing on stakeholder viewpoints. Section 4 explores

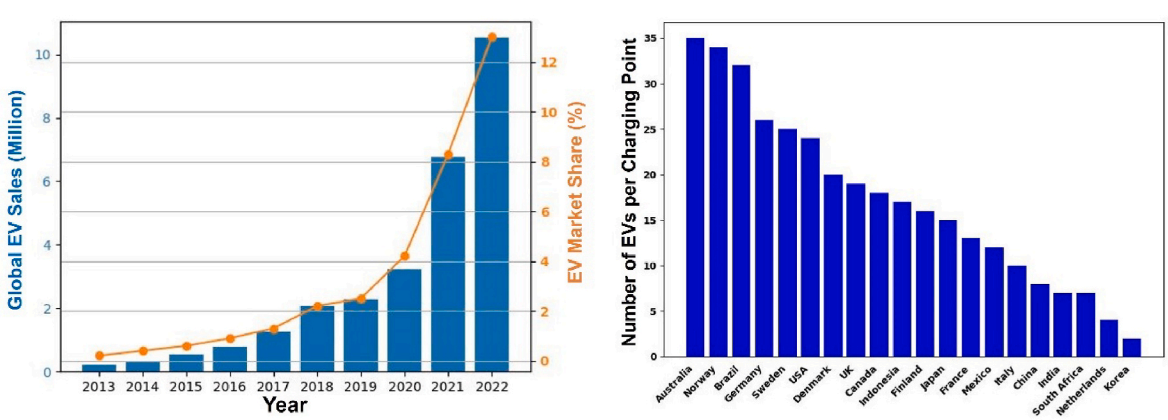

Fig. 1. Statistics on global EV sales and charging points.

Table 1
Comparison with existing review works addressing EVCS placement and scheduling.

Features	Unterluggauer et al. (2022)	Mastoi et al. (2022)	Gupta et al. (2021)	Ahmad et al. (2022)	Ding et al. (2020)	Singh et al. (2023)	Al-Ogaili et al. (2019)	Das et al. (2021)	Chen and Folly (2023)	Current Paper
Topic	P	P	P	P	P	P	S	S	S	P, S
Optimization methods	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Objective functions	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Constraints	✓	✓	×	✓	×	✓	×	✓	×	✓
Stakeholder benefits and priorities	Δ	×	×	Δ	×	×	×	×	×	✓
Impact of stakeholder-based EV scheduling	×	×	×	×	×	×	×	×	×	✓

P- Placement S-Scheduling Δ- Partial.

existing strategies and impacts, suggesting an integrated framework for EV scheduling. After that, Section 5 analyses relevant case studies and stakeholder priorities in EVCS placement and scheduling problems. Section 6 discusses proposed innovative strategies, practical implications, and future research perspectives. Finally, Section 7 summarizes findings with challenges and policy implications.

2. Methods

In this section, overall research steps and methodologies for the systematic literature review are illustrated for EVCS deployment and scheduling, as depicted in Fig. 2. It starts with identifying research problems by defining the scope and objectives, followed by an extensive literature review concerning stakeholder requirements in EVCS allocation and scheduling.

After analyzing existing studies and stakeholder priorities, efficient strategies for optimal placement and scheduling are proposed in this paper, integrating multiple stakeholders. Then, challenges and opportunities inherent to implementing these strategies while highlighting gaps in existing solutions for EVCS planning are discussed in this study.

2.1. Literature review process

This section describes the systematic review process on EVCS placement and scheduling using Scopus and Google Scholar databases. The keywords “Electric Vehicle Charging Station Placement” and “Electric Vehicle Charging Scheduling” are utilized in selecting articles from 2012 to the date. This search includes peer-reviewed journal articles and conference papers written in English from the energy systems field. Finally, the highly cited and more influential articles are selected only for this comprehensive review. After the screening phase, the bibliometric analysis was conducted to extract relevant data and insights. Fig. 3 represents two steps: research paper selection and analytical process for EVCS placement and scheduling. This systematic approach enables critical analysis of selected literature, identifies trends, synthesizes the findings, and identifies challenges and solutions to understand EVCS placement and scheduling comprehensively.

This review paper has several research questions as follows.

a) What state-of-the-art methods are used in existing studies for EVCS placement and scheduling considering stakeholder benefits?
b) What stakeholders are involved in the EVCS deployment process, and what are their prospective benefits & priorities?
c) How can EVCS placement and scheduling be designed to maximize stakeholder benefits?
d) What is the trade-off between different stakeholder benefits, and how can they be balanced to achieve optimal output?
e) What are the key factors for EVCS placement and scheduling that can ensure sustainable and equitable transition to electric mobility?
f) How can EVCS placement and scheduling contribute to achieving broader goals and promoting equity in stakeholder benefits?

3. Placement of electric vehicle charging station

Owing to several stakeholder-centric factors, such as the availability of EVs and charging facilities, government policies, price and incentives, and demographic profile, transport electrification phases vary in each region (Zhao et al., 2022; Mukherjee and Ryan, 2020). Thus, the recent EVCS placement studies are summarized in Table 2, highlighting stakeholder roles with location, type, objective function, optimization method, and studied network.

Most studies in Table 2 concentrated on a single stakeholder in the EVCS placement problem, which might not yield optimal solutions for other stakeholders. The existing literature reports EVCS placement is conducted on test feeders (Cadena Zarate et al., 2022; Datta and Sengupta, 2021; Bilal et al., 2021; Reddy and Selvajyothi, 2020; Sadhukhan et al., 2021; Gantayet et al., 2021; Jamatia et al., 2022; Deb et al., 2021; Hadian et al., 2020; El-Zonkoly and dos Santos Coelho, 2015; Pal et al., 2021), and only a few cases are demonstrated on real distribution and transport networks (Luo et al., 2015; Hao et al., 2022; Mehouachi et al., 2022; Bitencourt et al., 2021; Zhu et al., 2016). Minimizing power loss and the annual cost is the most common objective function in existing

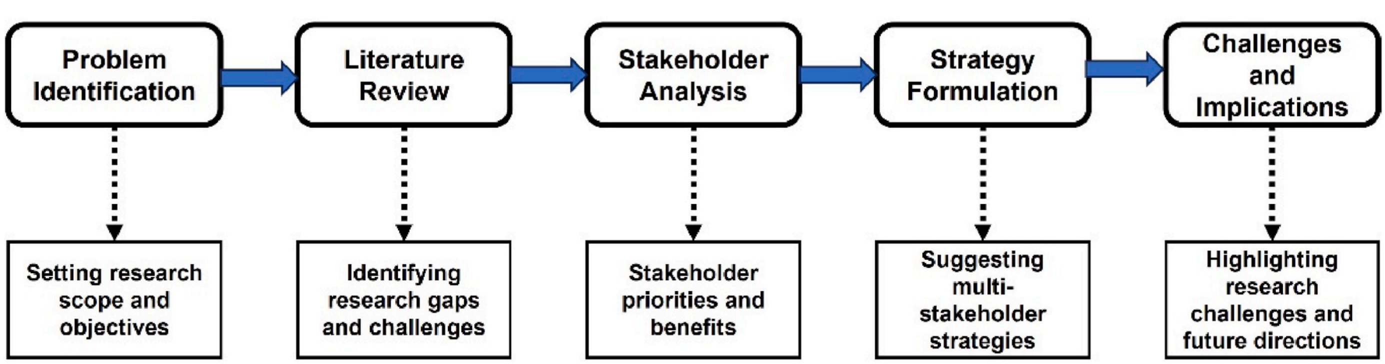

Fig. 2. Research procedure on EV charging station placement and scheduling concerning multiple stakeholders.

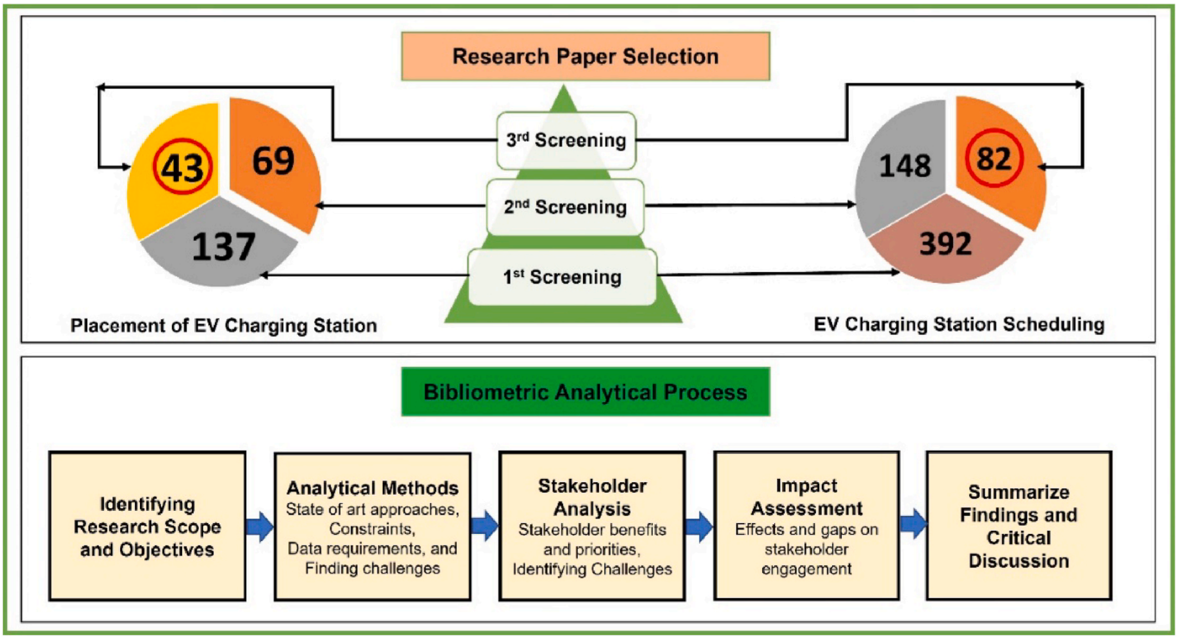

Fig. 3. Systematic literature review of EVCS placement and scheduling.

studies on charging station placement. Including distribution network impacts, EV uncertainties, traffic flow, and user satisfaction is essential in the EVCS allocation. Besides, a customer-oriented planning framework for EVCS positioning is necessary to increase EV penetration, which needs further investigation.

3.1. *Problem formulation for EVCS placement*

In optimal placement problems, the objective function and constraints formulation typically relied on techno-economic and environmental impacts where societal impacts such as residential charging, demographic profile, working hours, and traffic congestion may offer added advantages in EV adoption (Suhail et al., 2021). This research categorizes objective functions in terms of technical, economic, environmental, and societal contexts shown in Fig. 4(a). Fig. 4(b) summarizes stakeholder-centric constraints for solving optimal placement problems. Constraints for EV users and EVCS owners typically involve managing EV uncertainties and cost minimization, while DNOs focus on mitigating adverse impacts. Simultaneously, transportation network constraints incorporate traffic flow, vehicle count, and types.

3.2. *Optimization approaches in EVCS placement*

Selecting a proper optimization technique for EVCS placement is challenging due to the accuracy and complexities in convergence, execution time, and parameter tuning during implementation in different networks (Bilal and Rizwan, 2020). Current studies use diverse optimization approaches for EVCS placement based on problem statements and limited stakeholder needs involving single and multi-objective functions. Table 3 demonstrates optimization approaches, convergence, execution time, and optimized solutions in existing studies.

In several cases, Genetic Algorithm (Jordán et al., 2021) and Particle Swarm Optimization (Reddy and Selvajyothi, 2020) are used due to their easy implementation, although it has issues with early convergence and approximate solutions. Simulated annealing is easy to implement, although it has problems with complex tuning, long convergence, and sub-optimal solutions (Sousa et al., 2016). Ant Colony Optimization can adapt to continuous changes despite uncertain convergence speed and complex parameter tuning (Sharma et al., 2021). Also, Grey-Wolf (Shabbar et al., 2021), Teaching-Learning algorithm (Duan and Pour-soleiman, 2021), and Integer Programming (Faridpak et al., 2019) have problems with slow convergence and significant execution time. Besides, Artificial Bee Colony (Boonraksa and Marungsri, 2018), Greedy Algorithms (Jovanovic et al., 2022), and Fuzzy TOPSIS (Technique for Order Preference by Similarities to Ideal Solution) optimization (Guo and Zhao, 2015) have fast convergence and short execution times. A few studies conducted multi-objective optimization using hybrid approaches for higher accuracy and lessening computational time (Cadena Zarate et al., 2022; Sadhukhan et al., 2021; Gantayet et al., 2021) (see Table 3).

3.3. *Key insights from existing EVCS placement reviews*

Table 4 describes key insights from existing review papers, including challenges and research directions for EVCS placement problems (see Table 4).

In most cases, EV users, EVCS owners, and distribution systems are considered where the transportation network and local authorities are absent. Considering economic aspects may violate performance constraints of distribution networks and plug-in congestion in charging stations. EVCS planning includes geographical location, objectives, optimization methods, technology, network, and stakeholder integration. Optimal placement should consider technical, economic, environmental, and societal benefits. Policymakers must focus on distribution network impacts and cost reductions, while distribution planners should analyze existing networks for performance constraints (Ahmad et al., 2022). Integrating transportation data, EV uncertainties, V2G technology, renewables, and reliability indices must be considered in optimal placement solutions.

4. EV charging scheduling strategies

EV charging scheduling minimizes charging costs for users and maximizes profit for EVCS owners. EV charging scheduling using conventional approaches is grouped in terms of methods, objective functions, operational constraints, network type, outcomes, and future scopes, presented in Table 5.

In most cases, the scheduling algorithm does not consider distribution network impacts. Also, navigation of charging station location is essential as it affects travel time and waiting time for EV charging (Qiang

Table 2
Summary of recent studies on EVCS placement.

Ref.	Siting	Sizing	Objective function	Solution Technique	Type of EVCS	Stakeholder	Network
Reddy and Selvajyothi (2020)	✓	✓	Minimization of power loss	Particle Swarm Optimization (PSO)	FCS	DNO	IEEE 19 and 25 Bus DNs
Sadhukhan et al. (2021)	✓	✓	Minimization of network loss and travel loss, maximizing EVCS utilization factor	Genetic algorithm, non-dominated sorting genetic algorithm- II (NSGA-II)	FCS	DNO, TS	IEEE 33 Bus DN
Bilal et al. (2021)	✓	✓	Minimization of power loss, improving voltage profile, and voltage stability index	Hybrid Grey Wolf Optimization and PSO (HGWOPSO) approach	FCS	DNO, EV Users	IEEE-33 and 69 Bus DNs
Cadena Zarate et al. (2022)	✓	✓	Minimize the cost of energy losses and EVCS installation	Genetic Algorithm	FCS	DNO	IEEE-33 Bus DN
Pal et al. (2021)	✓	✓	Minimization of power loss, voltage deviation, and establishment cost	Differential Evolution and Harris Hawks Optimization	RCS and FCS	DNO, CSO	IEEE-33 node radial DN
Yu et al. (2021)	✓	✓	Minimization of the annual cost of EVCS	PSO	FCS	DNO, EV Users	33 nodes TN and 33 nodes DN
Gantayet et al. (2021)	✓	✓	Minimizing the total annual cost of EVCS	Genetic algorithm and whale optimization algorithm	FCS	CSO, DNO	IEEE - 33 bus radial DN
Hao et al. (2022)	✓	✓	Improving EV user satisfaction and load stability	Improved Ant Colony Optimization	FCS	TS, DNO	TN of Xian City, China
Jamatia et al. (2022)	✓	✓	Reducing power loss	PSO and Symbiotic Organism Search (SOS)	FCS	DNO	IEEE -33 Bus DN.
Mehouachi et al. (2022)	✓	✓	Minimizing the establishment and charging cost	Genetic Algorithm	FCS	TS	TN of a city in Tunisia
Faridpak et al. (2019)	✓	✓	Minimization of EVCS owner's costs	Two-step linear programming	FCS	DNO	CIGRE DN
Erdoğan et al. (2022)	✓	✓	Maximize traffic flow and vehicle mileage	An optimization-based approach using designated EV corridors	FCS	TS	Highway TN, Maryland
Kadri et al. (2020)	✓	✓	Maximizing the total number of EV recharging	Multi-stage stochastic model using Bender's decomposition and genetic algorithm	FCS	CSO	NA
Chen et al. (2021)	✓	✓	Minimization of establishment cost, power loss, and voltage deviation	Balanced Mayfly Algorithm	FCS	DNO, CSO.	30 bus DN in Allahabad, India
Deb et al. (2021)	✓	✓	Minimizing installation cost, penalty rate, and traveling cost	Chicken Swarm Optimization and Teaching-learning-based optimization	RCS and FCS	DNO, CSO, and EV users	IEEE - 33 nodes DN and 25 nodes TN
Tadayon-Roody et al. (2021)	✓	✓	Reducing installation cost and power loss	Genetic Algorithm	FCS	DNO, CSO	20 Nodes TN
Bitencourt et al. (2021)	✓	✓	Minimizing power loss and charging zone center deviation	Hierarchical clustering, Scenario Reduction method, and BAT algorithm	Semi-FCS	DNO, EV users	DN with 654 customers, Costa Rica
Li et al. (2021)	✓	✓	Reducing installation, travel distance, and waiting time cost	Multipopulational genetic algorithm (MPGA) and k-means algorithm	RCS and FCS	CSO and EV users	DN and TN
Datta and Sengupta (2021)	✓	✓	Lowering power loss and cumulative voltage fluctuation	Improved New Binary Particle Swarm Optimization (INBPSO)	FCS	DNO	IEEE -15 Bus DN
Liu et al. (2020)	✓	✓	Maximizing profit and user satisfaction, minimizing voltage deviation	Improved Harmony Particle Swarm Optimization (IHPSO)	FCS	DNO, EV users	IEEE-33 and the PG&E – 69 bus DNs
Gampa et al. (2020)	✓	✓	Minimizing power loss and voltage deviation	Fuzzy Grasshopper Optimization Algorithm (GOA)	FCS	DNO	51 bus and 69 bus DNs
Zeb et al. (2020)	✓	✓	Lessening installation costs and power loss	PSO	SCS, RCS, and FCS	DNO, CSO	Domestic and industrial feeder
Hadian et al. (2020)	✓	✓	Reducing power loss and voltage variation and boosting reliability	Multi-objective Particle Swarm Optimization (MOPSO)	RCS	DNO, CSO	IEEE - 69 bus DN
Hosseini and Sarder (2019)	✓	✓	Managing technical, socio-economic, and environmental criteria	Bayesian Network (BN) model	FCS	DNO, CSO, and EV users	NA
Zhu et al. (2016)	✓	✓	Minimizing ownership, traveling cost, and range anxiety for EV customers	Mathematical model and genetic algorithm	FCS	CSO and EV users	15 nodes TN and 23 links in China
Huang et al. (2016)	✓	✓	Minimizing installation cost and expanding coverage	Geometric segmentation for solving partial coverage problem	SCS, FCS	TS, CSO	The geographic location of Toronto and Hamilton in Canada
Luo et al. (2015)	✓	✓	Maximizing benefits among entities	Bayesian game network	SCS, RCS, and FCS	TS, DNO, and EV users	TN from Los Angeles, USA
El-Zonkoly and dos Santos Coelho (2015)	✓	✓	Minimizing overall energy cost	Artificial Bee Colony (ABC) and Firefly Algorithm	SCS	DNO, CSO, and EV users	IEEE - 33 Bus DN

DN – Distribution Network, TN – Transport Network, DNO – Distribution Network Operator, CSO – Charging Station Operator, TS – Transportation Sector, SCS- Slow Charging Station, RCS- Regular Charging Station, FCS- Fast Charging Station.

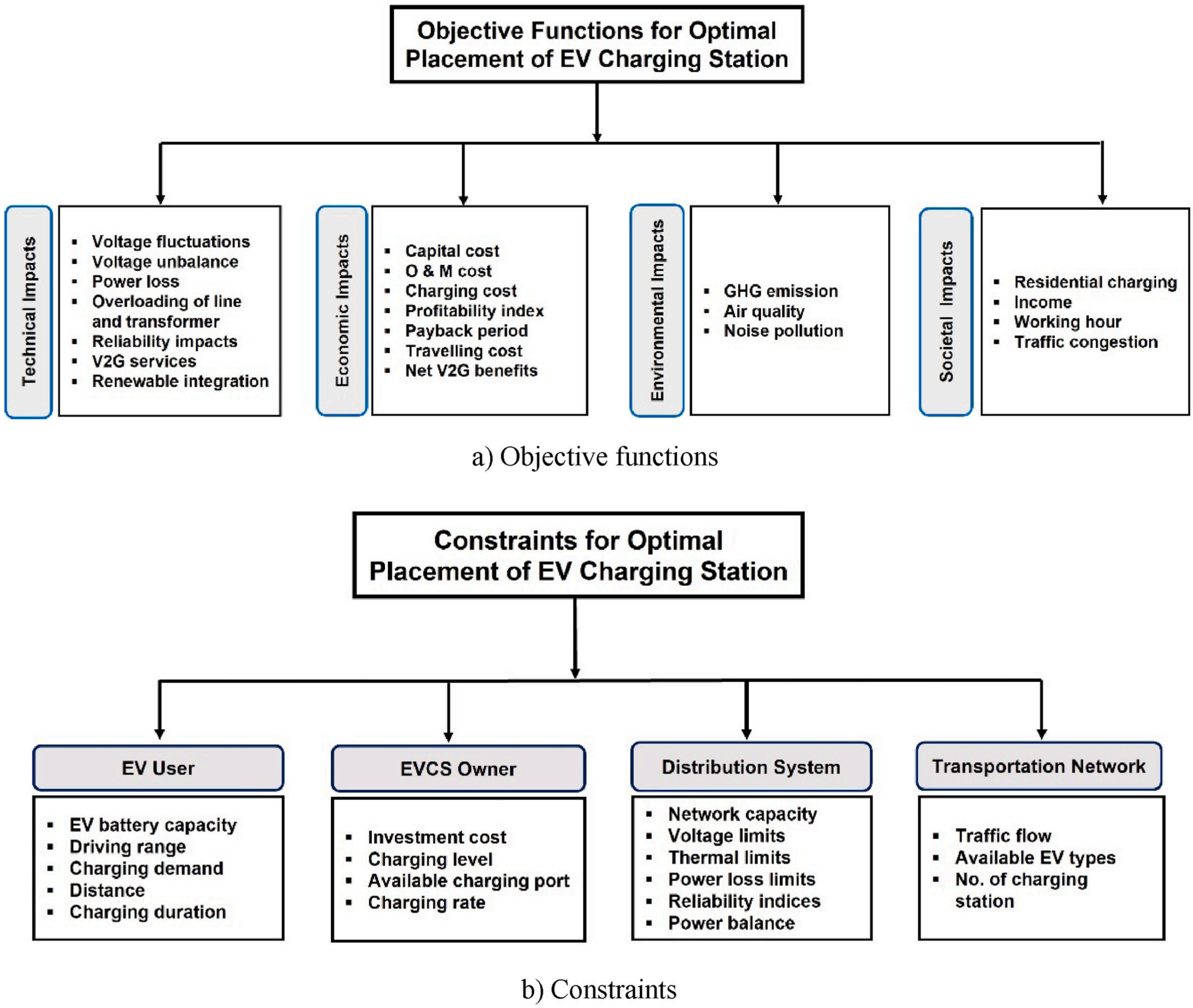

Fig. 4. Objective functions and constraints for EVCS placement.

et al., 2020). The existing literature on EV charging scheduling reports minimizing cost and maximizing profit where EV uncertainties are absent.

Artificial intelligence (AI) techniques have recently become popular in EV charging schedules. However, a lack of open-source EV data and uncertainties lead to inappropriate decisions and management for connected EVs. Existing literature on AI-based EV charging scheduling is summarized in Table 6, considering objective function, constraints, data used, outcomes, and research gaps. Current research targets individual EVs, overlooking broader market dynamics. Also, minimizing energy cost is the common objective function where an effective scheduling technique should include distribution network impacts, user satisfaction, and traffic volume.

The charging/discharging scheduling algorithms can be divided into two groups, i.e., conventional stochastic and AI approaches. Usually, the optimization algorithms used in traditional stochastic EV charging scheduling are as follows-genetic algorithm (Yu et al., 2021), ant colony optimization (Gantayet et al., 2021), particle swarm optimization (Gong et al., 2017), mixed integer linear programming (Gupta et al., 2022), and some other hybrid approaches (Ren et al., 2021). In AI techniques, deep reinforcement learning algorithms are primarily used in the existing literature (Lee et al., 2021b; Dorokhova et al., 2021; Qian et al., 2019; Nair et al., 2018; Mhaisen et al., 2020). Most of the AI-based approach uses single EV battery capacity and historical data from the previous day, which leads to improper control of scheduling problems (Wang et al., 2019a; Wan et al., 2018; Li et al., 2019). In addition, the distribution grid integrated with residential renewables via net metering needs to be considered in the scheduling algorithm. Conventional dynamic pricing scheme provides less charging cost for the EV users and maximizes the profitability index of the EVCS owner, although distribution network impacts are ignored. Also, the adaptive operative strategies for EVCS connected with renewables and the distribution grid during critical situations should be analyzed (Wang et al., 2019a). The performance validation of a V2G-featured EV charging scheduling algorithm considering stakeholder perspectives is absent in the existing literature (Amin et al., 2020).

4.1. Key insights from existing EVCS scheduling reviews

Based on the current literature on EV charging scheduling, an outline of contexts, challenges, and research gaps is presented in Table 7. Most of the scheduling algorithm reduces charging cost during off-peak hour,

Table 3
Comparison among different optimization approaches used in EVCS placement.

Optimization Approach and Application	Method	Implementation	Convergence	Execution time	Solution
Genetic Algorithm (Jordán et al., 2021)	Inspired by natural evolution	Easy implementation	Premature convergence	Large	It gives the approximate solution
Particle Swarm Optimization (Reddy and Selvajyothi, 2020)	Based on the concept of social interaction	Easy implementation	Early convergence, low precision	Less	Determines sub-optimal solution
Simulated annealing (Sousa et al., 2016)	Based on the physical annealing process of a metal	Easy implementation, however, makes it difficult to tune many parameters	Long convergence	Large	Identifies a global solution rather than a local one
Ant Colony Optimization (Sharma et al., 2021)	Inspired by the grouping behavior of ants	Adaptable to continuous changes while parameter tuning is difficult	Uncertain convergence speed	Uncertain	Provides optimal solution with changing environment
Artificial Bee Colony Algorithm (Boonraksa and Marungsri, 2018)	Inspired by the behavior of real bees	Simple and easy implementation, Limited search space	Fast convergence	Fast	Provides optimal solutions for large-scale practical problems
Teaching-Learning base Optimization (Duan and Poursoleiman, 2021)	Based on the effect of the influence of a teacher in a class	Easy implementation due to no parameter tuning required	Premature convergence	small	Offers optimal solutions through effective learning
Grey-Wolf Optimization (Shabbar et al., 2021)	Based on the hunting strategy of grey wolves	Easy to implement due to a few tunable parameters	Slow convergence	Long time	Provides local optimal solutions
Integer Programming (Faridpak et al., 2019)	Based on the real-life cost analysis	Simple, cannot be used for stochastic problems	Slow	High	Provides multiple optimal solutions
Greedy Algorithm (Jovanovic et al., 2022)	Based on human behavior for immediate benefits	Easy to implement	Fast but accuracy and efficiency problems	Small	Occasionally lack optimal solutions due to data oversight

which fosters traffic congestion and waiting time. Also, future research may be considered on long-term planning for the EV charging scheduling for various penetration levels.

4.2. Impact of EV charging scheduling

EV charging scheduling algorithm performs profit maximization and charging cost minimization. EV charging scheduling considering the interdependent stakeholders is necessary for better performance. The impacts of EV charging scheduling can be analyzed considering different stakeholders, i.e., distribution network, transport network, EVCS owner, and EV users, using the stakeholder engagement matrix shown in Fig. 5.

The management plan in Fig. 5 includes a stakeholder engagement matrix and step-by-step ways to analyze and map stakeholder benefits and engagement. The stakeholder engagement matrix helps to identify the actions required to achieve a specific goal, monitoring the actual engagement and advantages of the stakeholders from EV charging schedules.

Fig. 6 shows the integrated network performance monitoring and controlling mechanism in the EV charging/discharging schedule. The stakeholder benefits of EV scheduling drive the necessity of building an integrated network performance monitoring platform. This EV scheduling platform enables continuous coordination and communication, optimizing scheduling operations and efficient operation of resources among multiple stakeholders. The online visibility of this integrated platform will enhance reliability, accessibility, and user satisfaction while ensuring real-time monitoring of charging network performance.

4.2.1. Distribution network

The distribution network operator is pivotal in the EV charging ecosystem, overseeing infrastructure, deployment, and management. The study effectively optimizes generation and operating schedules by analyzing EV commuting behavior in tandem with distribution networks, as validated through simulations on IEEE-6 and IEEE-118 bus systems with EVs (Sun et al., 2018). Adaptive charging scheduling in research mitigates adverse effects from extensive EV integration in distribution networks (Hua et al., 2014). Active network management enhances power quality and voltage profiles in distribution networks, a technique applicable to scheduling EV charging/discharging in renewable-rich distribution systems (Dutta et al., 2022).

4.2.2. Transportation network

The transportation network is crucial for EV charging scheduling, aiding location planning, and providing EV routing and navigation. A study shows that optimizing for multiple vehicles in a real-world transit network in Daxing District, Beijing, can lower annual scheduling costs by 15.93 percent compared to traditional methods (Yao et al., 2020). Another study introduced an EV scheduling method employing a rule-based strategy incorporating user needs, traffic volume, and EV count, enhancing operational efficiency and alleviating traffic congestion through balancing load and generation (Luo et al., 2020). A review highlights challenges in traditional scheduling strategies and proposes a collaborative approach utilizing smart charging technologies within transport and distribution networks to enhance scheduling performance (Jawad and Liu, 2020).

4.2.3. EVCS owners

EVCS owners are crucial for managing charging operations and pricing to enhance user convenience and profitability while meeting network constraints. Various studies have been conducted on EV scheduling to control EVCS and provide dynamic charging schemes (Wang et al., 2019b; Amin et al., 2020). Most charging scheduling algorithms are considered EVCS with homogeneous capacity, number of ports, and charging levels, which is unrealistic. Also, investigation can be done for renewable-based EVCS scheduling to improve grid stability by reducing peak load.

4.2.4. EV users

EV users actively participate in charging scheduling, impacting charging station utilization and demand. Balancing user convenience and cost-effectiveness necessitates addressing uncertainties such as EV characteristics, plug-in habits, timing, and charging levels. A two-stage power charging schedule based on game theory demonstrates that charging costs are reduced by 8.59 percent, satisfying user demand and network constraints, as described in a study (Kim et al., 2022). In a smart charging scheme, the EV user gets control over charging with more flexibility in energy use. Assuming a fixed battery capacity instead of diverse models and neglecting uncertainties can lead to inaccurate charging power estimations in scheduling, which needs EV market analysis.

Table 4
Insights from existing EVCS placement review papers.

Ref. And year	Considered aspects	Suggestions
(Singh et al., 2023), 2023	Classification of planning models, problem formulations for combined transport and distribution networks	- Charging station planning needs government incentives and strategic support with specific charging requirements. - V2G-enabled charging facilities need consideration. - Location feasibility in the presence of renewable requires investigation.
(Unterluggauer et al., 2022), 2022	EVCS planning objectives, optimization approaches for integrated transport and distribution networks	- Probabilistic approach and concerns related to major stakeholders must be incorporated to capture spatio-temporal uncertainties. - Validation of the optimization approach in real networks is required. - Sequential adaptive planning for EVCS placement can be added.
(Ahmad et al., 2022), 2022	Placement strategies, objective functions, constraints, optimization techniques, and impact analysis	- Problem formulation should include EVCS owners, distribution networks, and EV users' perspectives. - EV demand and charging levels should be included in load modelling. - Demand-side-management and V2G technologies may include. - Integration of renewables and reliability indices - Sensitivity analysis for the EVCS parameters needs to be investigated
(Bilal and Rizwan, 2020), 2020	Placement studies based on objective functions, solution methods, geographic conditions, and demand-side management	- Multi-objective functions can be added During problem formulation, including operating and installation costs, reliability indices, and waiting time. - Traffic and renewable uncertainties may be considered. - Meta-heuristic combined with classical optimization may be used.
(Suhail et al., 2021), 2021	Different constraints and optimization methods are used in the optimal location of EVCS	- Adaptive artificial intelligence technologies may be employed. - Feasibility analysis of renewable-based charging stations can be used.
(Islam et al., 2015), 2015	Survey on different optimization approaches applied in optimal placement problems	- Problem formulation should be based on economic benefits and distribution network impacts.

5. Analysis and discussion: case studies and stakeholder engagement

In this section, real case studies on the placement and scheduling of EV charging stations are discussed, and alignment with the proposed strategies is indicated. Also, a multi-stakeholder analysis for EVCS placement and scheduling based on existing studies through relative weighting of different stakeholders is conducted in this section.

5.1. Analyzing recent case studies on placement and scheduling

Existing studies described mostly micro-level planning for placement and scheduling, especially for distribution networks at a small scale (Reddy and Selvajyothi, 2020; Gampa et al., 2020; Wirges, 2016). The large volume of real-EV parameters may constrain meso and macro-level planning computational efficiencies, leading researchers to work on micro-level planning for charging infrastructure (Torkey and Abdelgawad, 2022; Unterluggauer et al., 2022). As the network topology, capacity, customer demand, stakeholders involved, and other demographic profiles differ, scalable methods are needed.

Fig. 7 contains subplots representing charger installation types, stakeholder engagement, studied networks, and placement in existing case studies. Fig. 7 (a) illustrates that fast charging was considered in 68 percent of cases, followed by mixed (slow and fast) charging. Residential customers favor Level 1 ($\leq$3.6 kW) and Level 2 (7.2–22 kW) chargers for convenience on low-voltage networks, underscoring the importance of analyzing such distribution systems (Australian Electric Vehicle Council, 2022). Besides, Fig. 7 (b) shows stakeholders used in recent studies in placement and scheduling problems. The analysis reveals a lack of local authority involvement in EVCS placement optimization despite the importance of government support and initiatives in this context. Also, using stakeholders without prioritizing their contributions in the planning approach may fail to foster EV adoption (Ahmad et al., 2022).

Fig. 7(c) shows that only 15 percent of cases involve real networks for validating placement and scheduling algorithms, with the majority focusing on test networks. Real networks have diverse uncertainties and complexities that require investigation considering multiple stakeholders. Fig. 7(d) highlights that most planning problems pertain to urban and highway sectors, indicating a need for future studies to address suburban and rural areas (Jawad and Liu, 2020; Unterluggauer et al., 2022).

Several attempts have been made in the last decade to solve charging station location problems for fostering transport electrification. In recent case studies, capacity constraint issues are prioritized problems in EVCS deployment and management for only users and distribution grids (Sharma et al., 2021; Asna et al., 2023). Other stakeholders, such as transportation networks and government support, are essential for rapidly growing EV demand (Zheng et al., 2019).

The regional case studies on EVCS placement are distinguished into four regions – Asia-Pacific, Africa, the European Union, and the United States of America. According to published reports, the Asia-Pacific region is the leading area for accommodating EV chargers, closely followed by the European Union (EV Volumes, 2023; International Energy Agency, 2023). However, despite China, Korea, Japan, and Australia having the highest number of chargers in the Asia-Pacific, individual country rankings remain relatively low. A study from the European context underscores the importance of Fast charging stations on highways for increasing EV adoption (Jochem et al., 2019). Navigating challenges in scaling the infrastructure, workload distribution, profitability, and policy formulation is crucial for deploying fast charging stations to support EV growth in European markets (Schäuble et al., 2017). An Africa-based study for transforming electromobility indicates challenges such as a lack of electricity generation, government policies, and initiatives suggesting renewable-based EVCS installation (Longe, 2022). Recent literature analyzing public Level 2 and fast charging station utilization indicates that 50 percent of chargers can address about 90 percent of the total charging demand in the USA, underscoring the necessity for expanded charging infrastructure aligned with stakeholder needs (Borlaug et al., 2023).

Several studies on placement and scheduling tasks argue that inappropriate stakeholder interaction may deteriorate decision-making performance if thorough EV uncertainty analysis, efficient and scalable models, and refueling demand are not done properly (Ahmad et al., 2022; Chen and Folly, 2023; Asna et al., 2023). Limited access to EV user behavior and traffic data presents challenges when designing future flow models and energy demand structures (Visaria et al., 2022). Hence, many case studies rely on parametric assumptions to facilitate research, potentially impacting the scalability challenges in real networks. In

Table 5
Conventional approaches for EV charging scheduling employed in existing studies.

Ref.	Solution Techniques	Objective Functions	Operational Constraints	Network	Future Scopes
Gantayet et al. (2021)	Genetic Algorithm and Whale Optimization Algorithm	Minimize annual cost by integrating PV and BESS	Power loss, voltage, and current limits, battery output	IEEE-33 Bus System	• EV uncertainties are not included.
Hao et al. (2022)	Improved Ant Colony Optimization	EV user satisfaction, travel time and energy loss, charging rate	Energy consumption of EV, traffic performance index, and grid load model	Traffic Network with 39 nodes in Xi'an, China	• No network performance criteria are considered. • A fixed battery capacity of EVs is used, which is not feasible.
Xiong et al. (2018)	Unsupervised clustering algorithm and multilayer perceptron	EV demand by predicting driver behavior	NA	UCLA SMERC smart charging system	• Techno-economic analysis is required for the charging schedule.
Ren et al. (2021)	Spatial-temporal distribution with bi-level optimization	Profit maximization and cost minimization	Network capacity, EVCS capacity, user satisfaction	Transport network from China	• EV charging and discharging control strategy with distributed generation may be analyzed.
Rabiee et al. (2018)	Stochastic optimization technique	Maximize Profit	Number of EVs arrival and departure, energy price	NA	• Multiple EVs with different battery capacities need to be considered.
Yu et al. (2021)	Particle Swarm Optimization (PSO)	Minimize annual cost	Service range, charging demand, and power in the planning area	33 nodes transport and distribution network	• EV uncertainties and distribution network performances are not considered.
Gupta et al. (2022)	Mixed Integer Linear Programming	Reduction of operation costs and traffic congestion	NA	Modified IEEE-118 bus system	• Economic analysis of transportation networks may be performed in the future. • Demand response can be added.
Wang et al. (2019a)	Framework for adaptive operation strategies of EVCS	Charging cost, PV curtailment, penalty cost, revenue for PV and EV	EV battery dynamics, charging demand, PV curtailment, and power balance	Modified IEEE-13 Node Test Feeder	• Performance constraints for voltage profile, power loss, and thermal loading limits are not considered.
Ren et al. (2020)	Bayesian Network-based real-time EV charging scheduling	Minimization of the electricity purchase cost	Battery capacity, charging demand, PV output power	NA	• Daily EVCS demand and PV generation output can be included in the future.

Table 6
Summary of studies on AI-based EV charging scheduling.

Ref.	Methods and Network	Objective Functions	Considered Constraints	Network	Dataset	Future Research Scopes
Dorokhova et al. (2021)	Reinforcement Learning Control	Maximization of PV power consumption and SOC	SOC limits, PV, and utility grid power limits	EVCS in Switzerland	EVCS with at least one EV provides datasets for two months	• V2G capability may add to demand response services. • Pareto reinforcement learning for multi-objective EV charging may be explored.
Alqahtani and Hu (2022)	Deep Q-Network-based Reinforcement learning	Minimization of energy cost	Power and energy balance, PV power, energy storage, electricity transaction	EV charging profile for 20 users from Chicago, USA	Daily load profile, energy consumption data from 2019 T Model X EV	• The multi-agent reinforcement learning algorithm can be developed to distribute decisions among EVs for mobility and energy transactions.
Qian et al. (2019)	Deep Reinforcement Learning	Minimization of total travel and charging cost	Travel time, waiting time, and charging rate	Traffic network in Xian City	Road velocity, charging prices, and waiting time	• The impact of multiple EVs with a smart grid can be explored in a real network in the future.
Wan et al. (2018)	Model-free deep learning algorithm	Cost-efficient EV charging/discharging scheduling	Real-time tariff, arrival and departure times, SOC	NA	Past electricity prices and battery SOC	• Multiple EV battery capacities may be considered in the real network.
Wang et al. (2019b)	Reinforcement learning	Lessening charging costs and increasing profit for the EVCS owner	Optimize charging cost	NA	Hourly EV data, day-ahead tariff, and number of EVs	• The scalability can be checked with the existing network considering large-scale EV penetration.
Li et al. (2019)	Constrained Markov chain Decision Process with deep neural network	Minimize charging costs with fully charged EVs.	NA	NA	Past 24-h electricity prices and current EV battery SOC	• Multiple EV battery capacities and traffic network parameters can include.
Lee et al. (2021b)	Multi-agent Rainbow DQN with imparting preference	Minimize charging cost and charging time, maximize EV energy	NA	NA	Tariff variations and availability of charging stations	• In other cases, multiple routes or traffic network nodes may be added to check effectiveness. • V2G technology may add.
Nair et al. (2018)	Clustered load forecasting deep neural network and linear programming	Forecasting residential EV load demand and charging cost optimization	Charging demand, charger type, SOC, no. Of EVs, and customer	EV profiles from NREL in the Midwest region, USA	200 household demand profiles with 348 EVs	• EV uncertainties and the V2G system are not considered here.

addition, export limits constrained by grid operators from renewable and V2G technologies are complex scheduling solutions needing stakeholder acceptance (Azim et al., 2023). Although EVs promote less GHG emissions to the environment, indirect causes, including establishing charging infrastructure and end-of-life of batteries, should not be ignored during placement and scheduling problem formulations. Also, assessing the techno-economic and environmental feasibility of positioning charging stations for diverse vehicles is essential in placement and scheduling tasks.

Table 7
Challenges and future research directions on EV charging scheduling.

Ref., year	Considered aspects	Suggestions
(Amin et al., 2020), 2020	Optimal EV charging scheduling under dynamic pricing schemes (Real-time pricing, time of use, critical peak charging, and peak time rebates) and different optimization methods	- It suggests establishing a relationship between dynamic pricing and charging demand, considering uncertainties are critical in the charging schedule. - Evaluation of the performance of dynamic pricing schemes for different stakeholders - Integration of renewables and battery storage in flexible EV charging demand - The impact of V2G technology under a dynamic pricing scheme needs to be analyzed.
(Mukherjee and Gupta, 2014), 2015	EV charging scheduling approaches and research directions	- Consideration of decentralized charging instead of centralized charging for significant EV penetration. - The charging scheduling algorithm needs to consider the EV users' profile. - V2G impact may be considered in future work.
(Shahriar et al., 2020), 2020	Machine learning approaches for EV charging patterns in the scheduling algorithm.	- EV scheduling for long-term and short-term predictions of charging behavior needs to be considered. - High dimensional datasets such as traffic, weather, demographic profile, and EV clustering approach are required for training ML in a scheduling problem. - Deep learning reinforcement learning applications for multi-objective problems in EV charging scheduling may perform.
(Rong et al., 2021), 2021	Electric Bus charging schedule based on vehicle scheduling	- Dynamic charging intervals can be used in electric bus charging scheduling. - Long-term planning is required for charging scheduling, considering optimal placement, operational, and establishment costs. - Renewable integration for EV charging to mitigate storage and intermittent problems may include. - Battery aging may be considered in the charging scheduling and V2G services.
(Das et al., 2021), 2021	Optimization techniques used in EV charging scheduling	- Various approaches to optimization techniques, along with the dynamic pricing scheme, are reviewed in this paper. - Renewable integration into EV charging stations needs to be investigated.
(Zheng et al., 2019), 2019	Reviews V2G charging scheduling approaches and their impacts on the distribution grid	- The grid topology-independent model can be implemented for V2G scheduling in the future, reducing the computational cost. - A decentralized charging scheduling, considering battery degradation, may be helpful for significant EV penetration.
(Tang et al., 2016), 2016	Online charging scheduling considering uncertainties and randomness	- The integration of renewables needs to be investigated. - Stochastic modelling with random EV data can be used in the scheduling approach. - Economic incentive design for EV users may perform in the future.

5.2. Multi-stakeholder benefits and priority analysis

Stakeholder analysis in EVCS placement and scheduling involves identifying and assessing the various parties with benefits, influence, or roles. The requirements for charging infrastructure planning differ for multiple interrelated stakeholders, i.e., EV users, EVCS owners, DNOs, TNs, and regulatory bodies, as shown in Fig. 8.

Fig. 9 specifies the targeted benefits for primary stakeholders in EVCS deployment and scheduling tasks. EV users want to minimize charging and traveling costs, waiting times, and charging duration. EVCS owners intend to reduce costs (establishment and operational) and maximize profits. Besides, DNOs want to place the EVCS to minimize the detrimental impacts on distribution systems. Transport network demands minimizing traffic congestion and smooth traffic flow. EVCS planning consists of placement and scheduling where setting objective functions and constraints is vital for various stakeholders.

This study gathers impactful features for developing placement and scheduling strategies from various published articles (Suhail et al., 2021; Ahmad et al., 2022; Islam et al., 2015; Luo et al., 2015; Chen and Folly, 2023). Each of the twelve key factors for stakeholders is assigned a ranking using a color scale with four levels, spanning from 1 to 4, as shown in Fig. 10. Red represents the highest significance, while green signifies the lowest. The total number of features is denoted by 'n_f' while 'α_{max}' signifies the maximum weighting assigned to these features.

For selected features, the weights are represented by α_1, α_2, α_3, and α_4, with values ranging from 1 to 4. These selected feature weights correspond to n_1, n_2, n_3, and n_4, indicating the number of weights for each feature. The stakeholder priority index for a given stakeholder is denoted as ω_{sp}, and its calculation is based on Equation (1).

$$\text{Stakeholder priority index}, \omega_{sp} = \frac{(\propto_1 \times n_1) + (\propto_2 \times n_2) + (\propto_3 \times n_3) + (\propto_4 \times n_4)}{\propto_{max} \times n_f} \tag{1}$$

The bar chart in Fig. 11 illustrates the calculated priority indexing for different stakeholders, depicting their engagement in decision-making. The charging station owners and distribution companies are ranked as the most influential stakeholders for EVCS planning, followed by EV users and local authorities. The distinct placement and scheduling requirements can lead to variations in priority indexing due to differences in selecting significant features and their relative weights, posing a potential research gap for future studies.

6. Proposed strategies and future perspectives

In this section, proposals for stakeholder-driven placement and scheduling methods are described, along with their practical implications. Also, the future perspectives indicating stakeholder-centric placement and scheduling methods are included in this section.

6.1. Proposal for multi-stakeholder-oriented framework for EVCS placement

Based on the research trends and challenges identified during the

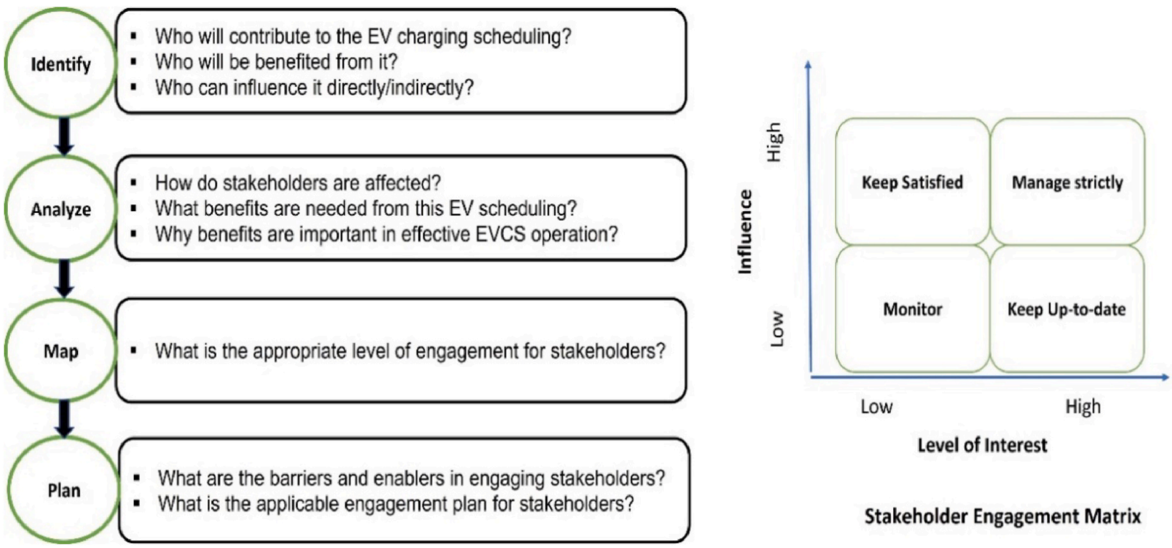

Fig. 5. Stakeholder management technique for EV charging scheduling.

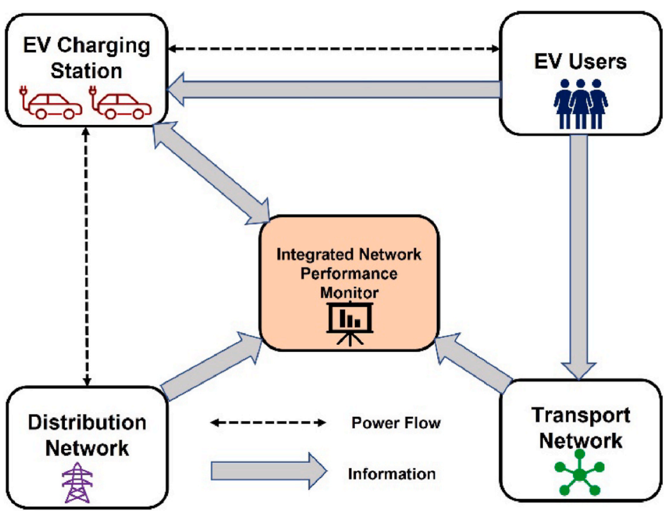

Fig. 6. Integrated network performance monitoring and controlling method in EV scheduling.

literature survey, Fig. 12 depicts a conceptual framework for multi-stakeholder-oriented EVCS placement comprising four major stakeholders, i.e., distribution network, charging station owner, EV user, and local authorities, identified using stakeholder analysis. The proposed framework involves three main steps-estimating hosting capacity, sensitivity analysis, and applying an optimization algorithm. EV hosting capacity is estimated using load flow analysis to understand network strength without violating performance constraints. Nodal strength can be computed by prioritizing performance constraints, including voltage and thermal limits, power loss, and voltage imbalance for every node in distribution networks. As the multi-stakeholder approach directs a complex problem with multiple objective functions and constraints, an optimization algorithm must be selected based on robustness, accuracy, and lower computational burden. Then, the quantity and scale of an EVCS can be determined using the number of EV users, charging levels, distance from the substation, traffic volume, and measured hosting capacity. The proposed multi-stakeholder strategies fosters cooperation, coordinated EVCS deployment, conflict reduction, market share expansion, and revenue growth.

6.2. Proposal for EV charging scheduling framework

To manage large-scale EV penetration, a charging scheduling algorithm considering multiple stakeholder benefits is challenging. Also, including demand-side management for accelerating the transport electrification process, the scheduling strategy selection is necessary. Fig. 13 shows the proposed multi-stakeholder-focused EV charging scheduling mechanism is presented. A real-time pricing scheme and charging control strategy will be the outcomes of the proposed approach, applying data from stakeholders and renewable resources. The scheduling algorithm may develop integrating distribution network impacts, profit maximization, and user satisfaction as the objective function. The selection of objective functions and constraints can be based on Fig. 4. EV scheduling can be classified as day-ahead, user-centric, real-time, and fleet scheduling. In this process, stakeholder-centric multi-objective scheduling can be used for managing large-scale EV fleets. Enabling a demand response program with multi-stakeholder participation is possible with the help of the proposed scheduling schemes.

6.3. Practical implications of proposed strategies

The practical implications for proposed EVCS placement and scheduling strategies, considering multi-stakeholder benefits with socio-techno-economic and environmental aspects, are multifaceted in transport electrification. These strategies promise a more balanced allocation and management of charging infrastructure across diverse regions, catering to urban, suburban, and rural areas. By incorporating inputs from various stakeholders, these strategies aim to optimize the location and scheduling of charging infrastructures, resulting in fair distribution of benefits among stakeholders. In EVCS placement, the processes intersect with the energy transition, requiring adjustments to accommodate increased electricity demand, promote renewable energy integration, and enhance grid resilience (Pal et al., 2021). The proposed scheduling scheme offers the potential for managing large-scale EV fleets by strategically scheduling charging sessions to curb strain on the distribution grid.

Economically, these schemes will enable equitable monetary distribution, and real-time pricing schemes incentivize prosumers to share self-generated solar and V2G power, driving participation in the energy transition. These strategies also prioritize environmental responsibility by encouraging renewable energy use in charging, aligning with sustainability goals. The process may include data sharing and privacy

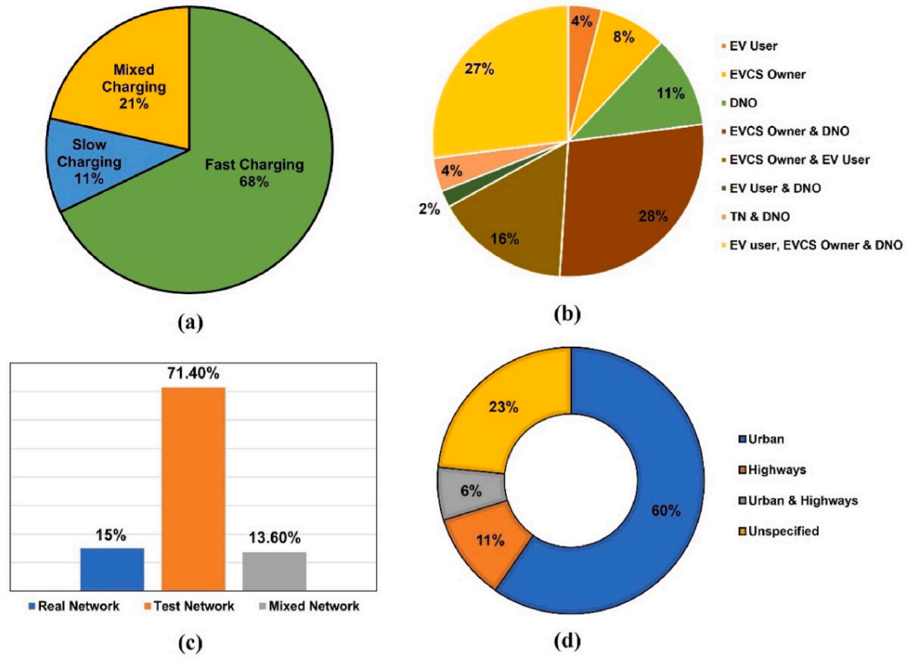

Fig. 7. Case studies on EVCS placement and scheduling a) type of charger, b) stakeholder considered in existing studies, c) type of network studied, and d) placement of chargers in existing analysis.

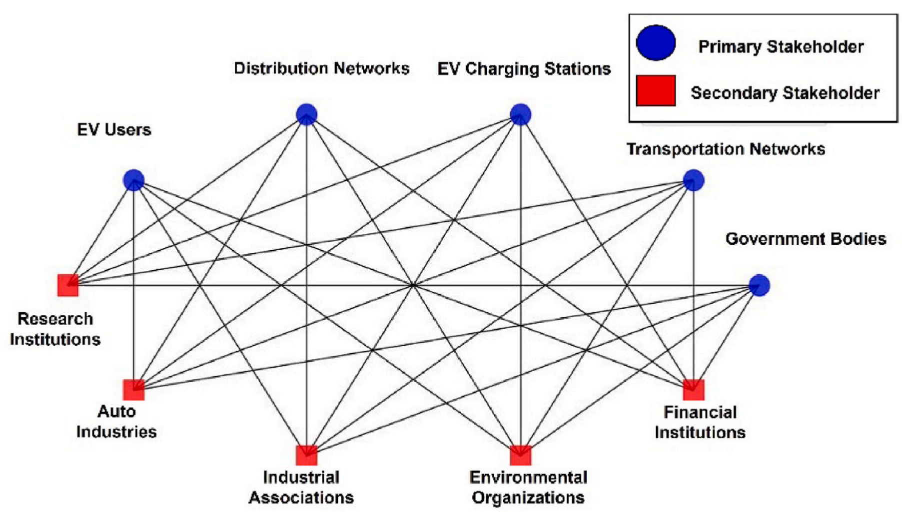

Fig. 8. Stakeholder's interrelation in EVCS placement and scheduling.

mechanisms to boost transparency and stakeholder trust for seamless implementation. In the nascent stage of transport electrification, these strategies inform policy formulation for EVCS establishment and management in both the short and long terms, including micro, meso, and macro-level planning.

6.4. Future research directions

The growing global adoption of EVs emphasizes the need to establish charging stations to mitigate range anxiety and drive heightened market share. Future research should consider the techno-economic, environmental, and societal impacts of establishing EVCSs while considering the perspectives of different stakeholders, as described in this section.

6.4.1. Renewable integrated EVCS

Integrating intermittent renewable energy sources like PV solar systems into EVCS offers several benefits, including reducing peak load demand, improving grid stability, and enhancing voltage profiles. While uncertainties exist in PV systems, hybrid renewables that combine different renewable sources can provide more effective solutions for EVCS. Previous studies have investigated optimal placement strategies and assessed the impact of PV solar systems on EV charging schedules, focusing on microgrid-based EVCS in future studies.

6.4.2. Strategic approaches for growing EV demand

The growing EV demand poses challenges in selecting effective placement and scheduling schemes for charging infrastructure development. Enhancing hosting capacity for EVs and renewables while minimizing detrimental grid impacts and maximizing stakeholder

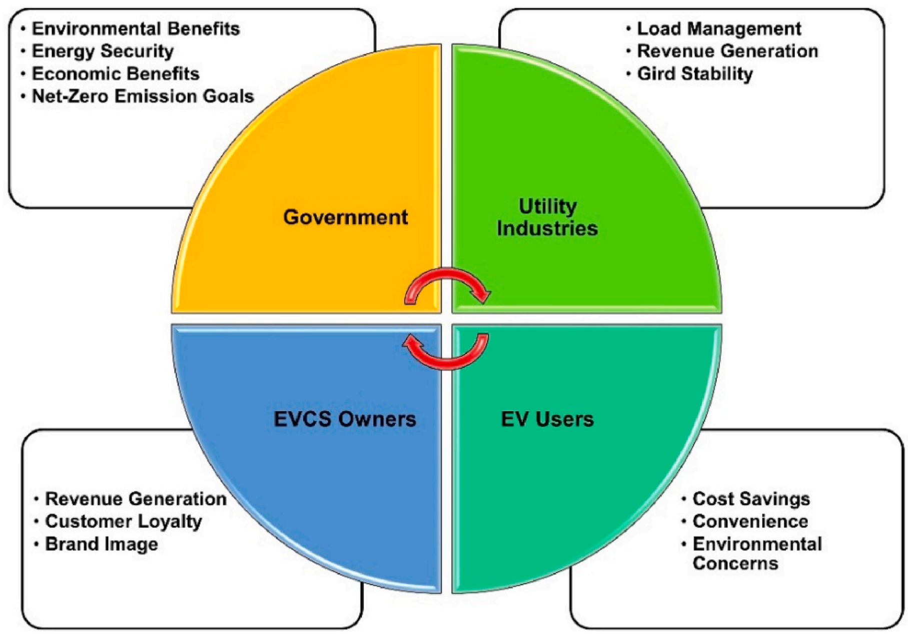

Fig. 9. Stakeholder targeted benefits for EVCS planning.

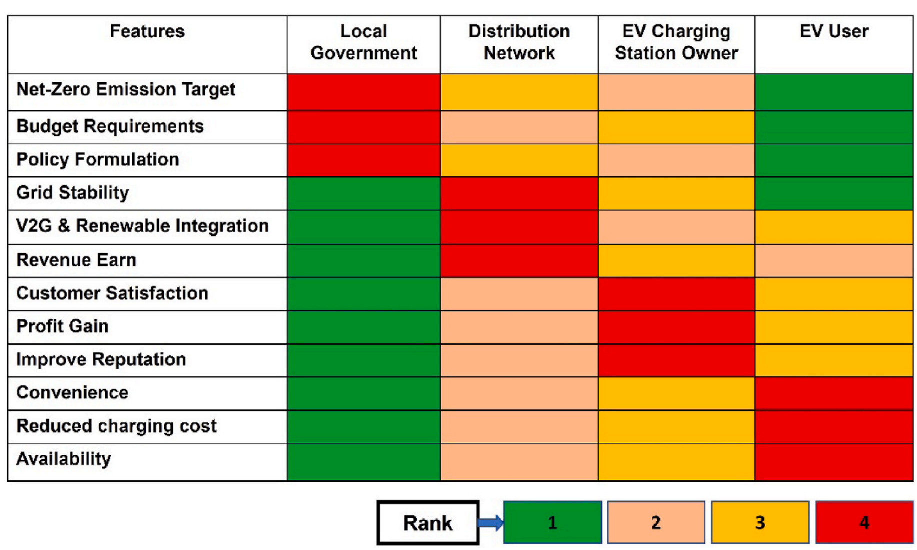

Fig. 10. Stakeholder priorities in EVCS deployment and scheduling.

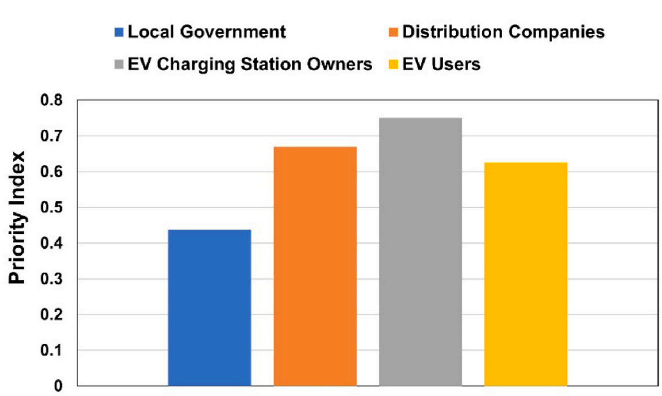

Fig. 11. Priority indexes for different stakeholders involved in EVCS planning.

benefits is essential. An adaptable strategy is required for developing charging infrastructure to overcome scalability and interoperability issues and the need for equitable access. Addressing planning and scheduling challenges for widespread EV adoption involving multiple stakeholders is complex, as prior studies mostly focused on lower penetration levels and left gaps in understanding the intricacies of extensive electrification.

6.4.3. *Multi-objective optimization approaches*

Addressing complexities and involvement of multiple stakeholders in EVCS placement and scheduling is challenging for single-objective optimization approaches that foster researchers to use multi-objective optimization frameworks. Also, incorporating EV uncertainties and objective functions for each stakeholder will increase the reliability and effectiveness of the optimal placement and scheduling tasks for charging facilities.

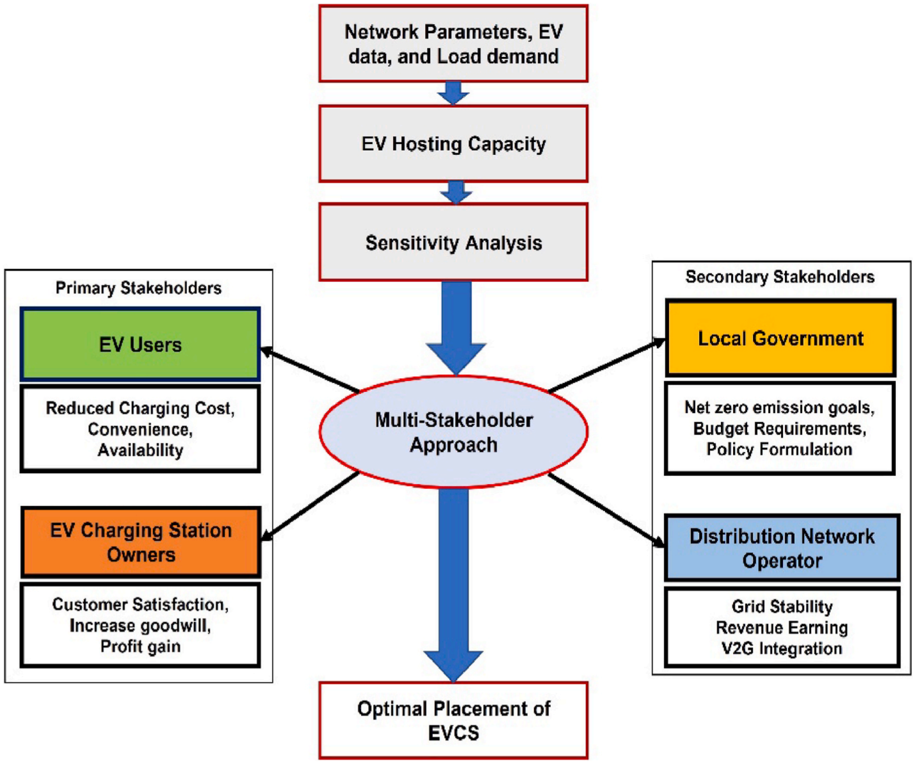

Fig. 12. Multi-stakeholder-based framework for EVCS placement.

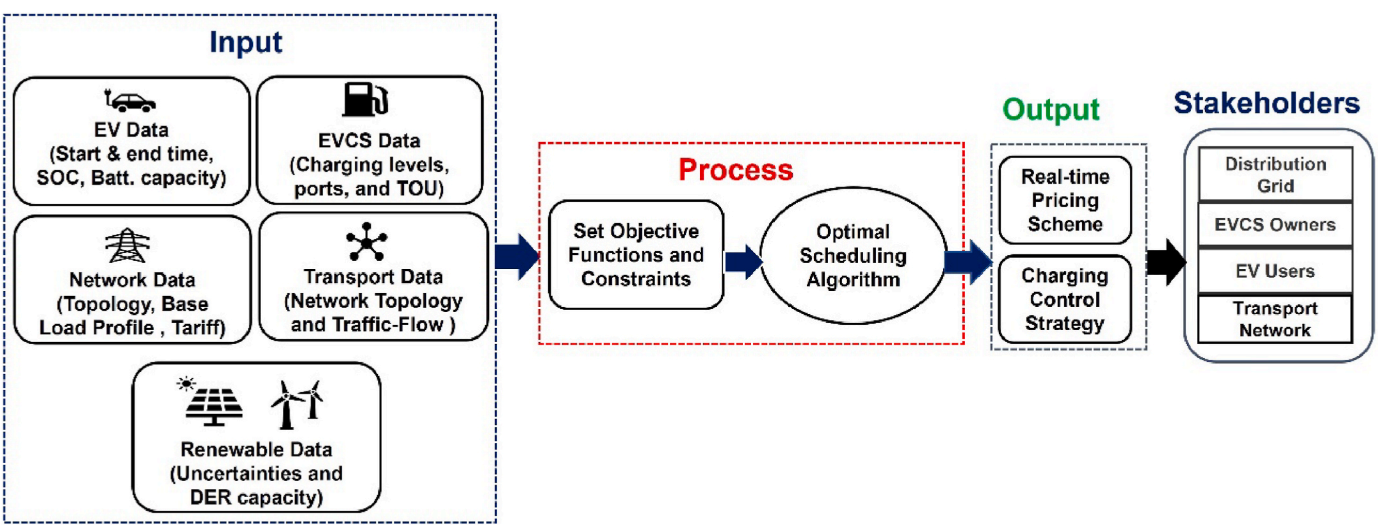

Fig. 13. Proposed EV charging scheduling framework.

6.4.4. V2G/V2V/V2H technology integration

Integrating energy-transferring technologies such as V2G, Vehicle-to-Home (V2H), and Vehicle-to-Vehicle (V2V) presents significant EV management and power exchange opportunities. These technologies provide techno-economic benefits to the stakeholders. Owing to several stakeholder benefits, energy-transferring technologies can be considered in designing optimal placement and scheduling of EVCS.

6.4.5. Validation with real distribution feeder

Optimal placement and scheduling are challenging when it deal with real-distribution feeders. Real-distribution feeders introduce stakeholder-centric uncertainties requiring consideration for real-time EV charging facility distribution. While existing studies often use standard test feeders, including real-distribution networks in EVCS deployment and scheduling is vital to offer meaningful insights to policymakers.

6.4.6. Consideration of EV uncertainties

Uncertainties related to EV variables such as arrival and departure time, charging duration, levels, type, charger efficiency, battery capacity, driving range, battery aging, and demographic profile strongly influence charging load profiles. Accounting for these uncertainties is vital for effective EVCS planning. Leveraging clustering methods can reduce prediction errors, enhancing charging demand forecasting accuracy and resource allocation efficiency.

6.4.7. Dynamic charging scheme

A dynamic pricing scheme facilitates EV users' flexibility for time-varying charging and enables renewable generation potential. Due to the low price, it creates traffic congestion during off-peak hours; hence, it needs to consider EV charging scheduling (Li et al., 2019). EV charging schedules for dynamic pricing and a coordinated charging scheme may be viewed.

6.4.8. Adaptive charging scheduling

EV charging scheduling from typical datasets cannot clarify the results for different scenarios, such as weekdays and weekends. EV charging behavior differs, leading to scheduling problems (Lee et al., 2021b). Also, the V2G services can strengthen the grid during peak hours, which must be investigated in the EV scheduling algorithm. Besides, adaptive operation strategies for the EVCS under various penetration levels and critical situations must be considered in EV charging scheduling (Wang et al., 2019a).

6.4.9. Multi-stakeholder scheduling algorithm

Due to rising EV adoption among various stakeholders, the research underscores the importance of a multi-stakeholder-oriented platform for large-scale deployment (Suhail et al., 2021). Integrated monitoring and control frameworks are vital for efficient scheduling, as depicted in Fig. 8, showcasing information and power exchange among stakeholders. Efficient management minimizes adverse impacts compared to unregulated charging, making a multi-stakeholder-centric approach crucial for successful EV scheduling.

6.4.10. Platform for transport modelling and forecasting

Research directions for developing a platform for transport modelling and forecasting in the context of EVCS placement and scheduling, including data-driven models for real transport networks. Data-driven models utilize diverse data sources (real or synthetic) for enhanced accuracy with multi-modal and multi-scale modelling to understand transportation dynamics (Ge et al., 2020; Loni and Asadi, 2023). The platform can incorporate real-time data from smart sensors and infrastructure by focusing on data-driven models based on various data sources for EVCS placement and scheduling.

6.4.11. EV deployment and visual platform

A visual platform for large-scale EV deployment can focus on optimizing EVCS placement strategies, developing user-friendly interfaces, integrating diverse data sources, employing predictive analytics for charging demand forecasting, ensuring scalability and interoperability, and prioritizing user-centric design. This platform enables informed decision-making, efficient EV deployment, and enhanced user experience.

7. Conclusion

This paper provides an extensive literature review addressing stakeholder interaction in EVCS placement and scheduling for accelerating transport electrification. After thoroughly reviewing recent studies, this study identified a noticeable gap in stakeholder-oriented placement and scheduling solutions. Stakeholder-centric objectives, constraints, and the pros and cons of currently employed optimization approaches are specified in this paper. Finally, the analysis in this paper shows stakeholder engagement accounting for the type and location of network and EV chargers in existing studies. The findings showed a predominant focus on distribution networks and EVCS owners within placement and scheduling strategies, while the involvement of other stakeholders remains comparatively limited. Approximately 80 percent of recent studies for urban and highway networks are often validated within test environments, indicating a need to validate real networks, especially in suburban and remote settings. Moreover, the investigation of conventional grid capacity and determining nodal strength must be known for the EVCS planning process.

This paper bridges a gap in the current literature by prioritizing stakeholders in placement and scheduling, extending beyond profit and user satisfaction maximization. It is suggested that including the distribution network impacts, EV uncertainties, and traffic flow may enhance the efficiency and effectiveness of EV scheduling. A multi-stakeholder-oriented platform is recommended in this paper to monitor and control EVCS operation that directs interoperability and coordinated load management schemes. The multi-stakeholder analysis considering specific features with assigned weights in the EVCS planning highlights the pronounced influence of charging station owners and distribution network operators. However, it's worth noting that EV users and local authorities also have substantial impacts in this context.

By prioritizing stakeholder engagement in the EVCS planning process, this study lays the foundation for advancing cleaner production technologies and ensuring equitable benefits. The proposed integrated network monitoring and control mechanism for charging stations will improve network visibility and resilience as EVs and renewables become more widespread. The emphasis on real-world validation in EVCS planning across urban, suburban, and remote networks will enhance the practicality of the proposed stakeholder-focused solutions. Despite the popularity of AI-based approaches for EVCS planning, the scarcity of real-world data due to the early stages of development could result in inadequate scheduling strategies for managing large-scale EV penetration, analyzed in this study. Data sharing and privacy policies are also needed to boost transparency and stakeholder trust for seamless implementation. The importance of regulatory and standardization frameworks for demand response programs initiated through bi-directional power transfer is highlighted for efficient scheduling solutions. Moreover, this review helps establish regulatory frameworks and region-specific planning strategies, further bolsters the growth of cleaner transportation technologies, and promises a more balanced and sustainable future.

In future studies, multi-stakeholder-oriented EVCS allocation and scheduling can be investigated in renewable-rich distribution networks for various penetration levels. While existing research predominantly centers on public charging infrastructure, future planning efforts must integrate private-owned and residential charging systems to analyze EV charging operations. Further research must examine energy-transferring technologies and address prosumer-end uncertainties in real distribution networks for managing EV penetration. Additionally, future research should explore enhancing network visibility and resilience by integrating stakeholder concerns within the suggested monitoring and control framework. Future studies must prioritize region-specific, meso-level planning, considering diverse objectives, infrastructure, and incentives of local authorities in tailoring transport electrification.

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.

Data availability

Data will be made available on request.

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