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A Systematic Review on power systems planning and operations management with grid integration of transportation electrification at scale

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ABSTRACT

Transportation electrification plays a crucial role in mitigating greenhouse gas (GHG) emissions and enabling the decarbonization of power systems. However, current research on electric vehicles (EVs) only provides a fragmented examination of their impact on power system planning and operation, lacking a comprehensive overview across both transmission and distribution levels. This limits the effectiveness and efficiency of power system solutions for greater EV adoption. Conducting a systematic review of the effects of EVs on power transmission and distribution systems (e.g., grid integration, planning, operation, etc.), this paper aims to bridge the fragmented literature on the topic together by focusing on the interplay between transportation electrification and power systems. The study sheds light on the interplay between transportation electrification and power systems, delving into the importance of classifying EVs and charging infrastructure based on powertrain design, duty cycle, and typical features, as well as methods of capturing charging patterns and determining spatial-temporal charging profiles. Furthermore, we provide an in-depth discussion on the benefits of smart charging and the provision of grid-to-vehicle (G2V) and vehicle-to-grid (V2G) services for maintaining power system reliability. With the holistic systems approach, this paper can identify the main objectives and potential barriers of power transmission and distribution systems in accommodating transportation electrification at scale. Concurrently, it paves the way for a comprehensive understanding of technological innovation, transportation-power system decarbonization, policy pathways, environmental advantages, scenario designs, and avenues for future research.

1. Introduction

1.1. Background

The trend of decarbonization has gained momentum in recent years due to the overwhelming contribution of CO2 emissions, which make up nearly 90% of ghg emissions, to global warming. This shift has had a significant impact on both the supply and demand sides of the global energy systems. The transportation sector, in particular, accounts for a substantial portion of GHG emissions, with estimates ranging from 23.5% in the European Union to 34% in the United States [1,2], respectively. The electrification of energy systems represents a move from non-electric to electric systems [3], and current, and future life-cycle emissions from ev are lower than those from traditional petrol vehicles and fossil-fuel boilers [4]. This means that vehicle electrification has the potential to greatly reduce transportation-related GHG emissions. In addition to environmental benefits, the widespread adoption of EVs would also bring social welfare benefits, such as improved emission reduction in city centers and economic benefits in suburban areas, as demonstrated by scenario simulations [5]. The growth in EV registrations and sales from 2016 to 2021 in various countries and regions, including the United States, China, Europe, and others, are depicted in Fig. 1. This figure highlights the current state of vehicle electrification globally. There is an increasing trend towards phasing out fuel-powered vehicles in the coming decades, as demonstrated by the international goals and activities outlined in [6]. The European Union ban on the sale of new fuel-powered vehicles in 2035. The zev Alliance has announced that the sale of fuel-powered vehicles will be banned by 2050 in 18 states in the United States. For example, New York State is also actively involved in implementing these goals, as indicated by its participation in the ZEV program implementation task force [7]. By 2035, all sales or leases of new light-duty passenger vehicles in New York State are ex-

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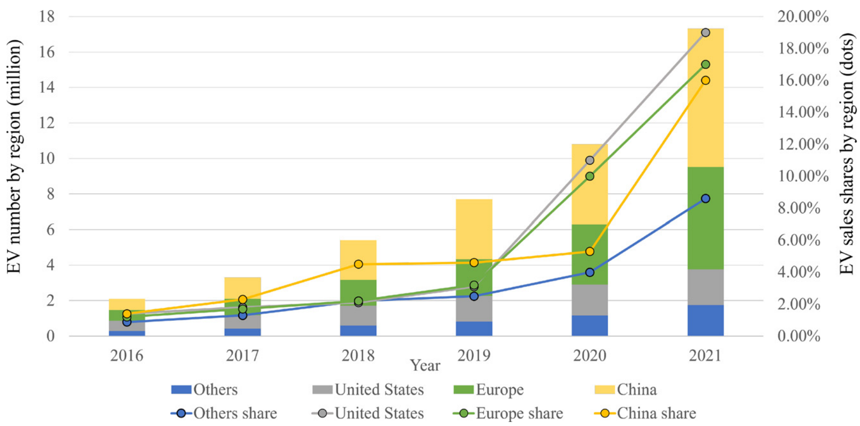

Fig. 1. Electric vehicle registrations and sales from 2016 to 2021 in various countries and regions, including the United States, China, Europe, and a selection of other nations [8]. Other countries include Australia, Brazil, Canada, Chile, India, Japan, Korea, Mexico, New Zealand, and South Africa.

pected to be ZEVs, and by 2045, the same will be implemented to all the new medium- and heavy-duty vehicles.

The widespread adoption of EVs is driving significant changes in energy consumption patterns, affecting electricity infrastructure and power systems [9]. One important barrier to decarbonizing ground transportation and affordably and reliably achieving high EV adoption is the increasing power demand for charging EVs. The social pressure and the impact of increased weight and horsepower on EV charging were measured in [10] using data from 255 EVs in the United States from 2011 to 2021. The results in [11] revealed that each 1% increase in EV weight could lead to an increase in electricity consumption by nearly 1% and that the transition to EVs could increase electricity consumption by more than 35%. However, the current design of the power system is built to supply load peak demand in just 1% of an hour [12]. On the other hand, large-scale EV deployment not only increases electricity demands but also presents an opportunity to use EV batteries to provide additional demand-side flexibility. For example, the long-term impact of VGI was simulated in [13] by integrating the power system and transportation system with behaviorally realistic and empirically derived EV charging models. Using smart charging techniques to optimally control EV charging loads, the adverse effects on the grid can be minimized, and investment costs can be reduced [13]. To fully understand the implications of widespread EV adoption on power system planning and operation, it is important to consider both the positive impacts and negative impacts of EVs on power systems. Further research is needed to systematically and comprehensively explore these impacts and to identify strategies for the benefit maximization and negative effect minimization of transportation electrification on power systems.

1.2. Motivation and contribution

To investigate the techniques for integrating EVs into power systems, previous studies have analyzed EV technology and infrastructure. In [6], the current state of EV design from the perspectives of energy management and electrified powertrain design were reviewed. In [14], a detailed simulation analysis for dcfc stations was performed. In [15], the state-of-the-art DCFC infrastructure and technology were investigated, with a focus on grouping DCFC stations into xfc stations. In [16], the development status of EV charging infrastructure in the United Kingdom was introduced, including the charging equipment protocols and standards, as well as the circuit topologies of charging infrastructure. In [16], three crucial factors for different business models of charging infrastructures, including design, location, and cost, as well as their management and operation, were identified. In [17], a technology development overview of transportation electrification, including prospective technologies for implementing EV charging infrastructure was provided. The technical challenges for developing transportation electrification in a sustainable way were discussed in [18], which evaluated the feasibility of a pv-powered EV charger and stationary storage system for eb. An analysis of EV performance [19] was provided based on the data collected from over 40 currently globally available EVs, which comprised powertrain and dimensional data. The advances and research challenges of EVs, such as trends in battery technology and charging methods, were reviewed in [20]. The economic impacts of EVs, which focused on the economic perspectives of battery cost and business model development, were reviewed in [21]. An 800-V powertrain design for high voltage EVs was explored in [22], which also analyzed the future trends regarding EV powertrains. An overview of EV technology was provided in [23], which focused on reviewing EV configurations and electrical machines. The present state of DC motor drives for EVs was introduced in [24], highlighting the commercial aspects of EVs. The solution of electromagnetic energy charging for static and dynamic charging was provided from the perspective of magnetically coupled coils [25]. A review of both the advantages and disadvantages of ess in EVs was summarized in [26], highlighting the characteristics and electricity conversion of ESS technology. In [27,28], the current techniques in wireless charging of EVs, including the techniques of static wireless charging and dynamic wireless charging, were reviewed. In [29], a review of different uncertainty modeling methods for grid-connected EV-PV systems was provided. In [30], typical models of energy sources of EVs and the environmental impacts of typical EVs were evaluated. The classification of different EVs was also reviewed, such as the technological readiness of bev [31], main features of hev and phev [32] and their modeling approaches and optimization techniques [33]. Various estimation strategies for battery management were summarized in hybrid and battery EVs [34]. However, the above reviews mainly focused on the technologies of EV charging infrastructure, EV battery design, and different types of EVs, and the interactions among EV charging infrastructure, EV scheduling, and power systems were not highlighted.

Some studies have explored how large-scale transportation electrification affects power systems and how power systems can adopt more EVs. A review [35] of renewable energy-powered EV charging techniques was presented to highlight the grid support functionality of EVs and the capability, benefits, and challenges of VGI. Some grid quality and performance indicators were summarized in [36] to assess the power grid performance issues caused by different EV charger topologies. In [37], the EV-grid integration and EV-renewable interaction were reviewed, which indicated that EVs could significantly reduce renewable energy curtailments. In [38], a future 2050 scenario with power-to-gas and power-to-liquid techniques in Germany was introduced, which considered the connection of power systems, gas systems, and transportation systems with the devices of gas heat pumps, gas heaters, and fcev. In [39], the main impacts of transportation electrification on planning, operation, electricity demand, and grid activities in power systems were summarized, and the expected electric technologies and solutions that might improve the grid integration of EVs were discussed. A review

[40] of the literature was provided by considering the coordination between transportation electrification and power distribution planning. In [41], the applications of dl-based methods for EV management and battery charge forecasting in power distribution systems and mg were reviewed. The typical optimization models and algorithms for EV charging infrastructure planning and EV charging operation were reviewed in [42]. In [43], the applications of rl for solving EV dispatch problems were discussed.

Moreover, the concepts of g2v and v2g were emphasized in studies when analyzing the impacts of transportation electrification on power systems. In [44], a survey of EVs in industrial informatics systems, which included charging infrastructure and battery charismatics, as well as the EV intelligent energy management and communication requirement in V2G mode, was provided. In [45], a review of G2V and V2G methods was presented for smart charging and EV fleet operators, highlighting the service relationships among EV fleet operators, transmission system operators, and distribution system operators. In [46], the opportunities and challenges of VGI were investigated and discussed, which focused on V2G technology. In [47], V2G technology and the challenges of its implementation in smart grids were reviewed. The implications and benefits of V2G technologies were evaluated in [48], which considered the environmental benefits and socioeconomic benefits with the impacts of the consumer side and utility side. The main technical challenges related to transportation electrification were identified in [49], which discussed the charging process management and energy return from the V2G. The major challenges of the V2G operation mode, such as cyber-attacks and communication time delays, which could impede the resiliency of the V2G system, were identified in [50].

The topics of existing work on transportation electrification in power systems, which cover G2V, V2G, power tp, power dp, power to, and power do, are summarized in Tables 1 and 2. However, it is evident that these studies lack a comprehensive and systematic evaluation of the effects of G2V and V2G on power system planning and operation across both the transmission level and distribution level. Instead, these studies only presented a piecemeal assessment of transportation electrification in power systems, focusing on isolated aspects or applications. This research gap motivates us to provide a systematic review to evaluate the impacts of transportation electrification on power planning and operation across transmission and distribution systems.

To close this research gap, this work presents a critical review of studies on the impacts of EV infrastructure and EV charging management on power system planning and operation at both the transmission level and distribution level. The paper also provides a comprehensive discussion of the power generation, transmission, distribution, and demand sides, which are heavily influenced by G2V and V2G from transportation electrification. The overall framework for this review is outlined in Fig. 2. The main objectives and contributions of this paper are highlighted as follows:

- The design and technologies related to EVs, including the design of the powertrain, duty cycle, management of EV batteries, and the grid integration technology of EVs into the power grid, are introduced.
- The state-of-the-art methods in G2V systems in terms of charging load profile estimation, battery management, smart charging, and charging infrastructure, are summarized.
- The advantages and limitations of V2G functionality, which simultaneously provide ancillary services and challenges to the power system operation, are explained.
- The main objective, barrier, and solution of power planning and operation in transmission and distribution systems to adopt larger-scale transportation electrification, are identified.
- Related topics of transportation electrification in power systems, including the environmental benefits of integrating EVs and renewable energy resources in power systems, innovative technologies for facilitating EV adoption in power systems, policy implications of transportation electrification on the power system, scenario design of

Table 1
Overview of recent studies on transportation electrification in power systems (Part I).

Ref.	[6]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]	[29]	[30]	[31]	[32]
Year	2021	2021	2019	2020	2015	2022	2016	2021	2020	2020	2017	2017	2019	2017	2018	2022	2020	2019	2017	2013
G2V	Y	N	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y
V2G	N	Y	N	N	Y	N	N	Y	Y	N	Y	N	N	Y	N	N	Y	N	Y	N
TP	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
DP	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
TO	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	Y	N	N	N
DO	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	Y	N	N	N

Table 2
Overview of recent studies on transportation electrification in power systems (Part II).

Ref.	[33]	[35]	[34]	[36]	[37]	[38]	[39]	[40]	[41]	[42]	[43]	[44]	[45]	[46]	[47]	[48]	[49]	[50]
Year	2021	2021	2019	2020	2013	2019	2022	2020	2021	2019	2023	2012	2016	2013	2018	2022	2018	2022
G2V	Y	Y	Y	Y	N	Y	N	N	N	Y	Y	Y	Y	Y	N	N	Y	Y
V2G	Y	Y	N	Y	Y	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
TP	N	N	N	N	N	N	Y	Y	Y	N	N	N	N	N	N	N	N	N
DP	N	N	N	N	N	N	Y	Y	Y	N	N	N	N	N	N	N	N	N
TO	N	N	N	N	N	N	Y	N	Y	N	Y	N	Y	N	Y	N	N	N
DO	N	N	N	N	N	N	Y	N	Y	N	Y	N	Y	N	Y	N	N	N

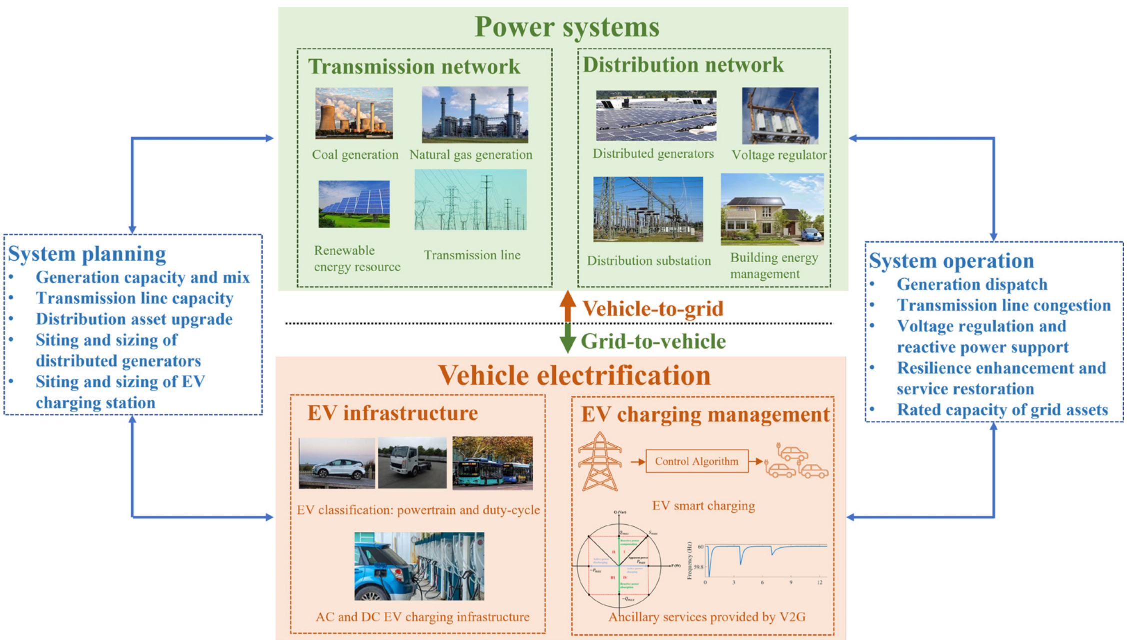

Fig. 2. Overall framework of this paper for evaluating the impacts of large-scale transportation electrification on system planning and operation in power transmission and distribution systems.

transportation electrification in power systems, and future research perspectives for large-scale transportation electrification in power systems, are discussed.

The remainder of the paper is organized as follows: we introduce the classification, battery design, and the G2V and V2G for EVs in Section 2. In Section 3, we evaluate the impacts of EVs on power transmission and distribution planning. In Section 4, the impact assessment of EVs on power transmission and distribution operation is conducted. Some related discussions and conclusions are presented in Section 5 and Section 6, respectively.

2. Transportation electrification

Before assessing the impact of transportation electrification on power planning and operation, it is imperative to have a thorough understanding of the classification, technology, and design of EVs and charging infrastructures, as well as the concepts of G2V and V2G. Therefore, first, this section classifies EVs based on their engine technology and duty cycle and examines the developments in battery and grid integration technology of EVs. Second, an in-depth discussion is provided to explore the impacts of G2V and V2G technologies on power systems, including the charging profile estimation methods, smart charging management methods, charging infrastructure features, vehicle grid technology, and ancillary services provided by V2G technologies.

2.1. Electric vehicle classification

2.1.1. Powertrain and engine design of electric vehicles

To accurately evaluate the impact of EVs on power systems, it is crucial to understand their charging profile. This evaluation involves analyzing factors such as battery size, charging rate, travel patterns, and travel distance. As depicted in Fig. 3, EVs can be classified based on their powertrain design and engine settings, and an overview of the diversity of battery and charging technology available in the market [20,23,32,47], is provided as follows:

- *Hybrid electric vehicles:* HEVs are a unique type of EV that incorporates both a conventional ice and an em. Unlike pure EVs, HEVs cannot be plugged into evcs or power grids. The batteries in HEVs provide energy to the EM and are charged by the power generated from the ICE during braking. When driving at low speeds or during low power demand, such as in urban areas, HEVs will primarily use electric propulsion systems. One notable example of an HEV is the Toyota Prius hybrid model, which features a 1.3 kWh battery that enables it to travel up to 25 km in all-electric mode.
- *Plug-in hybrid electric vehicles:* Equipped with an ICE, a fuel tank, a battery, and an EM, PHEVs can be powered by a pluggable external electrical source. Compared to HEVs, PHEVs primarily rely on electric propulsion and have a larger battery capacity. When the battery charge is depleted, the ICE provides additional power. Unlike HEVs, PHEVs can be charged directly from EVCSs and power grids, reducing fuel consumption and operating costs in normal driving conditions. A notable example of a PHEV is the Mitsubishi Outlander

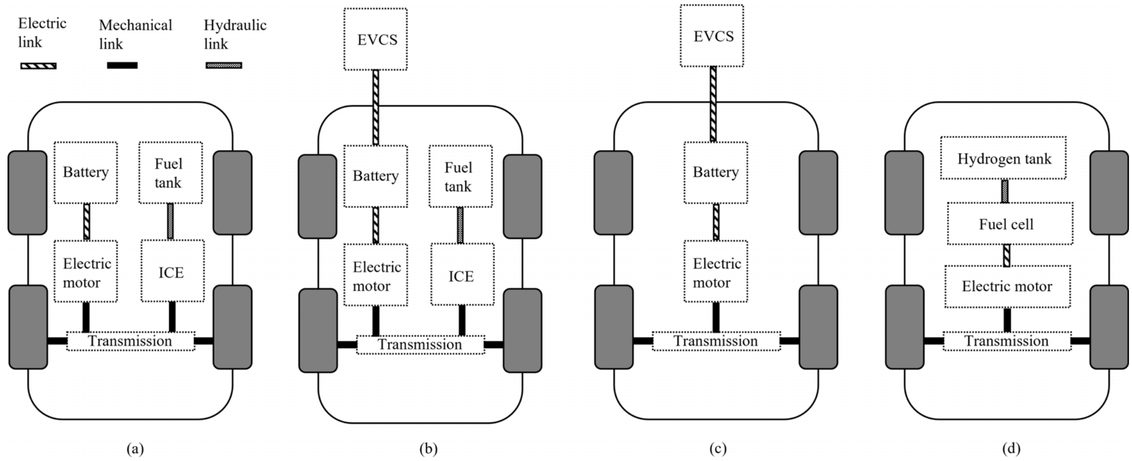

Fig. 3. Electric vehicle powertrain design and engine setting: (a) hybrid electric vehicles, (b) plug-in hybrid electric vehicles, (c) battery electric vehicles, and (d) fuel cell electric vehicles.

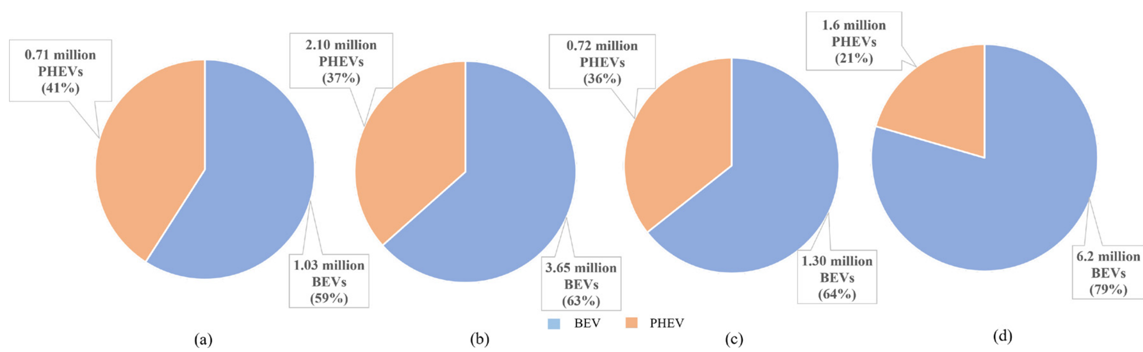

Fig. 4. Number of plug-in hybrid electric vehicles and battery electric vehicles by the end of 2021 in (a) the United States, (b) China, (c) Europe, and (d) other countries [8]. Other countries include Australia, Brazil, Canada, Chile, Korea, India, Japan, Mexico, South Africa, and New Zealand.

PHEV, which has a 12 kWh battery and can travel up to 50 km using only the EM.

- *Battery electric vehicles:* By only being equipped with an EM and a battery without any ICE or liquid fuel, BEVs are a type of pure EV powered solely by electrical energy stored in battery packs and can be charged from EVCSs. The driving range of BEVs largely depends on the battery capacity, with other factors such as driving patterns, road conditions, and battery conditions. On average, BEVs can have a driving range of 160 to 500 km. As an example of BEVs, the Nissan Leaf is 100% electric with a battery capacity of 62 kWh and a driving range of 360 km.
- *Fuel cell electric vehicles:* As another type of EV, FCEVs are equipped with an EM, a fuel cell, and a hydrogen tank. By combining compressed hydrogen and oxygen from the air, FCEVs can produce electrical power. Then FCEVs drive the wheels and store excess energy batteries or supercapacitors. A notable example of an FCEV is the Hyundai Nexo, which can travel up to 650 km without refueling.

As noted in [23], HEVs and PHEVs still have low emissions due to their ICEs, while FCEVs may have few to no emissions depending on their operating mode. On the other hand, BEVs are fully powered by batteries and thus have zero emissions. As PHEVs and BEVs can be connected to EVCSs and power grids, they are classified as pev. For the purpose of exploring the impacts of EVs on power systems, this review will primarily focus on PHEVs and BEVs. Data from iea [8] show the number of PHEVs and BEVs at the end of 2021 in the United States, China, Europe, and other countries, as depicted in Fig. 4.

2.1.2. Duty cycle of electric vehicles

It is crucial to understand the usage patterns, duty cycles, and various factors of EVs, which affect travel distance, charging opportunities, and travel patterns. Based on their weight and duty cycle, EVs can be categorized into three categories: ldev, mdev, and hdev. The survey in [51] revealed that the global sales of EVs cumulatively reached 18.6 million cumulatively by 2021, of which 98% were LDEVs and only 2% were MDEVs and HDEVs. The detailed introductions of LDEVs, MDEVs, and HDEVs are given below:

- *Light-duty EVs:* LDEVs have a weight of less than or equal to 10,000 pounds [51]. These vehicles, which include cars, vans, sport utility vehicles, and pick-up trucks, are utilized for an average of four trips per day and cover nearly 40 miles per person per day in the United States [12]. On average, LDEVs charge 10–20% of the day, leaving 75–85% of the time for potential charging, as reported in [12]. The preferred charging locations for LDEVs are homes, followed by workplaces and public fast-charging EVCSs.
- *Medium-duty EVs:* MDEVs weigh between 14,000 pounds to 26,000 pounds [51]. MDEVs include box trucks, delivery trucks, bucket trucks, school buses, and beverage trucks. The survey in [12] demonstrated that MDEVs could vary their routes daily or weekly depending on the type of delivery. Therefore, MDEVs can also serve as flexible resources with adjustable charging hours.
- *Heavy-duty EVs:* HDEVs weigh more than 26,000 pounds [52]. Unlike the drivers of LDEVs and MDEVs, the drivers of HDEVs are usually limited by the daily hours that they can drive and fixed routes, such as et [53,54] and EBs [18,55,56]. The results in [57] indicated that the charging load of long-haul ETs was nearly 5% of the annual consumption of electricity in the United States.

In Table 3, we list some examples of energy consumption models for LDEVs, MDEVs, and HDEVs, such as in [54,58–60], which use the battery capacity, energy consumption rate, and charging rate. Those EV

Table 3
Examples of energy consumption models for electric vehicles.

Model	Ref.	Battery Capacity (kWh)	Energy Consumption Rate (kWh/mile)	Charging Rate (kW)
LDEV	[58]	100	0.17	6.90
	[59]	40, 100	0.30, 0.35	3.60, 6.20, 150
MDEV	[54]	99	0.85	150, 350
	[60]	200	1.44	50, 150, 300
HDEV	[54]	238.3, 386.5	1.57, 2.08	150, 350
	[60]	1500	3	50, 150, 300

energy consumption models can be used to estimate the charging profiles of LDEVs, MDEVs, and HDEVs.

2.2. Grid-to-vehicle: Charging estimation, management and charging infrastructure

2.2.1. Charging estimation of electric vehicles

The estimation of EV charging demands is critical for assessing the impact of EVs on power system resources and charging infrastructures. Conventional modeling methodologies for estimating EV charging profiles are developed based on full-system tools and model-based methods. Based on the definition in [40], full-system simulation tools and model-based methods for charging load profile estimation can be classified as, node-based methods, flow-based methods, and agent-based methods. Node-based methods, such as those presented in [61] and [62], are aimed to locate charging infrastructures so that the charging demand at nodes can be met. In [61,62], the authors considered the charging demand as a node in a directed graph and aim to minimize the installation cost of charging infrastructures while restricting the distances between the charging infrastructures and the charging demand. In contrast, flow-based methods, such as the method presented in [63], model the EV charging demand with traffic flows and consider the temporal distribution of EVs. An extended flow refueling location model was proposed in [64], which allowed alternative driving paths. Agent-based methods, also known as activity-based methods, are driven by the behavior of representative drivers and use information about the charging decision and travel behavior to generate synthetic EV charging profiles. For example, in [59,65], an activity-based charging demand simulation model and stochastic simulation of trip chains were implemented to simulate complete trip chains and obtain the spatiotemporal distribution of EV charging demands. An agent-based model was developed in [66] to investigate not only the spatiotemporal distribution but also the dynamic characteristics of EV charging demand. In [67], the authors proposed an estimation model to calculate the charge and discharge powers of an EV cluster based on a trip chain. With the combination of activity-based analysis and the Bayesian method, an analytic framework was proposed in [68] for estimating the EV charging demand.

However, full-system simulation tools and model-based methods face scalability issues when predicting EV charging profiles for large transportation networks with a large number of EVs. To overcome this limitation, researchers have developed data analysis and model-free machine learning methods. For instance, in [69], a prediction model for urban EV fast-charging demand that takes into account human decision-making behavior was created using data mining technology. The model combined a single EV model and a decision-making model of human behavior to factor in the trade-off between time consumption and charging cost [69]. In [70], the EV market shares, charging patterns, and fleet composition were analyzed in New Zealand using multivariate probabilistic modeling and cumulative distribution functions to estimate aggregated EV charging demands. In [70], the authors applied vehicle travel survey data to quantify the charging behaviors and driving patterns of EVs and implemented non-smart and smart charging strategies to ensure charging completion. In [71], an AI-based method was developed to forecast PEV travel behavior and charging demand using recurrent ann that considered the correlation between arrival/departure time and trip length based on historical data. In [72], a novel probabilistic queuing model was utilized to explore the EV charging process and convert traffic flow into charging load using a DL-based cnn method to predict traffic flow and EV arrival rates. In [73], an RL-based method was proposed to predict PHEV charging loads under different charging scenarios using the Q-learning to improve forecasting accuracy. In [74], a two-layer ensemble learning method, that combined multiple machine learning algorithms to improve computational performance was developed to evaluate household EV charging demand. Various methods for estimating and predicting the EV charging profile are summarized in Table 4.

2.2.2. Battery management and smart charging of electric vehicles

Even though the EVs are effective to reduce GHG and pollutant emissions, the traditional bms and thermal energy management of EVs maybe not meet the requirement at high discharging rates and at high operating or ambient temperatures [75,76]. In addition, the random and variable travel behavior of EVs makes it more challenging to achieve the desired battery status. To address this challenge, researchers have explored smart EV charging methods, which could monitor the battery status, such as the state of charge and state of health (soc and soh, respectively) and remaining useful life, and ensure the optimal and reliable operation of EV charging by managing, monitoring, and protecting them. There are four main estimation strategies for a BMS: battery fault estimation, SOC estimation, SOH estimation, and battery life estimation [34]. Monitoring and predicting battery degradation is also essential for the effective operation of BMSs. As stated in [50], battery degradation can be considered a major technical challenge in deploying V2G technology, because even when cycling the EV battery within a charge range of 30% to 90% for grid support, the battery may still be damaged. To mitigate the effects of battery degradation and coordinate with power system operation, EV smart charging methods have been evaluated in studies. A cost-benefit analysis of battery degradation for V2G and a stochastic approach to smart charging showed that smart charging could reduce battery degradation costs compared to uncoordinated charging and render V2G implementation economically viable [77]. Based on cumulative prospect theory, in [78], the authors proposed a modeling method for determining BEV charging decisions and considered an individual's risk attitude in the decision-making process, including the charging time, location, and power demand profile. In [79], the authors investigated the charging mode and location choices of BEV drivers in Japan, using mixed logistic modeling methods, and revealed preference data. The EV optimal charging and discharging and route selection problems were solved in [80] to maximize the profits of EVs with the constraints of time-varying renewable energy supply, limited charging pile availability, and EV travel tolerance. Huo et al. [81] proposed a distributed EV charging control protocol that is scalable and privacy-preserving, while also protecting the privacy of participating EVs. Kara et al. [82] quantified the benefits of a battery EB fleet with smart charging, simulating the reactions of power grid operators in Texas and considering the role of smart charging in balancing renewable energy production. Dante et al. [83] proposed a stochastic and optimal PEV charging scheduling based on dynamic electricity prices and diver

Table 4
Summary of estimation and prediction methods for electric vehicle charging profile.

Ref.	Approach	Main Feature
[61,62]	Node-based approach	• Model-based method • Consideration of the charging demand as a node in a directed graph
[63,64]	Flow-based approach	• Model-based method • Consideration of traffic flows between origin and destination
[59,65–68]	Agent-based approach	• Model-based method • Consideration of travel behavior and charging decisions to generate synthetic charging profile
[69]	Data mining and fusion technology	• Model-free method • Combination of a single EV model and a human behavior decision-making model
[70]	Multivariate probabilistic function	• Model-free method • Utilization of vehicle travel survey data and cumulative distribution functions to estimate aggregated EV charging demands
[71,72]	Deep neural network	• Model-free method • Utilization of ANNs to consider the correlation between arrival/departure time and trip length Utilization of CNNs to predict traffic flow
[73]	Reinforcement learning algorithm	• Model-free method • Utilization of RL to predict PHEV charging loads Utilization of Q-learning to improve forecasting textcuracy
[74]	Ensemble learning algorithm	• Model-free method • Combination of multiple machine learning algorithms to improve computational performance

Table 5
Main features of alternating current and direct current charging systems [35,84].

Charging mode	Level	Charging Rate (kW)	Output Voltage (V)	Output Current (A)	Typical Location
AC charging	Level 1	1.44-3.6	120	12-16	Home
	Level 2	<14.4	240	16-80	Home/Work
DC charging	Level 1	<36	200–450	<80	Work/Public
	Level 2	<90	200–450	<200	Work/Public
	Level 3	<240	200–600	<36	Work/Public

preferences. All these studies demonstrate the ongoing effort to effectively manage, monitor and protect EVs to achieve optimal and reliable operation for providing ancillary services to power systems.

2.2.3. Typical features of charging infrastructure

Deployment of charging infrastructure is crucial for high EV adoption in power systems, as it directly reflects the availability of charging options. Per the definitions in [35,44,84], AC charging systems, require an onboard charger built within the EVs and are divided into two levels; DC charging systems, require an off-board charger and are divided into three levels [35]. The AC charging system directly supplies AC current to EVs, while the DC charging system requires the conversion of AC current into DC current within the charging system before it can be supplied to EVs. Different regions adopt different standards for EV charging infrastructures. For instance, Europe follows the IEC 62,196 standard, while China follows the GB/T 20234-2011 standard that also permits AC charging following the IEC 62,196 standard. In the United States, the SAEJ1772 charging standard is adopted, and the recognized plug types are similar to those of IEC62196. Table 5 summarizes the output power levels and charging locations of AC and DC charging systems.

In recent years, DCFC options have gained popularity in public EVCSs due to their ability to increase the adoption of long-range EVs by decreasing their range anxiety [14,85]. There are also Level 4 and Level 5 chargers, such as Tesla's superfast Level 4 chargers and Level 5 XFCs, available for long-distance trips. One potential solution to relax range anxiety for current and prospective EV drivers is the wireless charging system. In [27], an overview of wireless charging was presented with detailed descriptions of static and dynamic wireless charging infrastructures. In [28], a critical survey of recent studies and developments for wireless power transfer systems was provided. Study [86] established a wireless charging system for EVs and evaluated the impact of the wireless charging system on the power grid under resonant, capacitive, and inductive operation conditions. Another alternative business model for EVs is the bss, where EV batteries are leased to drivers and can be replaced and charged during off-peak hours [87].

2.3. Vehicle-to-grid: Vehicle grid integration and ancillary services

2.3.1. Vehicle grid integration technology of electric vehicles

The advent of V2G technology and the ability for flexible EV charging offers numerous opportunities for increased flexibility across various sectors, including power systems, transportation, buildings, and homes [88,89]. In the V2G mode, energy can be transferred back and forth between EVs and the power grid [90,91]. Unlike the unidirectional power flow in conventional G2V mode, the V2G mode allows for bidirectional power flow between power grids and EVs via EVCSs and leverages the energy storage capabilities of EVs as a means of storing surplus energy and transferring it back to the power grid. The development of V2G has created opportunities to provide ancillary services, further improving its stability and reliability [35]. To implement V2G via the VGI technique, EVs are usually equipped with bidirectional converters in EVCSs. Unlike unidirectional converters, bidirectional converters allow for power flow in both directions. The differences between bidirectional converters and unidirectional converters have been analyzed in [92]. As depicted in Fig. 5, EVs with unidirectional converters only permit power flow from the power grid to EVs, while those with bidirectional converters can both charge from the power grid and feed battery power into it, enabling VGI functionality and V2G technology. The operation and ancillary services of V2G technology are discussed in further detail in Section 4.

2.3.2. Ancillary services with vehicle-to-grid

Efficient power system operation requires ancillary services to ensure security and reliability. With an increase in EV adoption, the proper management and coordination of EV charging in V2G mode become crucial to address potential issues such as load stability, energy supply quality, and voltage fluctuations. V2G enables EVs to act as mobile energy storage units or dg and provide ancillary services, including resilience enhancement, peak shaving, voltage support, spinning/non-spinning reserve, frequency regulation, and current compensation. By utilizing the high energy storage capacity of EVs, V2G can greatly enhance power sta-

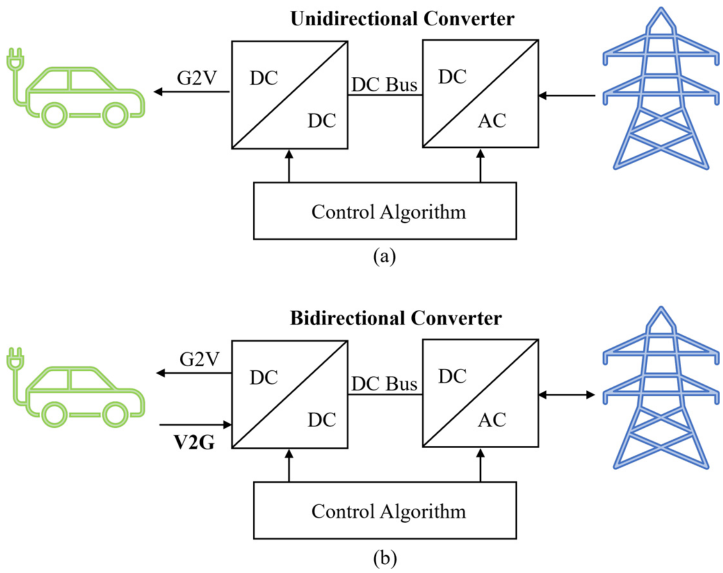

Fig. 5. Vehicle-grid-integration for electric vehicles: (a) unidirectional converters and (b) bidirectional converters that enable V2G.

Table 6
Summary of the ancillary services provided by V2G technology in power systems.

Ancillary service	Ref	Main Feature	
Resilience enhancement	[55]	Active power control	• Joint DN restoration and EB scheduling problem
	[56]	Active power control	• Coordination of VRP and DN restoration
	[94]	Active power control	• Autonomous load restoration • Communication protocol
	[95]	Active power control	• Preposition of mobile energy storage • Reallocation of the mobile energy storage
	[96]	Active power control	• Distributed control method • Reduce load shedding
Peak shaving	[97]	Active power control	• Stochastic driving habits • Monte Carlo method
	[98]	Active power control	• Number of connected EVs • Characteristics of the EV battery packs
Voltage support	[100]	Reactive power control	• Kernel-based predictive model • Distributed reactive power control
	[101]	Reactive power control	• Elimination of the impact of the DC fast charger • V2G outperforms DG in voltage control
Spinning and non-spinning reserve	[102]	Power reserve	• Dispatch probability of EV battery
	[103]	Power reserve	• Increased flexibility in ERCOT • Maximized profit of the EV aggregator • Hypothetical group of 10,000 EVs
Regulation up and down	[104]	Frequency regulation	• Ancillary service market • Daily cost reduction
	[105]	Frequency regulation	• Combination of inertial emulation and droop control
Compensation of harmonics in grid current	[106]	Harmonic compensation	• Harmonic modulation technique • Bidirectional onboard charger
	[107]	Harmonic compensation	• Output-voltage control • Virtual impedance term

bility and reliability. Previous studies have highlighted some ancillary services provided by V2G and their impact on power system operation, as outlined in Table 6 and discussed in [29,45–48,50,93].

- *Resilience enhancement:* With the ability to transfer energy to power grids at different locations, EVs with V2G technology can be used to enhance the resilience of power grids. Several studies have proposed methods for enhancing the resilience of power systems using EVs. A milp-based distribution system restoration method was proposed in [55], where the EBs served as a temporary mobile power source to feed power back to the power distribution system via V2G technology during hurricanes. The vpp of EBs was coordinated with power distribution system restoration [56]. In [94], an EV-assisted load restoration method was proposed based on a communication protocol for distribution feeder-level resilience enhancement. A two-stage stochastic model was proposed in [95] to enhance the resilience of power distribution systems, where the first stage pre-allocated mobile resources, and repair crews, and the second stage generated the intraday operation decisions for generator dispatch and network reconfiguration. In [96], a distributed control method of an EV fleet was proposed for the resilience enhancement of an urban energy system under extreme contingency, where the charging and discharging schedules of the EV fleet were coordinated to mitigate load curtailment while considering the power transfer among the multi-energy MGs.
- *Peak shaving:* V2G technology allows EVs to act as energy storage devices, which can store excess power during off-peak hours and discharge it during peak hours to mitigate power shortages in the power grid. By providing the peak shaving ancillary service, V2G enables demand response in the power market and offers financial benefits to EV drivers. In [97], the optimal charging and discharging strategies for peak shaving were explored using actual EV usage data, considering factors such as the driver's driving habits, charging demand, and vehicle battery state-of-charge. In [98], V2G peak shaving and valley filling control strategies were presented, taking

into account the number of connected EVs, battery pack characteristics, and driver parameters.

- *Voltage support:* Renewable energy sources can lead to over-voltage or under-voltage issues in power grids, particularly at the grid-edge buses [99]. To address this problem, V2G technology provides a solution by enabling EVs to regulate the grid-edge voltages by injecting or absorbing reactive power. A kernel-based predictive model was proposed in [100] to investigate the available capacity from EVCSs and a distributed optimal reactive power management method for voltage support provided by EVs via V2G operations. Additionally, V2G technology was adopted in [101] to minimize the impact of fast chargers on the power distribution system and ensure the power network operates within acceptable limits with a minimal effect on consumers.
- *Spinning and non-spinning reserves:* To maintain frequency in power systems, spinning reserves and non-spinning reserves are two crucial services [45]. Unlike large generators, EVs equipped with V2G technology have been shown to be an effective and attractive solution for frequency regulation. By considering the dispatch probability of the EV battery, the utilization of EVs for frequency regulation can save secondary regulation capacity and spinning reserve [102]. In [103], a study of a hypothetical group of 10,000 EVs was conducted to maximize the profits for the aggregator while providing increased system flexibility, where the spinning reserve was tested in the ercot system.
- *Regulation up and down:* Regulation of frequency is accomplished by automatic generation control, also known as regulation down and up, which is aimed to balance supply and demand within a minute [45]. The potential of V2G technology to enable EVs to participate in the frequency regulation market was explored in a study [104], where a significant daily cost reduction was achieved. In [105], the authors proposed a frequency regulation method for isolated power systems with EVs, integrating inertial emulation and droop control to improve frequency regulation performance.
- *Compensation of harmonics in grid current:* V2G technology has the potential to improve power quality by actively filtering and compensating for the harmonic content in grid currents. This improvement is achieved by adhering to the harmonic limits prescribed by the IEEE-519 standard. In [106], a bidirectional onboard charger that also regulated input harmonics was developed for EV charging and discharging. This technology was achieved by adopting a high power factor and structure change method to accommodate a wide range of line voltages. In [107], the authors proposed an output voltage control method that includes harmonic compensation and a virtual impedance term. This method promises high power quality and effective damping in the EV battery charger.

An example of voltage regulation and voltage support via the V2G technique is shown in Fig. 6. Bidirectional chargers equipped with EV batteries allow for power injection or absorption into the power grid. According to the operation conditions of the EV battery's active and reactive powers, there are four possible modes of operation, including (I) active power charging and reactive power compensation, (II) active power discharging and reactive compensation, (III) active power discharging and reactive power absorption, and (IV) active power charging and reactive power absorption. For instance, if the distribution system requires reactive power while the EV is charging, the charger could operate in the capacitive mode and inject reactive power, as shown in operation mode IV in Fig. 6. On the other hand, if the distribution system requires reactive power while the EV is discharging, the charger can operate in inductive mode and absorb reactive power. The apparent, active, and reactive power ratings of the EV batteries are represented by $S_{\max}$, $P_{\max}$, and $Q_{\max}$ in Fig. 6.

However, the evaluation process in some of the above research on G2V and V2G failed to examine the impact of their proposed EV charging schedules for the system planning and operation of power systems. As a result, the potential violation of power system planning and operational constraints cannot be fully considered, and the bottlenecks on power systems to adopt more EVs cannot be fully identified. For instance, in [82,83,108], the authors only estimated the impact of EV charging on the load profile without examining their effects on power system operation. The widespread adoption of spatiotemporally varying EV charging loads presents a significant challenge to power systems; further discussions are provided in Section 3 and Section 4.

3. Impacts of transportation electrification on power system planning

In this section, we evaluate the impact of EVs on power system planning across transmission and distribution levels from different perspectives. As shown in Fig. 7, we mainly discuss studies on planning power system resources and EV infrastructures in power systems to increase the adoption of EVs and identify the main metrics that can be applied to power planning with a high penetration of EVs.

3.1. Power transmission planning with electric vehicles

The planning of EV charging infrastructure and its integration with the power system have become crucial issues in recent years. The national-scale planning model presented in [109] is aimed at assessing the United States mainland interstate highway network, but it only considered EV charging infrastructure planning and did not take into account the planning of power system resources. The limited generation and transmission capacities of power transmission systems are a hindrance to large-scale EV integration. The importance of including a power tn in charging infrastructure planning was discussed in [39], where the focus was mainly on new generation and transmission resources. An assessment methodology was proposed in [110] to understand the impacts of end-use electrification on long-term power planning, which demonstrated how transportation electrification has the highest share of demand-side load flexibility and that LDEVs are more flexible than MDEVs and HDEVs in power system planning and operation. Widespread electrification could lead to significant changes in power systems [111], such as generation addition, transmission expansion, fuel use, system cost, and air emissions. The effects of large-scale EV deployment on the power system in the United Kingdom were evaluated in [112], where a MILP-based opf model was used to determine the investments of power infrastructure for EV adoption and optimize the operational schedule on an hourly basis. The EV charging demand was modeled as an additional zonal demand by considering the data for annual energy demand increase and daily charging profiles. The works mentioned above present deterministic methods for power transmission system planning, but uncertainty is a critical aspect to consider, especially in the context of high EV penetration. To address this issue, a stochastic planning framework was developed in [113] using the scenario tree method, which considered investment and operation models for G2V and V2G to plan network expansion over a large-scale and long-term timeframe under multiple uncertainties. A robust adaptive optimal planning model was proposed in [114] with scenario-based ambiguity sets, which considered PEV charging controls over the planning horizon to enable more economical and realistic PEV penetration cases.

Here, we give an example of an optimal planning problem in power transmission systems with high EV adoption. This problem can be succinctly expressed as a set of mathematical equations, from equation (1) to equation (5). In this work, we specifically focus on transmission and generation needs that result from the growth in electricity demand due to transportation electrification. Therefore, only the most commonly employed objectives and constraints in optimal planning problems in power transmission systems are included. Depending on the research questions that are being addressed, additional constraints, such as the CO_2 emission constraints that were considered in [112], may also be added.

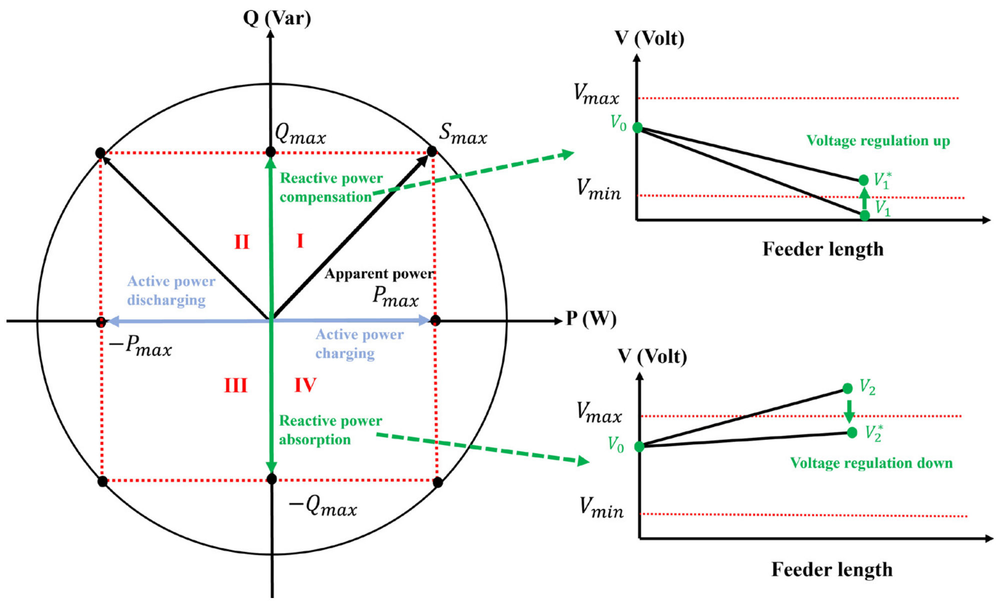

Fig. 6. Example of ancillary service provided by the vehicle-to-grid technique with reactive power support and voltage regulation.

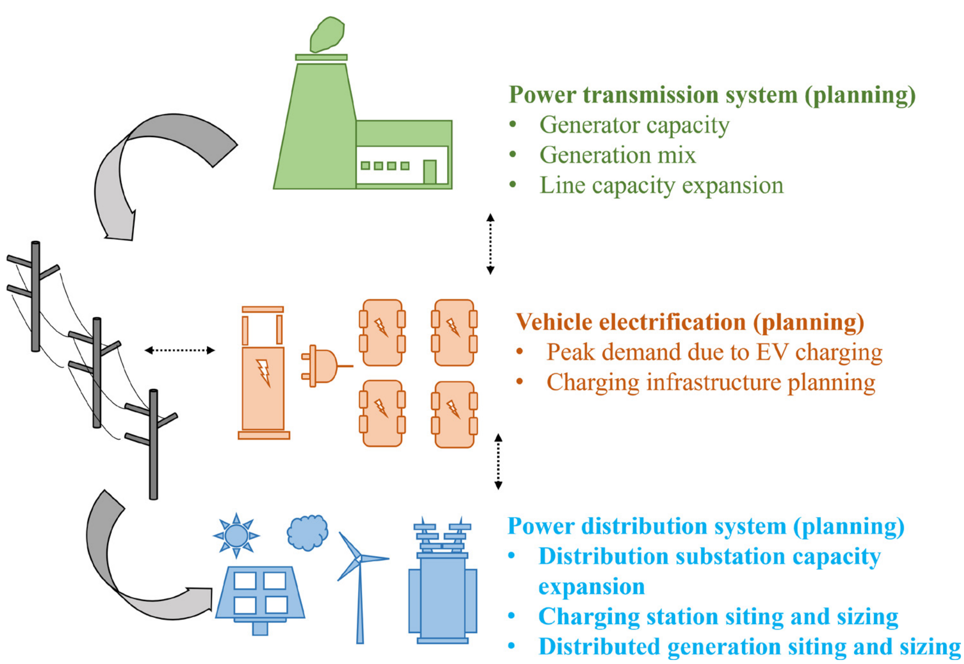

Fig. 7. Impacts of electric vehicles on power system planning for transmission and distribution systems.

$$\text{Objective} \underset{x}{\text{Minimization}} \text{ of planning cost,} \tag{1}$$

$$\text{s.t. Power flow and operational constraints in the power transmission network,} \tag{2}$$

$$\text{Generation capacity expansion,} \tag{3}$$

$$\text{Generation mix,} \tag{4}$$

$$\text{Transmission line capacity expansion.} \tag{5}$$

The objective of the power transmission planning problem, as stated in equation (1), is usually aimed at minimizing the total system cost, taking into account various expenses such as capital costs for power supply, transmission capacity expansion, operational costs of generators, CO_2 transport and storage, and power import [110–112]. In addition to the investment cost in power systems, the investment costs for different types of smart chargers, such as £1500 per G2V charger with unidirectional charging and £2500 per V2G charger with bidirectional charging, were considered in [113]. An incentive cost of $ 5000 per PEV was considered to maximize the PEV penetration over the planning horizon [114]. The power flow and operational constraints model, as stated in equation (2), are commonly modeled using either acopf or dcopf models, which take into account bus power balance constraints, bus voltage constraints, and line power flow constraints. Notably, the ACOPF model has nonlinear bus voltage constraints, while DCOPF is a linear approximation of ACOPF. The constraints listed in equations (3) to (5) are explained in further detail in Section 3.1.1 to Section 3.1.2. In addition to solving optimization problems, simulation-based methods are also widely utilized, as demonstrated in Fig. 8.

3.1.1. Generation capacity expansion and mix planning with decarbonization target

The trend of increased peak demand from transportation electrification is one of the several factors affecting long-term power system planning and transforming the future capacity and generation mix, leading to a shift away from fossil fuels and toward more solar and wind gener-

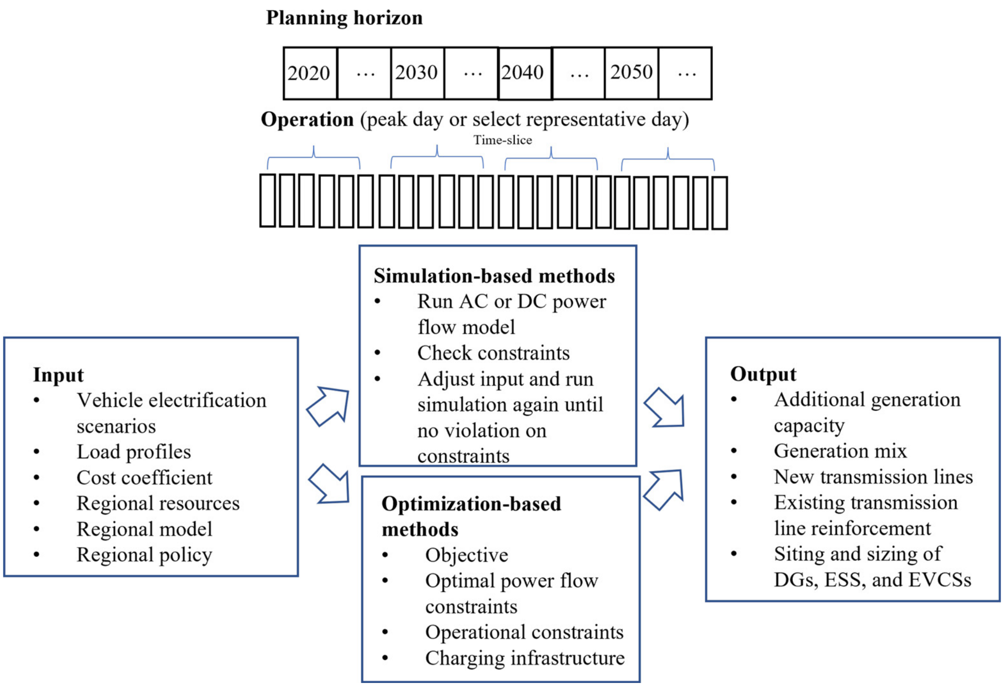

Fig. 8. Simulation-based and optimization-based methods for solving planning problems in power systems.

ation, as discussed in [39]. According to research from [110,111], the widespread adoption of EVs could spur the growth of renewable energy and natural gas-fired electricity generation. The decline in natural gas consumption due to electrification could lower natural gas prices and make natural gas-fired generation more cost-competitive. The continued growth of renewable energy is expected to be further amplified by electrification [110,111]. In addition to renewable energy and natural gas, energy storage could play a crucial role in accommodating the changes caused by electrification, particularly in meeting higher demand peaks. To meet the growing energy needs resulting from electrification, reliance on local and distributed energy resources is increasing, reducing the need for long-distance transmission expansion. Research in [112] has shown that the charging patterns of EVs are well aligned with wind power production, reducing the waste of wind generation. Similarly, the widespread deployment of dg could relieve the generation requirement and mitigate transmission-level issues [112]. The capacity expansion problem of DGs is further discussed in Section 3.2 on power distribution system planning. To meet the carbon reduction goals, the carbon intensity of power generation, including system-wide carbon emissions targets and the operational emissions from technology-specific power generation and imported power, was considered in [112]. In [114], a joint planning model was employed to minimize emissions while increasing the supply of high EV charging. However, the simulation results in [114] showed a different outcome compared to [110,111]. The high emission cost of natural gas power generators was factored into the planning model, which concluded that natural gas power generators had no significant impact on the generation mix.

3.1.2. Transmission line capacity expansion

In addition to planning new power plants to accommodate increased transportation electrification, the aging transmission infrastructure and the prevalence of short transmission segments could pose challenges in connecting new generation resources with the demand from electrified vehicles. As shown in [115], rural areas where wind and solar energy resources are commonly located often lack adequate transmission infrastructure, leading to the inability of local communities to consume all the generated electricity and a lack of energy storage capacity. Upgrading transmission infrastructure to better facilitate the transmission of electricity from rural areas to high-demand regions, such as areas with many EVs, would mitigate these challenges. Based on the findings in [110,111], the growth of renewable energy sources and the corresponding expansion of transmission capacity was positively correlated. A case study in the United Kingdom transmission grid, as presented in [112], highlighted the significant differences in power transmission expansion between scenarios that consider EV demands and those that do not consider EV demands. To illustrate this point, the majority of the 29 modeled zones in the United Kingdom transmission grid had a power flow of less than 2 TWh/year. However, specific power transmission lines connecting zones with an abundant renewable capacity to those experiencing an increase in EV charging demand could experience an increase of more than 5 TWh/year. In response to this, the hvdc lines between Scotland and England were strengthened to transfer more wind power from the north to the south of the United Kingdom [113]. Moreover, in [114], the authors discovered that adopting smart EV charging could reduce the transmission capacity requirement by 78% to supply the same load during the planning horizon. This finding highlights the potential of smart EV charging to mitigate the impact of EVs on power system planning in transmission systems. The impacts of EVs on power system planning for transmission systems are summarized in Table 7.

3.2. Power distribution planning with electric vehicles

Because of the limited range of EVs, the deployment of charging infrastructure is crucial for drivers to undertake long-distance trips. Several studies have focused on the planning problem of EV infrastructure, including the siting and sizing problems of EVCSs. In [116], a solution was proposed to accommodate multiple types of EVs with different driving ranges by determining the optimal siting of EVCSs. A two-stage stochastic programming model was developed in [117] to determine the optimal EVCS locations considering uncertainties in arrival and dwell times for EVs. A mixed integer programming-based model was proposed in [118] to maximize long-distance trip completions, providing an effective method for deciding the number and locations of fast EVCSs for different conditions. A siting problem of fast EVCSs was investigated in [119] with a multiperiod decision-making horizon to support the maximum and uncertain EV charging demand within a limited budget. However, these studies [116–119] did not consider the planning of EV infrastructure within power distribution systems, which could lead to operational constraint violations in power systems. To support the widespread adoption of EVs, dn must be updated to accommodate ad-

Table 7
Review of the selected studies related to the impact of EVs on power transmission planning.

Ref.	Power System Model	EV Model	Planning Solution
[110]	• National-scale ReEDS in the United States	• LDEVs with allowable 8-h flexible duration and multiple charging options	• Two-year planning problem through 2050 • Demand-side flexibility
[111]	• National-scale ReEDS in the United States	• Transportation electrification shares 10% of flexible load under reference electrification • Transportation electrification shares 60% of the flexible load under high electrification	• Two-year planning problem through 2050 • Supply-side scenario
[112]	• 29-bus synthetic TN in the United Kingdom	• Function of EV fleet size and EV charging demand	• Five-year optimal planning problem • Hierarchical multicut benders decomposition
[113]	• IEEE 24-bus • TN 37-bus synthetic TN in the United Kingdom	• Different EV load shapes by vehicle specifications and driving patterns	• Multistage stochastic planning framework
[114]	• IEEE 118-bus TN • 10-bus synthetic TN in Ontario	• Scenario-based ambiguity sets of renewable energy and PEV mobility	• Minimization of planning investment • Maximization of EV penetration • Minimization of CO_2 emissions • Transmission and generation capacity expansion • Adaptive distributionally robust optimization

ditional capacity requirements and opportunities for adding DGs and EV charging infrastructures. Previous studies have investigated the impact of EVs on power distribution systems and developed methods for optimal planning of EV charging infrastructure. For example, in [120], the authors generated charging profiles for 100 EVs at a workplace and used time-series-based power flow calculations to assess the impact on a European mv distribution grid. The impact of short-haul HDEV depot charging on power distribution system upgrades was evaluated in [52]. The study found that nearly 78% of substations could supply 100 HDEVs with 100 kW charging without upgrades and that 90% of substations could accommodate 100 HDEVs if charged at the slowest possible rates [52]. A reliability-index-based approach was proposed in [121] to determine the siting and sizing of slow and fast EVCSs in power distribution systems, including the reliability indices of voltage stability and power quality. An optimal siting and sizing problem of BSSs of EVs in distribution systems in [87] was modeled to maximize the net present value, where an evolution algorithm was implemented to solve the problem. In [122], the siting and sizing problem of Level 1 to Level 3 EVCSs was optimized and analyzed in power distribution systems, where the EV load was estimated based on the number of EVs, and arrival and departure times at the particular EVCSs. A heuristic pso method was adopted to solve the optimal EVCS siting and sizing problem to minimize the installation cost of the EVCS and the cost of power losses in the distribution system. A real-world distribution network was modeled in OpenDSS to simulate power flow and evaluate operational constraints with different planning solutions for EVCSs [122]. In [123], a siting method of distributed wind and PV generators was proposed to mitigate the impacts of PEV integration on power losses, power reliability, and voltage stability in the distribution systems. A line flow test was conducted in the IEEE 33-bus DN to calculate the total power loss and assess the impact of the placement solution on the voltage magnitude [123].

To better present the objective and restrictions of distribution system planning for adopting more EVs, an example of a compact form of the optimal planning problem in the power distribution system is presented as follows:

$$\underset{x}{\text{Objective Minimization of the planning cost,}} \tag{6}$$

$$\text{s.t. Power flow and operational constraints in the power distribution network,} \tag{7}$$

$$\text{Distribution assets upgrade,} \tag{8}$$

$$\text{Siting and sizing of electrical vehicle charging stations,} \tag{9}$$

$$\text{Siting and sizing of distributed generators.} \tag{10}$$

The objective of the power distribution planning problem, as stated in equation (6), is to minimize the costs of upgrading the distribution assets and installing EV charging infrastructure. However, other objectives, such as profit maximization, power loss minimization, and carbon emission cost minimization, have also been considered in the literature. The compact constraints in equations (8) to (10) are further discussed in Section 3.2.1 to Section 3.2.2, and the power flow and operational constraints are explained in Section 4. To evaluate the feasibility of the planning solutions, various indices are applied to assess the performance of the power distribution system in the presence of high EV adoption. The planning indices, as summarized in Table 8, play a crucial role in determining the feasibility of the planning solution. If the indices are within the acceptable range, the planning solution is considered feasible; otherwise, the planning problem must be solved again with adjustments to the planning solution.

3.2.1. Distribution assets upgrade and emission costs

As noted in [39], the increasing number of EVs and their charging loads have prompted the need for significant upgrades in the distribution level to increase the capacity of the system and address voltage regulation issues. These upgrades, which are referred to as distribution asset upgrades, typically involve increasing the capacity of existing substations by adding new distribution lines and new secondary transformers. For example, in [52], the authors discussed the upgrades of distribution feeders and substations for the deployment of short-haul HDEV fleet charging. The results showed that the magnitude of the HDEV charging profile was a more significant indicator of the need for substation upgrades compared to the timing of the charging. A case study in [52] estimated the cost of upgrading a substation to be $400,000 per new feeder breaker and $ 35 million for a new substation.In some studies, such as in [120], the authors specifically focused on upgrading secondary transformer capacity. Commuting patterns were also found to heavily influence the interaction between EV charging and the power distribution system [120]. In [124], the maximum number of simultaneous EV charging events in each service area was evaluated by considering the transformer loading and host capacity. In [125], the authors proposed a multiobjective optimization model to balance the cost and emissions of grid reinforcement and transformer capacity expansion while charging EVs. The model accounted for production emissions while reinforcing electricity cables and upgrading transformers, with the parameters of 12.5 tCO_2/km and 163.3 tCO_2 for extending one km of electricity cables and upgrading a 630 kVA transformer, respectively. A case study in [125] showed that the EV charging cost and emissions could be reduced by 13.2% and 23.6%, respectively, by optimizing the charging strategy in a low-voltage distribution network.

Table 8
Summary of important indices in the power distribution planning problem with electric vehicle charging and electric vehicle charging station deployment.

Planning Index	Description
Transformer loading	To represent the pressure of transformers to connect an EV charging load, the transformer loading was calculated in [120,124].
Line loading	To reflect how much of the line's full capacity is utilized due to EV charging, the line loading was calculated in [120].
Voltage stability	To maintain an acceptable level of system bus voltage with EV charging, a voltage stability standard, such as the Bus vsi, was obtained [121,123].
Power reliability	To measure the total duration of an interruption caused by EV charging, a sri, such as saifi and saidi, was employed [121].
Power quality	To determine the power quality caused by EV charging, a lsf was applied [121].

Table 9
Review of the selected studies related to the impact of EVs on power distribution planning.

Ref.	Power System Model	EV Model	Planning Solution
[52]	• 36 DN substations in Texas	• Deport charging of short-haul HDEV fleet	• Likelihood between HDEV charging and substation upgrade
[87]	• IEEE 15-bus DN • IEEE 43-bus DN	• LCC of BSSs • Comparison between BSSs and fast EVCSs	• Optimal siting and sizing of BSSs • Differential evolution method • Comparison between deterministic planning and stochastic planning
[120]	• CIGRE MW DN in Europe	• EV charging profile with trip chain • 100 EVs charging at workplace	• Time-series power flow • Check of transformer loading, line loading, and nodal voltage
[121]	• IEEE 33-bus DN	• DCFC	• Reliability-index-based placement and allocation of EVCSs • Check of voltage stability, power reliability, and power quality
[122]	• 58-bus DN in Pakistan	• Probability distributions of EV arrival and departure time	• Optimal siting and sizing of EVCS • Minimization of the installation cost and total power loss • PSO • Check of constraint violation in OpenDSS
[123]	• IEEE 33-bus DN	• PEV load is modeled as a voltage-dependent load with power factors	• Optimal placement of DGs • Minimization of the total power loss • Check of voltage stability • Mitigation of impact of EVCSs
[125]	• 400–630 kVA transformer upgrade • LV DN in the Netherlands	• Unidirectional charging • Bidirectional charging with V2G communication	• Multiobjective optimization • Grid reinforcement • Transformer capacity expansion

3.2.2. Siting and sizing of electrical vehicle charging stations and distributed generators

The arbitrary placement of EVCSs may impede the reliability of power systems. It is crucial to assess the feasibility of EVCS placement and sizing before implementation. In [121], the authors evaluated the effects of EVCS placement on key power distribution indices, including reliability indices, such as the VSI, SRI, and LSF. The results showed that slow EVCSs could be placed at weak buses without affecting the planning indices, but installing DCFC stations at these locations could negatively impact the power distribution system. The study also demonstrated the optimal location of EVCSs to improve voltage stability. When heavy charging loads were placed at weak buses, the study found that reliability indices were affected more than the VSI and LSF for DCFC. The impact of EV charging and DCFC can be reduced by incorporating DGs and ESSs. The active and reactive power compensations provided by DGs can mitigate the impact of PEVs and minimize power losses in the power distribution systems [123]. The effects of EVs on power system planning in the distribution systems are summarized in Table 9.

4. Impacts of transportation electrification on power system operation

As we have introduced in Section 2.3, the integration of V2G technology can benefit both EV owners and power grid utilities, as shown in Fig. 9. With the ability to store surplus energy and feed it back to the power grid during peak demand periods, EVs can serve as not only load demands but also a source of distributed generation and energy storage. However, if the integration of V2G into the power system is not properly coordinated, it can negatively impact the power system's operation and performance with high EV adoption. Therefore, we examine the impact of EV charging on power operation in this section.

4.1. Power transmission operation with electric vehicles

Studies have analyzed the impact of EV charging on the power transmission system. For example, a framework that integrated power transmission network and transportation network simulations was proposed in [126] to evaluate the effects of EV charging on the power grid. In [126], the authors obtained the hourly EV charging demand by simulating regional-level charging behavior and incorporating it into an OPF model in a 160-bus synthetic power transmission system for Travis County, Texas. A mapping was created between the nodes in the transportation network and the substations in the power transmission network. In [127], the authors examined the impact of EVs on generator emissions and wind curtailment by using a scopf model with different EV penetration levels and charging strategies. In [128], the impact of EV charging on the locational marginal pricing and line loading in Houston was evaluated by considering EV penetration levels of 5% and 15%. An approximate model was developed to estimate the EV charging load based on travel patterns. These studies highlight the importance of considering the interaction between EV charging and the power transmission system to ensure a secure and reliable power grid. However, the above studies either only considered LDEVs or did not differentiate between the types of duty classifications of EVs. In [129], the impact of 10 million PEVs, including small, medium, and large-sized PHEVs and BEVs, was evaluated on a 401-bus county-level power grid in 2030 using a one-year simulation horizon. The mobility behavior of EV drivers was modeled, and their annual driving profiles were aggregated at the transmission grid substation level for the simulation. The impact of HDEVs on a large power grid was examined in [130], which considered grid voltage violations as one critical grid parameter. The large power grid in [130] consisted of a 2000-bus synthetic power transmission system and multiple distribution grids in Texas. The transportation network in

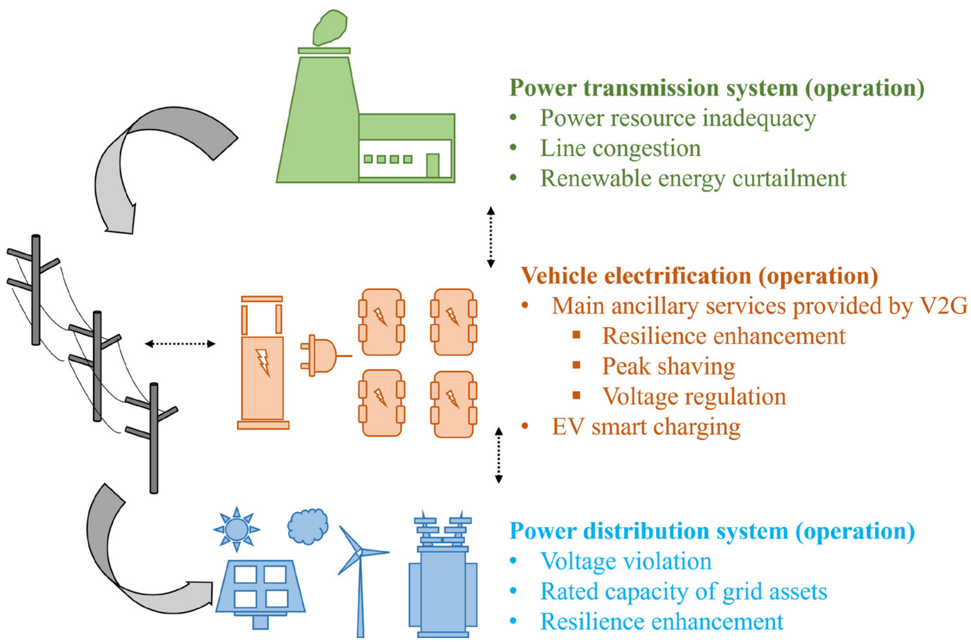

Fig. 9. Impacts of electric vehicles on power operation in transmission and distribution systems.

[130] was modeled as a graph, whose nodes represented the EVCS location, and edges represented the roads. By simulating the destinations and arrival schedules of HDEV fleets, the spatiotemporal movement of the HDEV fleet was obtained in [130] to show how the number of HDEVs there were at each EVCS. The results in [130] indicated that the simultaneous charging of 30 thousand HDEVs could destabilize the power transmission systems, which revealed the correlation mobility of HDEVs and grid-wide voltage problems. The impacts of large-scale EVs on power transmission systems were evaluated with at-scale EV deployment [60]. The analysis in [60] applied the EV penetration assumptions for the 2028 scenario expressed as a national figure in the United States with 24 million LDEVs, 200 thousand MDEVs, and 150 thousand HDEVs. Then the national figure was applied to the wecc power transmission systems by a 0.4 scaling factor. By running a production cost modeling approach, the solutions for accommodating high EV loads could be obtained for a 2028 scenario, including the generation mix and production cost. However, the optimal investment of new grid infrastructure for new EV loads and generation capacity expansion analysis were not considered in [60].

To analyze the impact of high EV adoption on power transmission systems, several simulation-based and optimization-based methods have been proposed. One example of the latter is the formulation and solution of an optimal operation problem, which can be stated as follows:

$$\text{Objective} \ \underset{x}{\text{Minimization of operational cost,}} \tag{11}$$

$$\text{s.t. Power flow and operational constraints in the power transmission network,} \tag{12}$$

$$\text{Generation dispatch and power resource adequacy,} \tag{13}$$

$$\text{Line congestion,} \tag{14}$$

$$\text{Renewable energy curtailment.} \tag{15}$$

The objective (11) of the power transmission operation problem usually refers to the total system operational cost. Other objective functions, such as the minimization of residual load residual [112], are also considered. The power flow model and operational constraints in power transmission systems, such as SCOPF in [127] and ACOPF in [128], have been discussed. The compact constraints in (13) and (14) are explained in the following Section 4.1.1 to Section 4.1.3.

4.1.1. *Generation dispatch with emission factors and power resource adequacy*

Integrating numerous EVs into the power transmission system raises several critical issues. A key concern is the availability of sufficient power and energy resources to meet the growing demand from the EV fleet. This issue is closely tied to the resource adequacy problem. Additionally, the operational changes, such as the generation mix and production cost, required to accommodate the increased EV demand must also be considered. In [126], the authors discovered that the increased EV demand caused an increase in the MW output of natural gas and coal generators, while the output of nuclear, wind, and solar generators remained constant. Another study showed that just a 5% penetration of EVs in Austin and Houston could change not only the generation dispatch but also the CO_2 emissions. In [127], CO_2 emission factors were adopted for different fuels, such as 406.87 lb/MWh for coal, 165.56 lb/MWh for natural gas, and 2619.5 lb/MWh for petroleum coke, to calculate the hourly emission value of each generator. The results indicated that natural gas combined cycle power plants and combustion turbines were responsible for most of the additional generation needed for EV charging, accounting for 85–89% of all new generation capacity throughout the WECC.

4.1.2. *Line congestion and locational marginal price*

Electricity from power plants is transmitted via high-voltage transmission systems to local utility distribution systems. However, line congestion, caused by the overloading of line segments or the inability to deliver low-cost electricity to some consumers, can lead to increased electricity prices [131]. As indicated in [129], the challenge of EV charging is not in the power demand itself but its concentration in certain regions and time frames. For instance, in [129], the authors found that the concentration of EV charging in high-population areas in western Germany caused an increase in line congestion from north to west. A case study in [128] found that while the number of highly loaded lines increased with the inclusion of EV charging loads, the most heavily loaded lines experienced a slight decrease in loading during high-load day simulations. Therefore, in some cases, the EV charging demand may be evenly distributed across the power systems, which could reduce congestion on some heavily loaded transmission lines but increase congestion on some moderately loaded lines. A case study of the WECC power grid [60] also revealed that line congestion is a limiting factor in delivering power to load centers with high EV adoption, with the largest congestion ob-

Table 10
Review of the selected studies related to the impact of EVs on power transmission operation.

Ref.	Power System Model	EV Model	Operation Solution
[60]	• WECC TN in the United States	• Deterministic charging profiles • EV scenario at WECC in 2028 • LDEVs, MDEVs, and HDEVs	• Production cost modeling • Minimization of system operation cost
[126]	• 160-bus synthetic TN and DN in Texas • Geographic mapping of transportation network to the power transmission substations	• Traffic flow model • Charging behavior model • Transportation network model • 20% EV penetration	• Minimization of system operation cost • Hourly generation dispatch • OPF
[127]	• 160-bus synthetic TN in Texas • 7000-bus synthetic TN at Texas • Generation mix that is 90% carbon-free	• Traffic flow model • Charging behavior model • 5% EV penetration	• Impact of EV charging on generation dispatch and CO_2 and NOx emissions • SCOPF
[128]	• Houston area within the 7000-bus synthetic TN in Texas	• Traffic flow model • Charging behavior model • 5% and 15% EV penetration	• Impact of EV charging on line loading and bus LMPs • Unit commitment • ACOPF
[129]	• 401-bus county-level TN in German • PV and wind generation based on weather data	• Mobility behavior model for time- and location-dependent PEV load • 10 million PEV fleet in Germany in 2030 • Comparison of uncontrolled and controlled EV charging	• Residual load smoothing • Minimization of the difference between load and renewable generation • Comparison of county-level and national-level optimization
[130]	• 2000-bus synthetic TN in Texas	• The number of HDEVs is simulated at each EVCS	• TN simulation in PowerWorld • DN simulation in OpenDSS • Impact of EV charging on grid voltage violations

served in California. Uncoordinated charging of EVs could exacerbate this problem.

4.1.3. Renewable energy curtailment

Balancing supply and demand is crucial, particularly during the evenings when an oversupply of energy can lead to the curtailment of renewable energy sources. However, as shown in [37], the coordination of EV charging can alleviate this issue and minimize solar power curtailment. According to the WECC transmission grid study in [60], a reduction in solar power curtailment caused by the integration of EVs can reach 75%. Furthermore, coordinated EV charging has the potential to reduce solar power curtailment by an additional 16%. The United Kingdom transmission grid also revealed that wind power production aligns with EV charging patterns [112]. By 2050, a fleet of 14.6 million EVs has the potential to decrease the curtailment of wind power by 5% over the period of 2015–2050. However, solar power has low curtailment rates, averaging below 1%, but EV integration could potentially reduce these rates by 20–50%. Time-of-use tariffs that incentivize charging during off-peak hours, when general demand is low, can increase wind power utilization and further reduce curtailment. On the other hand, combining PV generation systems with thermal energy storage and EVs could also be beneficial for PV prosumers [132], such as in reducing the annual total cost of energy. The impact of EVs on the power transmission system is summarized in Table 10.

4.2. Power distribution operation with electric vehicles

The study conducted by Al et al. [133] is aimed at addressing the joint optimization of EV charging and routing, with a consideration of several factors, including peak demand at charging depots, time-of-use tariffs, partial recharging, wait times, and public charging station characteristics. However, the study's results are limited because they do not account for the potential impact of the proposed EV charging profiles on the power distribution system. As the number of EVs on the grid increases, there is a risk of thermal overloading constraints and reaching the rated capacity of grid assets, particularly during fast-charging conditions. Additionally, high ramping EV charging loads during fast charging may cause voltage constraint violations in the distribution system. To evaluate the impact of EV charging on power distribution systems, simulation-based methods are commonly employed in the literature. For example, in [58], the authors evaluated the risk of power system violations caused by home charging of private EVs using direct charging and price-optimized charging strategies on a synthetically generated Swedish LV distribution grid. The findings showed that cities and urban areas were more prone to violations, while rural areas had fewer issues. In [134], the authors analyzed the challenges and opportunities of integrating BEVs into power distribution systems by testing three charging strategies and six LV urban and rural distribution grids. The results indicated that charging many EVs overnight in rural areas can lead to grid problems, as purely market-oriented charging strategies can cause high load peaks and overloading of transformers and lines. In terms of temporal power system violations, in [135], the authors analyzed the impact of a high EV penetration scenario on a Swedish LV power distribution grid in 2050, assuming a 35% linear increase in the total EV fleet from 2016 to 2050, with 100% penetration in 2050 (i.e., 6 million EVs). The simplified voltage drop method was utilized to check for thermal and voltage conditions of feeder cables and transformers with combined EV and residential demands. The findings showed that frequent power system violations were expected, especially during the evening and winter peaks. Several studies have proposed methods to mitigate the impacts of EV charging on power distribution systems. For instance, in [136], the authors proposed an online Generic Algorithm-based real power charging method and a decentralized droop control-based reactive control method to minimize voltage unbalance and fluctuations in power distribution systems. The study tested the proposed methods on a real unbalanced distribution network in Perth, Western Australia. In [137], a voltage regulation method for power distribution networks was proposed to address simultaneous voltage violations caused by EVCSs and PVs. The method was tested on a 45-bus MV distribution grid in Europe, and the results showed that it could effectively mitigate concurrent voltage violations. The dynamics and effects of fast chargers on power distribution networks were investigated in [101], where a Level III DCFC with changing power rates of 50 kW and 250 kW was connected to a practical MV/LV distribution network. The voltage profiles and load currents were analyzed during peak network demand when EVs were charging, and a local voltage control method with V2G technology was proposed to mitigate potential effects. In [138], a decentralized droop control-based method was proposed to coordinate EV charging and rooftop PV systems in a semirural Australian LV power distribution network, which was aimed at mitigating voltage rise and phase unbalance.

Optimization-based methods have been applied in several studies to obtain an optimal solution for coordinating the charging of EVs and the operation of power distribution systems. A decentralized spmds-based control method was proposed in [139] to charge a large group of EVs. The authors also developed a dimension reduction method to overcome scalability barriers by grouping EVs and creating voltage-updating subsets. In [140], a two-layer active management method that considered the flexible output power of grid-connected parking lots to minimize power losses was proposed. The authors modeled the arrival and departure times of EVs and their initial charger state, taking into account the uncertain behaviors of EV drivers. In [141], the impact of EV charging on distribution grid performance was analyzed using conventional and fast charging modes. The authors proposed a ga-based optimization method to minimize grid losses and reduce voltage fluctuations by coordinated charging times and locations. The power flow simulation results with 10% and 50% EV penetration levels showed that uncoordinated EV charging could lead to increased energy losses and voltage deviations [141]. In [142], the impacts of EV commuting on power distribution systems were evaluated by a tri-level optimization problem. The study considered the interactions among EVs, charger service operators, and electric network operators in a driving and charging congestion game. The tri-level optimization problem was validated using an integrated power distribution-transportation network.

Machine learning has also been extensively utilized in the field of EV charging control in power systems. In [143], drl was proposed as a promising solution to minimize the total travel time and charging costs for EVs at EVCSs. In [144], a DRL method that incorporates hybrid classification was introduced to consider the travel patterns of EV drivers and to identify an optimal charging solution while enforcing voltage and current limits in the distribution network. An asynchronous learning-based bidding strategy was also proposed in [145], where the EV aggregators were treated as distributed energy resources in the local energy market and trained using a modified ddpg algorithm. The simulation results in [145] showed that the proposed algorithm could effectively accelerate the training process. In [146], a marl method was proposed for PHEV charging using distribution network-level phasor measurement unit data, with the aim of maximizing the power delivered from power distribution systems to EVs while considering the constraints for transformer capacity and voltage limits. Simulation results in [146] on a test distribution network showed that the proposed MARL method could effectively track network capacity in real-time and outperform other decentralized feedback control methods.

In the field of power system operation with high EV adoption, several approaches, such as simulation-based, optimization-based, and machine learning-based methods, can be utilized. Here, we provide a concise representation of the optimal operation problem in a power distribution system with high EV adoption.

$$\underset{x}{\text{Objective}}\ \text{Minimization of operational cost}, \tag{16}$$

$$\text{s.t. Power flow and operational constraints in the power distribution network}, \tag{17}$$

$$\text{Voltage regulation and reactive power support}, \tag{18}$$

$$\text{Resilience enhancement and service restoration}, \tag{19}$$

$$\text{Rated capacity of grid assets}. \tag{20}$$

The objective function (16) of the power distribution operation problem is typically designed to minimize the total system operational cost. However, other objectives, such as minimizing the vuf [136,138], have also been considered in the operation problems of power distribution systems. While some studies use full AC power flow models or DistFlow models, these models can result in nonconvex and NP-hard optimization problems due to the presence of nonlinear terms. To reduce computational complexity, other studies have dropped nonlinear terms [147] or used first-order Taylor expansions at fixed points [99]. In contrast to traditional power flow models in power distribution systems, service restoration, and network reconfiguration must also be considered in the optimization problem. This approach involves reconfiguring the radial distribution network and line switches' on/off operation. More information on service restoration and network reconfiguration is provided in [148]. The compact constraints in equations (18) to (20) are further explained in Section 4.2.1 to Section 4.2.3 on voltage regulation, capacity management, and protection of assets.

4.2.1. Voltage regulation and reactive power support

As discussed in Section 2.3.2, the integration of EVs into the power distribution system is driving a need for improved voltage regulation. The high demand for charging EVs leads to increased electric current levels in distribution wires and transformers, resulting in voltage drops and reduced voltage levels at customer connection points. To comply with ansi regulations, which require voltages to be kept within ± 5% limits [149], voltage regulation is becoming increasingly difficult, particularly during periods of high and variable load demand, such as during EV charging. Several studies have shown that uncontrolled EV charging can negatively impact the system voltage profile, leading to extreme voltage variations during peak hours. Therefore, the trend toward transportation electrification can directly lead to increasing load demand consumption in power distribution systems, which renders voltage regulation more challenging. For example, in [136], a decentralized PEV reactive power discharging approach was proposed for ancillary voltage support by EVs. This approach minimizes the VUF by discharging reactive power at selected nodes. In [137], a distributed reactive power control of EVCSs and DGs was proposed for voltage regulation in MV distribution systems, ensuring even reactive power support and avoiding the overloading of converters. These approaches demonstrate the potential for innovative solutions to address the voltage regulation challenges posed by EV integration into the power distribution system.

4.2.2. Resilience enhancement and service restoration

As discussed in Section 2.3.2, EVs with V2G technology can serve as temporary mobile power sources for improving the resilience of power distribution systems during extreme events and outages. For example, in [55], the authors proposed a joint method to schedule EBs and send power to EVCSs via V2G during power outages. The study in [95] introduced a two-stage stochastic optimization method for pre-event resilience enhancement in power distribution systems, which considers the pre-positioning of mobile resources in the first stage and their operation in the second stage. In [94], an autonomous EV-assisted load restoration method was developed using the IEC 61,850 communication protocol, which aggregates EVs as a post-event restoration resource via V2G technology. The technique in [94] involved incorporating the combined EV load profiles into the ZIP load models, which were then tested by hlp simulations utilizing a real-time digital simulator and an actual MV power distribution grid.

4.2.3. Rated capacity of distribution grid assets

The fast charging and discharging of EVs can lead to an imbalance in the power supply, potentially causing the overloading of grid assets such as transformers in the power distribution system [48]. This situation can negatively impact system reliability and cause disruptions. Research has shown that the capacity limit of the distribution feeder cable is a concern, with the potential for power outages if too many EVs are simultaneously charged [150]. The available grid capacity for EV charging is determined by subtracting the base load power from the capacity limit of the feeder cable. Studies have estimated that with a 35% EV penetration rate, the grid in a community of 40 households may experience outages once every 50 days [150]. The effects of EVs on power distribution system operation are summarized in Table 11.

5. Discussion

5.1. Decarbonization of power systems with transportation electrification

Governments worldwide are promoting the adoption of EVs as a crucial element in reducing GHG emissions and energy consumption. transportation electrification is critical to meeting emission reduction and

Table 11
Review of the selected studies related to the impact of EVs on power distribution operation.

Ref.	Power System Model	EV Model	Operation Solution
[55]	• Modified 15-bus DN • IEEE 123-bus DN • LinDistFlow	• EB scheduling problem with adjustable times tables	• Joint post-event DN restoration and EB scheduling method • Total benefits maximization • EB rental cost minimization
[58]	• Rural and urban LV DN in Sweden	• Three charging strategies (direct, w/o V2G, and w/-V2G)	• Simplified voltage-drop method • Examination of thermal and voltage violations
[144]	• 21-bus MV DN	• DRL-based PEV behavior model • Flexible EV charging in the real-time market	• Minimization of PEV charging costs • Run linear AC power flow • Enforcement of voltage and current limits
[94]	• 11-bus MV DN • HIL simulation platform	• ZIP load models for aggregated EVs	• Autonomous EV-assisted load restoration • IEC 61,850 communication protocol
[101]	• 15-bus MV/LV DNs	• Grid integration of (50kW and 250kW) Level III DC fast EVCS •	Local voltage control • Mitigation of negative effects of DC fast EVCS
[134]	• Three rural DNs • Three urban DNs	• Driving profiles • Apply three charging strategies (greedy, balanced, and market-oriented) • Scale up based on vehicle fleet size	• Run of power flow • Examination of voltage, line overloads, and transformer overloads
[136]	• Unbalanced DN in Australia	• PEV switching structure among the three phases	• Reactive capability of PEVs for voltage regulation • Active power compensation of PEVs • Minimization of VUF
[137]	• 45-bus MV DN in Europe	• EVCS grid connection • Grid-side converter • Battery-side converter	• Distributed control • Coordination of EVCS and OLTC • DG curtailment
[138]	• IEEE 13-bus DN • LV DN in Australian • DN simulation in OpenDSS	• Spatial distribution of EV charging	• Minimization of VUF • Decentralized droop control-based method
[139]	• LinDistFlow model • IEEE 123-bus DN	• Group EVs and establish voltage subsets to reduce dimension	• Decentralized Skrunken subgradient optimization method
[140]	• IEEE 33-bus DN	• Probability density function for EV schedule	• Minimization of power losses • Flexible output power of grid-able parking lots along with voltage control
[141]	• IEEE 33-bus DN	• Coordination of the charging time • Identification of charging location • 10% and 50% EV penetrations	• Minimization of grid losses • Reduction in voltage fluctuations • GA
[142]	• IEEE 33-bus DN	• EV behaviors coupled in realistic urban network • Transportation network at Sioux-Falls	• Minimization of grid losses • Tri-level optimization • Iterative algorithm • Simulated annealing
[145]	• IEEE 33-bus DN	• EV aggregators in the local energy market	• Minimization of grid losses • Reduction of voltage fluctuations • Bidding strategy for EV aggregators • DRL method
[146]	• Integrated 33-bus MV and 1760-bus LV DN	• Decentralized and coordinated scheduling of EV charging	• Maximization of power delivered to EVs • Avoidance of transformer overloading • Check of voltage violation • Actor-critic RL
[150]	• Test capacity limit of the distribution feeder cable	• Probability of a single EV charge • Joint behavior of a set of EVs	• Approximates the outage probability in the LV grid due to EV charging
[151]	• 24-bus DN in Sioux Falls	• Driver equilibrium traffic assignment problem • Transportation networks in Xi'an and Hangzhou cities	• Maximization of the total benefits • Optimal charging price game • DRL

climate change mitigation goals. However, a sustainable power system with a clean energy mix is also necessary to support transportation electrification. The use of EV batteries as flexible energy storage and their potential environmental impact was investigated in [152] with the aim of moving the United Kingdom power system toward net-zero emissions by 2050. The findings showed that the implementation of EV batteries and retired EV batteries as energy storage devices via battery swapping could mitigate environmental impacts and reduce CO_2 emissions. As noted in [153], to prevent global warming and meet sectoral CO_2 emission targets, the United States would need more than 350 million on-road LDEVs. However, a fleet of 350 million on-road LDEVs would result in an annual electricity demand that reaches 1730 TWh, which is equal to 41% of the United States' electricity generation in 2018. A bottom-up energy system optimization model was proposed in [154] to analyze the impacts of electric grid CO_2 intensities and EV adoption rates on CO_2 reduction policies in New York City. The results showed that, although LDEVs were crucial for reducing air emissions early, substantial reliance on fossil fuel-based power generators would challenge cost-effective CO_2 reductions. As noted in [21] and [30], the generation of electricity from coal is a significant obstacle to EV growth and GHG emissions reduction. The consumption of EVs may increase GHG emissions from fossil fuel-based power generators, prompting for additional generation [23]. The emissions of BEVs and FCEVs powered by natural gas are 58.83 and 74.21 gCO_2/km, respectively, but if powered by renewable energy, the emissions could be reduced to 0 and 2.99 gCO_2/km [30]. Furthermore, charging HDEVs with a generation mix that contains slightly more than 10% coal could result in a 63% decrease in fuel consumption-related emissions [155], respectively. In [156], the authors proposed a probabilistic method to quantify GHG emissions from battery electric hgv given their electricity emissions intensity. Compared to hydrogen fuel cell HGVs, this work found that battery electric HGVs emitted fewer GHG emissions. Specifically, battery electric HGVs could reach 50% GHG savings could with an electricity emission factor of 350 gCO_2/kWh [156]. Therefore, the clean energy transition from fossil fuel-based power generators to renewable energy-based power generators is crucial for EVs to achieve the CO_2 reduction targets aimed at decarbonizing our energy systems [157]. In [158], the authors found that transitioning to renewable energy sources could significantly reduce GHG emissions in China by increasing EV penetration levels. Similarly, the analysis in [159] revealed that increasing investment in wind power could positively impact EV adoption in China and also facilitate wind integration by providing power flexibility. In [160], a multi-objective method was proposed to minimize the operation cost and emissions in cchp unit with PHEVs and tes. In [161], the authors found that the integrated system of rooftop PVs and EVs could reduce CO_2 emissions by 88% from the consumption of gasoline and supply 89% of electricity demand. Coordination of EV charging is another important aspect of reducing the carbon intensity of our power grids. In [162], the authors showed that the average grid carbon intensity in the United Kingdom power grid could be reduced by 20–30% from 35 to 56 gCO_2/km to 28–56 gCO_2/km by coordinating EV charging. Additionally, the study found that if 20% of Scotland's current vehicle fleet, approximately 500,000 EVs, was electrified, then nearly 75% of onshore wind generation curtailment could be avoided. These findings highlight the importance of a combined approach that includes both the transition to renewable energy sources and the coordination of EV charging for reducing carbon intensity and mitigating the impacts of climate change.

5.2. Innovative technologies for facilitating electrical vehicle adoption in power systems

Section 3 and Section 4 highlight how advanced optimization and machine learning methods have been extensively utilized in previous studies. For instance, researchers have employed RL techniques to predict PHEV charging loads [73] and dispatch EV charging [143–146]. However, beyond these approaches, there exist several other innovative technologies and novel concepts that have significant potential in addressing EV-related challenges. Some examples of such innovative technologies are presented as follows:

- *Virtual power plant:* The vpp has been widely utilized in the EV sector to aggregate and coordinate behind-the-meter distributed energy resources and EVs to provide ancillary services by V2G functionality. In [163], a joint stochastic optimization model that schedules stored energy from EVs and wind generators to minimize wind power fluctuations was proposed, with the VPP serving as the EV aggregator. The study [164] proposed a distributed online optimization method to coordinate EVs and PV generators, where the VPP operator offers an active power tracking service to the power system. In [165], the VPP was modeled as a price taker and optimized the unstable outputs from wind and PV generators, as well as controllable EV loads, to maximize revenue from the power market. In [166], a DRL algorithm was implemented within the VPP to learn the bidding strategy for EVs and improve the overall operating economy.
- *Blockchain framework:* Blockchain technology can greatly enhance the security and reliability of V2G communication, as indicated in [167]. The use of decentralized devices and specialized data structures creates a peer-to-peer transaction platform that records all transaction data, providing information equivalence and transparent openness for all participants. In [168], a blockchain framework was employed to implement an adaptive EV charging and discharging scheduling method, which is aimed at minimizing the power fluctuations caused by EV charging and discharging events and simultaneously meeting the charging needs of EVs. The simulation results in [168] showed that the blockchain-based method was effective. Additionally, in study [169], the authors proposed a localized peer-to-peer power trading model using a private blockchain-based EV aggregator, which optimizes price singles and power trading among EVs.
- *Quantum computing:* By leveraging the power of quantum bits and the counterintuitive phenomena of quantum mechanics, quantum computing algorithms have the potential to greatly improve the efficiency of solving problems in the realm of EV charging. For example, in [170], the authors proposed a quantum approximate optimization developed for EV smart charging and found that the algorithm performed similarly to conventional optimization methods, but with the added potential for improved performance. Additionally, in [171], a complex combinatorial optimization problem of EVCS planning was solved using a quantum algorithm, resulting in a 500% improvement in speed compared to traditional optimization methods. These findings suggest that quantum computing has the potential for addressing challenges in the field of EV charging and infrastructure planning.

5.3. Policy implications and incentives for improving electrical vehicles adoption in power systems

Compared to conventional vehicles, the purchase price of EVs remains high. In addition, other factors also reduce consumer purchase intention for EVs, such as the low density of EVCSs, and induced range anxiety. Hence, policy and incentive programs are crucial in promoting widespread EV adoption. To encourage higher penetration rates of EVs, countries have implemented various policies such as monetary rebates, tax credits, and the deployment of charging stations. To gain a deeper understanding of how these policies and incentives can drive the transition to EVs and develop an effective program for EV adoption, it is important to analyze these measures, as follows:

- *Energy policies and incentives:* According to research in [172], understanding drivers' preferred charging times and forecasting EV charging patterns can assist policy-makers in taking proactive steps to enhance the electricity supply infrastructure and shape future energy policies. In [173], the impact of energy policies and incentives on the development and deployment of EVs and DCFC was analyzed using a system dynamics approach. A case study in the United States, as presented in [173], revealed that increasing incentives for wind generation capacity from 20 $/MWh to 30 $/MWh would boost the total number of installed DC charging stations and the total number of PEVs from 38,227 and 53.7 million to 41,477 and 57.84 million. The simulation results in [173] further showed that the sensitivity of EV penetration to natural gas prices was greater than the sensitivity of wind generation penetration to natural gas prices, implying that natural gas prices affect not only the marginal cost of natural gas generators in power systems but also the purchasing intentions of EVs.
- *Monetary policies and incentives:* As discussed in [21], direct subsidies were widely employed in several countries to support EV adoption and reduce purchasing costs. This step was achieved by exemptions in registration, emission, and tax fees. The results from [174] indicated that rebates should be provided prior to the installation of charging infrastructure, as the neighborhood effects of EV adoption and expenditure minimization were more pronounced in the earlier stages. According to a study in [175], dynamic electricity pricing could support the growth of fast-growing EV charging markets. The integrated energy modeling and life cycle assessment method presented in [176] was utilized to compare different policy scenarios aimed at accelerating the low-carbon transition of light-duty vehicles. The results from [176] showed that pricing indirect emissions and carbon pricing of stationary sources could significantly contribute to EV adoption. According to a study [177] by Jenn et al., an increase of $1000 in personal credit leads to a 2.6% rise in EV registrations. Additionally, raising EV supply equipment subsidies by $1000 results in a 1.9% increase in registrations.
- *Public service policies and incentives:* In addition to financial incentives, the public services and government regulations aimed at im-

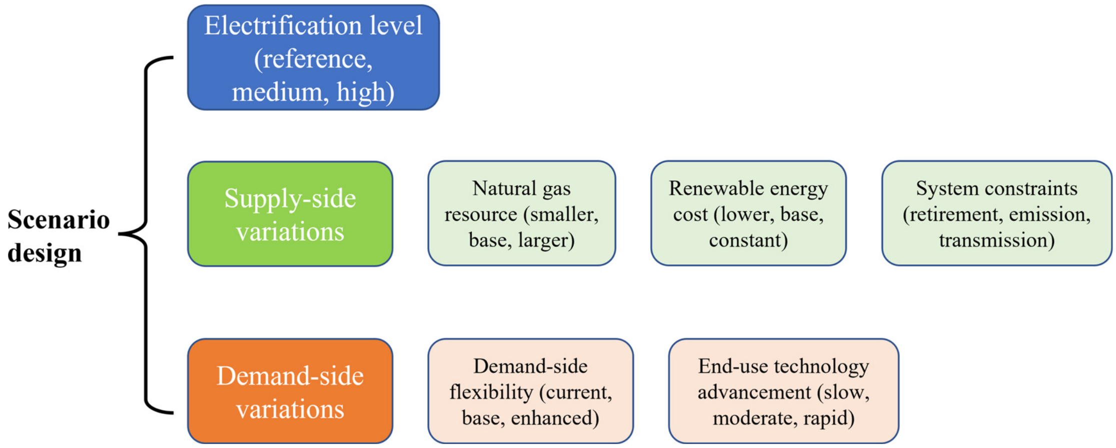

Fig. 10. Example for scenario design of transportation electrification in power systems [3,110,111].

proving the convenience of EV drivers can also promote EV adoption [21]. This kind of public service may include free charging, free parking, toll tax exemptions, and exclusive highway lanes for EVs. Some innovative business models were proposed in [42] to overcome the barriers to EV adoption, such as battery swapping, battery leasing, and EV sharing. Similarly, in [178], the authors showed that the new business model of battery leasing could increase EV adoption and reduce GHG emissions due to a decrease in consumers' anxiety about battery resale value.

- *Resource policies and incentives:* To facilitate the growth of the EV industry, several countries have taken policy-level decisions to assist original equipment manufacturers, dealerships, and fuel suppliers. A critical analysis of the metal requirements for transportation electrification was conducted in [179], which revealed that the global metal reserves are sufficient for short- and medium-term demands, but are insufficient for the long-term needs of the industry. The historical and future global cobalt cycles were analyzed in [180], which covered traditional and emerging end uses in various regions. The results showed that the supply security levels of cobalt vary by region and highlighted the importance of increasing the primary cobalt supply to support global transportation electrification efforts. The impacts of lithium resources on the electrification of heavy-duty vehicles were evaluated in [181]. The study found that the large-scale adoption of HDEVs would greatly increase the demand for lithium and pose a strain on the global lithium supply. Policy-makers and entrepreneurs were advised to approach the ambitious growth of HDEVs with caution, based on these findings. In [182], an optimal supply chain model was proposed to reuse retired EV batteries as distributed energy resources, which demonstrated significant potential value chain profits of $2.65 million achieved by deploying 10.7 /MWh of retired EV batteries with optimal retired battery price of 138 $/kWh.

5.4. Scenario design of transportation electrification in power systems

transportation electrification is highly dependent on various factors over the long-term horizon, such as government incentives, customer preferences, price, and technology advancements. Accurate prediction of these factors is crucial for successful scenario design in power system studies involving transportation electrification. A comprehensive scenario design for electrification studies, which takes into account different electrification levels, supply-side variations, and demand-side variations, is presented in Fig. 10.In [3,110,111] explored the system constraints, cost of natural gas resources, renewable energy, and energy storage technology across the supply-side variations, were explored. The demand-side variations take into account different levels of load flexibility and advancements in electric end-use technologies. This type of scenario design is adopted from various studies, including [3,110,111]. In addition to the scenario design outlined above, the implementation of a carbon tax significantly impacts the progress of electrification. Because a carbon tax can enforce CO_2 emissions targets across the entire energy system, rather than just the transport sector. For example, the scenario design presented in [183] took into consideration three different carbon tax scenarios: a tax starting at $10, $20, and $50 in 2020 and increasing annually by 5% to reach $43, $86, and $216, respectively, by 2050.

5.5. Comparison between electric vehicles and hydrogen vehicles

In Section 2.1, we examine the distinctions among PHEVs, BEVs, and FCEVs. While PHEVs and BEVs rely on electricity as their primary power source, FCEVs utilize hydrogen as their fuel, with a fuel cell converting hydrogen's chemical energy to electricity to drive an electric motor. Thus, electric and hydrogen vehicles present two promising technologies for reducing GHG emissions and enhancing power grid sustainability. Although both technologies outperform traditional internal combustion engine vehicles, their suitability for various use cases depends on several factors. However, the adoption of hydrogen vehicles remains constrained by a lack of hydrogen refueling infrastructure and the high costs of hydrogen production, storage, and transportation. On the other hand, EV charging infrastructure is more widely available [184]. While EV costs have significantly dropped in recent years, making them more competitive with gasoline-powered cars, hydrogen cars are generally pricier than electric ones, primarily due to hydrogen production and storage expenses [185]. Although hydrogen fuel cells convert more than 60% of the energy in hydrogen to electricity, rendering them more efficient than EVs, the latter benefit from regenerative braking, which can recover energy that would otherwise be wasted [186]. While both electric cars and hydrogen cars generate zero emissions at the tailpipe, the environmental impacts of producing and distributing electricity and hydrogen depend on their generation and sourcing. Nevertheless, it is feasible to produce hydrogen using renewable energy sources, whereas the electricity used to charge EVs may originate from a mix of renewable sources and nonrenewable sources.

5.6. Future research directions of transportation electrification studies in power systems

To further advance the field of transportation electrification in power systems, several key research areas require more attention. These areas include improved methods for estimating EV charging loads, the development of high-voltage charging infrastructure, and secure and efficient V2G services. Additionally, power system planning for new charging infrastructure, as well as the integration of machine-learning techniques in power system operations, are important areas of research. While these topics are within the scope of this review, related fields have been discussed in previous studies, such as advancements in electrified powertrain design and control [6] and the impact of shared EV fleets on communication, management, and road congestion [48], as well as the implications of autonomous driving on EVs [21].

5.6.1. Stochastic charging and new business model in grid-to-vehicle systems

Additionally, as noted in [29,40], most of the models for power planning and operation in the reviewed studies only estimated EV charging loads in a deterministic manner, disregarding the randomness and variability in drivers' behaviors and charging decisions, as well as their charging profiles over space and time. This approach results in models that are based on averages and deterministic perspectives, which could underestimate the benefits of flexible and smart charging in power system planning and operation. Thus, future research should focus on developing a more realistic representation of EV charging profiles that takes into account spatial and temporal variations, such as probability distributions that geographically and temporally vary. The research discussed in [172] also suggested incorporating information about drivers' current vehicle usage and charging patterns to estimate EV charging profiles. Moreover, future research directions for EV charging infrastructure are discussed in [14,29,187]. As indicated in [187], the current charging infrastructure can meet the demands of LDEVs, but the situation is different for HDEVs with large battery capacities. Even DCFCs or XFCs are not capable of providing shorter charging times compared to the refueling times of conventional gasoline vehicles for HDEVs. Therefore, high-voltage EV batteries and EVCSs are emerging trends [14] and need to provide high charging power while not exceeding the current limits of the connectors.

5.6.2. Communication failure and cybersecurity of vehicle-to-grid technology

Current V2G systems offer essential services to the power grid, improving the reliability and stability of the power system in the presence of renewable energy sources and DGs. However, the coordination and communication among the aggregated EVs pose challenges, as any time delay or communication failure can cause unstable V2G system operation. As suggested in [50], the impact of these time delays can be reduced by using high-bandwidth communication networks such as LAN and WAN, which warrant further investigation. Moreover, cybersecurity is a crucial research area to preserve the privacy of EV drivers and enhance the resilience of V2G systems against cyberphysical attacks. Further research on the iot and its has the potential to address transportation challenges such as traffic congestion, vehicle platooning, accidents, and pile-up crashes by using V2G technology.

5.6.3. Multistage power system planning for adopting more electric vehicles

The current planning of power system resources and charging infrastructure for EVs is often limited by the one-shot optimization approach, which fails to take into account the possibility of strategically bundling investments and adjusting them over different stages. As suggested in [40], future planning should move toward a sequential multistage framework that incorporates multiple objectives and considers key performance indicators from transportation networks. This approach would result in better planning solutions for different stages of connection. Additionally, it is important to collect real system data to make practical planning solutions and evaluate different load and weather scenarios with EV integration [40,128]. Other areas worth exploring in the future include the impact of the total cost of ownership of non-residential EVCSs on the upgrading cost of power distribution systems [188].

5.6.4. Machine learning-assisted real-time control of power system operation with electric vehicles

Traditional model-based methods have limitations in addressing computational complexity and scalability issues raised by the integration of EVs, and the advancement of smart grid and V2G communication technologies presents the opportunity to create innovative control algorithms and frameworks based on RL. For example, the integrated RL-OPF method and physical-aware MARL method have been proposed to address these challenges [189,190]. However, five key challenges must be addressed to implement RL in EV dispatch and power system operation, as outlined in [43]. These challenges include the availability of real-world data, the development of an RL environment, the robustness of trained policies, the optimization of training performance, and the deployment of RL in real-world scenarios. Future research should focus on overcoming these challenges and developing advanced methods for the coordination of power system operation and EV charging management to enable more efficient EV integration into these systems.

6. Conclusion

This paper presents a systematic review of the impact of transportation electrification scale on power system planning and operation by transmission to distribution levels and provides insightful discussions for power system planners and operators seeking to enhance the grid integration of EVs. We have the following main findings from the perspectives of power system planning and operation with G2V and V2G. It is important to identify the main objectives, barriers, and solutions in power systems with an increase in EV adoption, including power generation adequacy and emission costs, transmission line capacity expansion and congestion, power facility upgrades, and the siting and sizing of EV charging infrastructure and DGs. One of the main challenges faced by power systems when integrating EVs is an increase in peak demand caused by EV charging. This situation has implications for power system planning, as it requires the expansion of existing generation and transmission capacities and a shift toward the use of more renewable energy sources and natural gas. However, a lack of available transmission infrastructure could be a barrier to interconnecting new generation resources and EV demand centers. To mitigate these challenges, it is important to consider the placement and sizing of distributed resources and EVCSs in power system planning, as this can reduce investment costs and increase EV adoption. To accurately understand G2V systems and accurately represent EV charging demand, it is crucial to gather information about the driving behavior and spatiotemporal distribution of EV charging events. Additionally, the methods used to estimate the charging profiles of EVs may vary depending on the specific characteristics of the EVs and charging stations, such as battery capacity, charging rate, and availability. Coordinating the power system operation and the ancillary services provided by V2G can alleviate the strain on power systems caused by the high penetration of EVs. Additionally, incorporating smart charging for EVs into power systems can reduce the curtailment of renewable energy and improve system resilience.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

CRediT authorship contribution statement

Qianzhi Zhang: Conceptualization, Methodology, Software, Writing – original draft. **Jinyue Yan:** Conceptualization, Supervision, Writing – review & editing. **H. Oliver Gao:** Conceptualization, Supervision, Writing – review & editing. **Fengqi You:** Conceptualization, Supervision, Writing – review & editing.

Data availability

No data was used for the research described in the article.

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