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Review article

A review of energy storage systems for facilitating large-scale EV charger integration in electric power grid

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ABSTRACT

The swift increase in electric vehicle (EV) into modern power grids presents both significant opportunities and challenges, particularly in maintaining power quality (PQ) and managing peak loads. This review synthesizes current research, providing a comprehensive analysis of the pivotal role of energy storage systems (ESS) in enabling large-scale EV charger integration while addressing critical PQ issues. A key contribution is the comparative evaluation of various ESS typologies—battery ESS (BESS), hybrid ESS (HESS), and distributed ESS (DESS)—each offering distinct advantages in mitigating PQ challenges such as harmonic distortion, voltage regulation, and peak demand control. Ensuring compliance with IEEE-519 standards is emphasized as vital for maintaining grid reliability and high PQ standards. This review paper further examines the diverse impacts of plug-in electric vehicles (PEVs) on power grids, including their charging and storage characteristics, which influence grid stability and efficiency. It highlights the transformative potential of vehicle-to-grid (V2G) technology, which facilitates bidirectional power flow to support grid stabilization, energy balancing, and ancillary services. Additionally, it addresses the mitigation of harmonic distortion from PEV charging, preserving transformer performance and lifespan, and explores strategies to manage large-scale PEV integration through predictive and adaptive control techniques. This study introduces innovative approaches to improving grid recovery following disturbances and evaluates the synergistic integration of renewable energy sources with PEVs to foster

Abbreviations: AI, artificial intelligence; ASD, adjustable speed drive; BEV, battery electric vehicle; BESS, battery energy storage systems; BESS-based solutions, battery energy storage system-based solutions; CBESS, centralized battery energy storage system; CCS, combined charging system; CIL, constant impedance load; CPL, constant power load; CPES, cyber-physical energy system; DC/AC, direct current/alternating current; DC/DC, direct current to direct current; DERs, distributed energy resources; DESS, distributed energy storage systems; DBESS, distributed battery energy storage system; DG, distributed generation; DSM, demand-side management; DR, demand response; EMS, energy management strategy; EISA-2007, Energy Independence and Security Act of 2007; ESS, energy storage systems; EV, electric vehicle; FLC, fuzzy logic control; GA, genetic algorithm; HEV, hybrid electric vehicle; HEMS, home energy management system; HEMSs, home energy management systems; HESS, hybrid energy storage systems; HEVs, hybrid electric vehicles; IEEE, institute of electrical and electronics engineers; $I_{derated}$, derated RMS current; (I^1_{rms}), rated RMS load current of the transformer; kVA, kilovolt-ampere; kWh, kilowatt-hour; SSR, self-sufficiency rate; AAC, advantage actor-critic; ICE, internal combustion engines; ML, machine learning; V2X, vehicle-to-everything; V2H, vehicle-to-home; MW, megawatt; MPC, model predictive control; NNs, neural networks; K, harmonic derating factor; p.u., per unit; PHEV, plug-in hybrid electric vehicle; PEV, plug-in electric vehicle; PI, proportional-integral; PQ, power quality; LV, low voltage; MWh, megawatt-hour; MG, microgrid; mGen, micro-generator; WAC, wide area controller; WT, wavelet transform; UC, ultracapacitor; $P_{Bat-loss}$, battery loss; P_{CE-R}, core loss ratio (power loss in transformer core); $P_{DC/DC-loss}$, DC/DC converter loss; $P_{ESS-loss}$, total power loss of the energy storage system (battery, ultracapacitor, DC/DC); $P_{UC-loss}$, ultracapacitor loss; PV, photovoltaic; RES, renewable energy sources; RL, reinforcement learning; rms, root mean square; SG, synchronous generator; SMES, superconducting magnetic energy storage; SVSI, short-circuit voltage sensitivity index; TEMS, transformer energy management system; TEMSs, transformer energy management systems; P2P, peer-to-peer; THD_i, total harmonic distortion for current; THD_v, total harmonic distortion for voltage; V2G, vehicle-to-grid; PPO, proximal policy optimization; SAC, soft actor-critic; SOC, state of charge; FF-LSTM, feedforward-long short-term memory; V2V, vehicle-to vehicle; V2B, vehicle-to-building.

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sustainable energy systems. Models for PEV interaction with microgrids are also discussed, emphasizing their role in enhancing energy resilience and grid flexibility. This paper underscores the critical role of advanced energy management strategies (EMS) in optimizing EV-grid integration and improving overall system efficiency. These strategies include rule-based EMSs employing fixed rules, fuzzy logic, and wavelet transforms; optimization-based EMSs utilizing techniques such as dynamic programming, genetic algorithms, model predictive control, and particle swarm optimization; and intelligent EMSs leveraging neural networks and reinforcement learning for adaptive and predictive control. By outlining innovative solutions and highlighting the importance of strategic collaboration among utilities, policymakers, researchers, and technology developers, this review provides a comprehensive roadmap for overcoming the technical, economic, and regulatory challenges associated with EV charger integration, laying the groundwork for a reliable, efficient, and sustainable energy future.

1. Introduction

1.1. Background and motivation

Internal combustion engines (ICE) of cars powered by fossil fuels are a major source of greenhouse gases today, accounting for around 16 % of the total CO2 generated by humans [1]. Air pollution caused by internal combustion (IC) engines is harmful to human health. The use of electric vehicles (EVs) is preferable to ICE in this situation. Positive It aids in cutting down on those dangerous emissions, so that's a plus. In addition, electric cars are more efficient than ICE vehicles because they employ induction motors, which have an efficiency of >60 %, and because the energy released during braking can be transformed back into electricity and stored in the vehicle's batteries [2]. Many nations have committed to replacing internal combustion engines (ICE) with EVs over the next few years [3]. However, there are a few obstacles that must be overcome before EVs can achieve widespread adoption. These include the following: the high price and low number of life cycles of batteries; the lack of proper fast charging systems that can charge EVs in short intervals of time and make EVs a good alternative for long-distance journeys; the introduction of harmonics in the input line current, which degrades the power quality (PQ) of utility supply; the low input power factor of the fast charging station, which draws more current from utility supply Therefore, the first step toward the widespread adoption of EVs is the design of quick-charging infrastructure that has minimal of an effect on the quality of the electricity supplied by existing utilities. However, issues in the utility supply develop when a significant number of EVs are charged simultaneously, including variations in line voltage and frequency, increases in total harmonic distortion (THD) in the line current of the utility, and increases in peak load. Upgrading the current power system is one potential response to these issues, but this does not seem to be a feasible option anytime soon. The previous utility grid issues may be mitigated by developing rapid charging stations for EVs that consume utility current at unity power factor and do not affect the power quality (PQ) of input line current.

As the number of EV fast chargers increases, PQ considerations become crucial, necessitating compliance with the IEEE-519 criteria. To meet these standards, various single and multistage charger topologies that enable unidirectional and bidirectional power flows using power electronics have been proposed in the literature. Compliance with IEEE-519 standards is essential to address the PQ issues within the power system, and it is also important for the charger system to maintain a high input power factor to maximize useful energy drawn from the utility. The smart grid, defined by the Energy Independence and Security Act of 2007 (EISA-2007), integrates various intelligent electrical devices, including smart appliances, smart meters, and renewable energy sources, to create a secure and reliable power infrastructure that can meet the growing demand. The U.S. strategy aims to modernize national electrical transmission and distribution networks, encompassing ten key features that contribute to the smart grid's functionality [4]. Dynamic optimization of grid resources and operations, taking into account entire cybersecurity needs:

i) increased application and deployment of control technologies and digital information to improve the security, efficiency, and reliability of the electrical grid.
ii) the inclusion and development of demand response (DR) programs, energy-efficiency resources, and demand-side resources.
iii) the integration and deployment of distributed generation (DG) and resources, including renewable energy sources (RES).

Most definitions of "smart grids" emphasize "smart devices" and "digital communications," representing various ongoing efforts to modernize electric networks, particularly in distribution automation and substations. The smart grid is an umbrella term that encompasses the several ongoing efforts to modernize electric networks, most notably those focused on distribution automation and substation [5]. The EVs, which include hybrid EVs (HEVs), plug-in HEVs (PHEVs), and battery EVs (BEVs), are among the latest technologies that can be integrated into smart grids [6]. The origins of EVs date back to the mid-nineteenth century when they first emerged as a practical energy source for motor vehicle propulsion, offering superior performance compared to competing technologies of that era. The evolution of EVs has significantly transformed the automotive industry, even amid advancements in internal combustion engines. Renewed interest in EVs within the electricity sector has arisen due to technological advancements and a focus on renewable energy sources (RESs). This technology can benefit power grids by reducing peak loads, providing spinning reserves, enhancing grid management, and compensating for reactive power. However, to fully realize these environmental advantages, research into the potential negative impacts of EVs on PQ issues is essential [7]. Providing the power system with voltage and current waveforms that are very close to sinusoidal at the rated amplitude and frequency is what is meant by the phrase "power quality" [8]. Several variables, including voltage and frequency shifts, imbalance, interruption, flicker, and harmonics [9], might impact PQ. Therefore, the PQ is one of the crucial factors in the safe and dependable functioning of smart grids, and the rising demand for EVs will soon affect it [10]. As a result, examining PQ concerns in smart grids is essential when considering the integration of EVs. Technical literature has paid a lot of attention to PQ problems brought on by EVs during the last decade. However, up to this point, there has been no effort to gather all of these works together into a single review article.

Currently, there are nearly ten times as many private EV chargers as public ones, with most owners choosing to charge at home, making home charging the predominant method for EV refueling. EV owners with access to private parking can conveniently charge overnight, typically benefiting from lower electricity rates during off-peak hours. To facilitate the transition to EVs, governments are investing in enhancing public charging infrastructure. In 2023, the public charging stock increased by over 40 %, with fast chargers witnessing remarkable growth of 55 %, outpacing the growth of slow chargers. By the end of 2023, fast chargers constituted over 35 % of public charging stock. Although private chargers are more prevalent, developing public charging and ensuring the interoperability of its infrastructure are vital for promoting broader adoption and equitable access to EVs. Fig. 1 shows the number of public and private installed light-duty vehicle charging points categorized by power rating and type from 2015 to 2023 [11]. It offers a detailed breakdown of the growth in charging infrastructure over the years, emphasizing the differences between public and private installations and showcasing the variations in power ratings across each category.

1.2. Literature review with related works

While the literature contains a wealth of review studies examining various aspects of energy storage systems (ESS) and their role in facilitating the large-scale integration of EV chargers into the power grid [12], no comprehensive effort has been made to consolidate these findings into a single, cohesive review. Existing reviews often focus on specific technologies, grid stability solutions, or regional case studies, but a comprehensive review that synthesizes these diverse perspectives into one resource is lacking. The authors in [13] review the latest power electronics converter systems, including AC-DC and DC-DC stages in off-board EV chargers, which connect the grid, PV systems, and EVs for efficient power transfer. In [14], the paper reviews the effects of the EVs on power transmission and distribution systems, with an emphasis on grid integration, planning, and operational challenges. It consolidates diverse research on the impact of transportation electrification on power systems, identifying key challenges and opportunities for improved EV integration and management. In [15], the paper emphasizes integrating renewable energy sources with multiport converters, offering insights into a novel EV charging station framework tailored for enhanced performance in extreme fast charging (EFC) systems. In [16], the authors discuss the impacts of vehicle-to-grid (V2G) integration, focusing on charging facilities and key aspects like frequency modulation, power angle stability, voltage regulation, and harmonic filtering. In [17], the authors provide a comprehensive review of various mathematical models for EV integration, emphasizing the optimization of factors such as operating costs, energy consumption, and emissions. The review highlights significant outcomes, including reductions in operating costs and enhancements in stability and efficiency, while also offering insights into the models' objectives, validation processes, and limitations. In [18], a comprehensive overview of modular battery ESS (BESS) is provided, concentrating on the classification of modular electrical configurations into various types based on parallel or cascaded connections on either the DC or AC side. Furthermore, the literature reviews presented in Table 1 offer a clear comparison that highlights how this paper distinguishes itself from earlier works in the field, showcasing its unique contributions and insights.

Grid-connected EVs possess the capability to offer supplementary spinning reserves [19] and can serve as an alternative for energy storage [20]. A substantial number of EVs (charging/discharging) can be effectively managed by additional equipment, including metering devices, power electronics interfaces, energy converters, and bi-directional communication interfaces for interaction with the aggregator entity [21]. Incorporating V2G, which synchronizes generation and load in real-time, facilitates greater integration of renewable energy while preventing surplus electricity production [22]. Moreover, the integration of EVs might diminish the construction and operational expenses of peak generators, while also absorbing surplus electricity [23].

The study in [38] examines the circumstances in which EVs can yield profits by offering auxiliary services, utilizing real market data. Furthermore, the implementation of large-scale energy storage is crucial for facilitating the integration of renewable energy and minimizing operational expenses [39]. Energy storage methods encompass pumped-storage hydro power facilities, superconducting magnetic energy storage (SMES), compressed air energy storage (CAES), and various battery systems. Research has been undertaken regarding the integration of ESSs and combined heat and power (CHP) units into electricity markets [40]. An energy storage optimization technique utilizing day-ahead electricity rates is formulated to maximize revenues from pumped storage hydro in [41]. A deterministic model assesses the economic potential of a CAES plant in an integrated energy system with cooling, heating, and electricity supplies. Wu et al. (2023) highlight CAES's role in optimizing system performance and maximizing economic efficiency [42]. Incentives ought to be provided for investment in energy storage technology [43]. Wind patterns fluctuate daily and are affected by elements such as meteorological systems and geographic location. The absence of reliability is hindering the incorporation of renewable energy into the system. For practical use, renewable energy sources require distributed storage systems on the demand side to accumulate surplus energy during off-peak generation hours and release it during peak demand periods

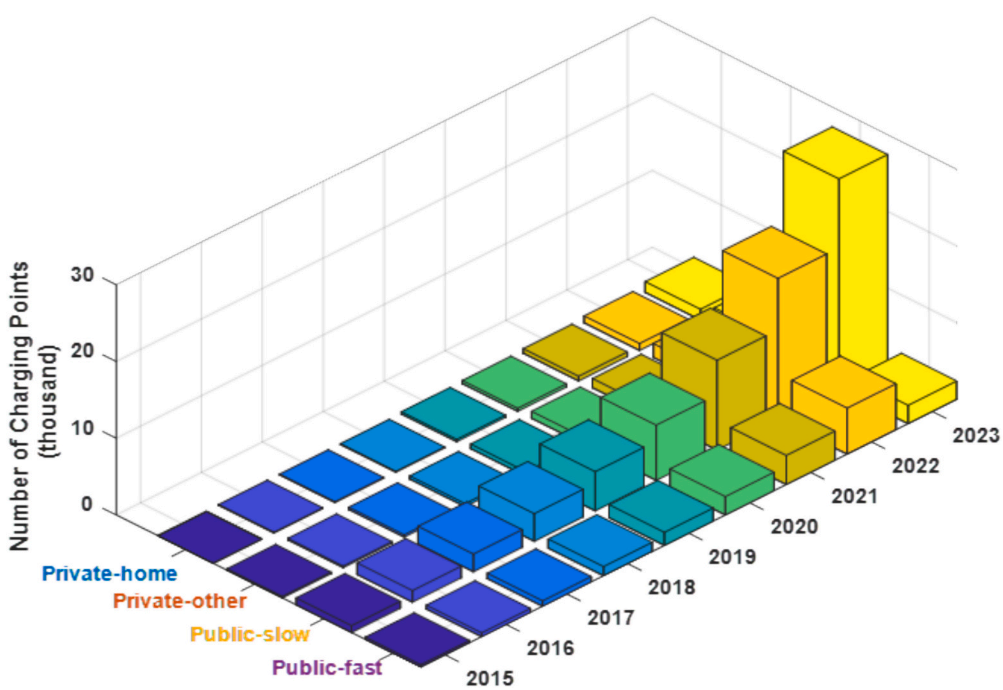

Fig. 1. Trends in light-duty vehicle charging infrastructure (2015–2023): public vs. private installations by power rating.

Table 1
Comparison of the proposed paper with existing reviews.

Ref.	Study fields	Study goals
[24]	Managed EV charging	Reviews acquired revenues, implementations, costs, and methodologies for analysing managed EV charging.
[25]	V2G technology	Provides an overview of V2G services, challenges, and market potential.
[26]	EV distribution grid integration	Discusses technical, economic, regulatory, and user-related barriers to EV integration in distribution grids.
[27]	Coordinated charging	Shows how more EVs can be integrated into distribution grids through coordinated charging without the need for grid reinforcement
[28]	EV charging standards	Conducts a comprehensive review of EV states, charging standards, and grid integration impacts.
[29]	Fast charging stations	Clarifies the grid impact of fast-charging stations, focusing on technology, standards, and PQ issues.
[30]	Industrial electronics in transportation	Discusses charger classification, AC charger converter topologies, and Li-ion battery characteristics.
[31]	Extreme fast charging	Explores extreme DC fast charging standards, system configurations, and converter topologies.
[32]	EV-grid integration infrastructure	Reviews the infrastructure for EV and Distributed Energy Resource (DER) integration, and smart V2G systems.
[33]	Energy management strategies	Provides a comprehensive overview of V2G operation and DER integration strategies.
[34]	Power electronics converters for EV charging	Surveys contemporary trends in EV power electronics converters.
[15]	Renewable integration, converter design, grid stability	Optimize extreme fast charging systems by enhancing converter efficiency, maximizing renewable energy utilization, and improving grid interaction through advanced control algorithms and energy management strategies (EMSs).
[35]	Economic incentives and Machine learning for EV energy integration	Provide essential machine learning algorithms, covering both supervised and unsupervised learning, and emphasizes their distinct abilities in prediction, clustering, dimensionality reduction, and generative modelling.
[36]	Hierarchical operation of EV charging stations in smart grids	Emphasizes the benefits of battery-powered vehicles in comparison to traditional fossil fuel cars, while examining different powertrain technologies, battery innovations, vehicle charging methods, and concepts such as vehicle-to-grid (V2G), grid-to-vehicle (G2V), and vehicle-to-building (V2B).
[37]	Multilevel EV aggregators	Reviews the system modelling and operation strategies of EV aggregators at substation, feeder, and microgrid (MG) levels.
Proposed paper	EV charger integration	Providing a comprehensive review of the ESS and their role in mitigating PQ challenges, enhancing grid stability, and facilitating large-scale EV charger integration into both traditional and smart power grids.

[44]. The EVs possess substantial batteries that can function as distributed storage systems, capable of storing surplus energy and discharging it at optimal times. The operation and development of electric cars are interdependent. Consequently, governments worldwide are advocating for policies centered on green energy. Currently, there is a heightened popularity of EVs, evidenced by their growing production and sales rates [45]. A method to improve the accuracy of state of charge (SOC) estimation for lithium-ion batteries is introduced in [46]. This method utilizes an Improved particle swarm optimization-adaptive square root cubature Kalman filter to fine-tune the filter parameters, leading to more precise SOC tracking. The approach dynamically adjusts the estimation window using PSO, ensuring reliable and accurate SOC estimation. An advanced energy management strategy (EMS) for enhancing the performance of lithium-ion batteries, commonly used in EVs, is presented in [47]. This study introduces an improved feedforward-long short-term memory (FF-LSTM) modelling technique for whole-life-cycle SOC prediction. By incorporating variations in current, voltage, and temperature, the FF-LSTM method significantly enhances SOC prediction accuracy. This refined modelling technique is essential for optimizing energy supply regulation to EV chargers, ensuring efficient battery performance and extending its lifespan throughout the lifecycle. In the context of ESSs facilitating large-scale EV charger integration into the power grid, Wang et al. (2023) propose an improved anti-noise adaptive LSTM neural network technique. This approach focuses on the robust prediction of the remaining useful life (RUL) of lithium-ion batteries by addressing the mutual coupling of diverse state parameters [48]. By improving noise resistance and prediction accuracy, this method plays a critical role in ensuring reliable battery performance and longevity in dynamic operational environments.

1.3. Review aims and contributions

This paper addresses a critical gap in the literature by providing a comprehensive review of ESS and their role in facilitating large-scale EV charger integration into the power grid. While the technical literature has extensively explored PQ challenges associated with EVs over the past decade, no unified review has yet consolidated these findings. This paper fills that gap by synthesizing key research contributions, offering a holistic perspective on ESS-supported EV charger integration, and identifying opportunities for future advancements. The specific contributions of this paper are as follows:

- **First comprehensive review:** This paper presents the first cohesive review consolidating findings from various studies on the integration of ESS with EV chargers. It addresses key PQ challenges in a unified framework, which has not been done in prior literature.
- **In-depth analysis of EV, ESS, and grid stability:** The paper offers a thorough analysis of the interaction between EVs, ESS, and grid stability, examining both traditional and modern grid configurations. It explores how smart charging, Vehicle-to-Grid (V2G) technology, and different ESS typologies can mitigate PQ issues and enhance grid reliability.
- **Evaluation of energy management strategy (EMS):** This review introduces an evaluation of various EMS approaches, including rule-based, optimization-based, and intelligent algorithms. It highlights their critical role in maintaining PQ, ensuring optimal EV integration into the grid, and addressing the technical, economic, and regulatory challenges in this evolving field.

The key contributions discussed in this article include:

- **Examination of PQ issues:** A detailed analysis of PQ challenges in both traditional and modern grids, focusing on voltage fluctuations, harmonic distortion, and load imbalances caused by large-scale EV integration.

- **Overview of EV characteristics:** A comprehensive examination of EV characteristics, including charging profiles, energy consumption patterns, and their impact on grid stability.
- **Enhancement of PQ in conventional networks:** Exploration of how smart charging and ESS integration can mitigate PQ issues such as voltage sags and flicker in traditional power grids.
- **Role of EVs in smart grids:** Analysis of the potential for EVs to improve PQ in smart grids through advanced grid-support functions, such as V2G technology, frequency regulation, and demand response.
- **Comparative overview of PQ challenges:** Compares PQ issues in traditional and modern electrical networks, highlighting the impact of PEV charging, V2G integration, and related challenges. PEVs can cause harmonic distortion, reduce transformer life, and disrupt supply-demand balance and voltage regulation. The integration of renewable energy sources and MGs helps improve grid stability, support V2G operations, and address PQ issues caused by large-scale PEV deployment.
- **Impact of plug-in EVs (PEVs):** Evaluation of the impact of PEVs on grid infrastructure, including their effects on peak demand, grid stability, and integration challenges across various grid configurations.
- **BESS typologies in EV charger integration:** Discussion of different BESS typologies—hybrid ESS (HESS), distributed BESS (DBESS), and centralized BESS (CBESS)—and their role in supporting EV charger integration, mitigating peak demand, and stabilizing PQ.
- **EMSs and control techniques:** Exploration of various EMS approaches, including rule-based, optimization-based, and intelligent algorithms, alongside real-time optimization and smart charging strategies. These methods are vital for ensuring optimal integration of EVs into the grid while maintaining PQ and system reliability.
- **Challenges and opportunities:** A comprehensive discussion of technical, economic, regulatory, and policy challenges and opportunities, including issues related to computational complexity, optimization performance, and the development of fair and reliable assessment systems.

1.4. The organization of the review paper

The following overview is provided to guide readers through the document, as illustrated in Fig. 2. Section 2 begins with a comprehensive overview of PQ issues in both traditional and modern electrical networks. Section 3 delves into the impacts of the PEVs on power grids, examining their effects on load demand, voltage stability, and power distribution. In Section 4, the document explores various BESS typologies that support the integration of EV chargers into the power grid. Different types of energy storage solutions are evaluated for their role in balancing supply and demand, enhancing grid flexibility, and mitigating PQ issues caused by EV charging loads. Section 5 presents a detailed review of the EMS and control techniques, such as real-time optimization, demand-side management, and intelligent algorithms like smart charging. Section 6 outlines the challenges and opportunities associated with EV charger integration, focusing on the technical, economic, and regulatory aspects. Finally, the research concludes by summarizing key findings, emphasizing the importance of strategic planning for large-scale EV charger deployment, and identifying potential areas for future research, such as improved energy storage technologies, advanced grid management techniques, and enhanced EV-grid

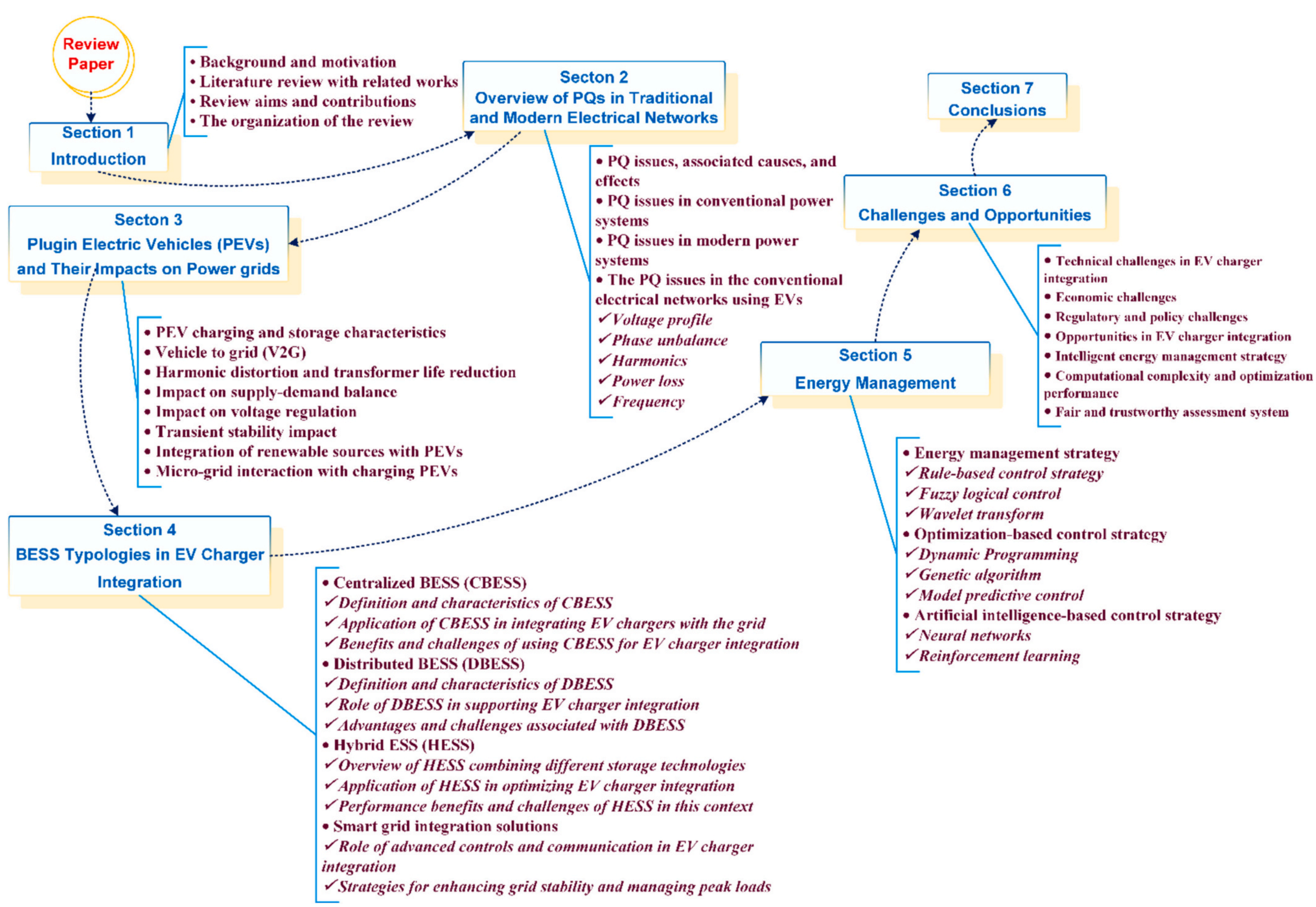

Fig. 2. Structure of the proposed review paper.

interaction models.

2. Overview of PQs in traditional and modern electrical networks

2.1. PQ issues, associated causes, and effects

In this part, we will discuss some of the most common PQ problems that a 21st century power grid may encounter. In addition, we provide a brief overview of where these problems stem from and what effects they have. Using the categories illustrated in Fig. 3, the PQ problems can be broadly categorized into technical, economic, and regulatory challenges. You can classify transient-based PQ issues by their peak amplitude, frequency component, rising time, and signal duration. Differences in severity are used to categorize problems into categories of short- and long-term duration. Power system waveform distortion is often identified using total harmonic distortion (THD) and harmonic spectrum investigations. The voltage changes may be recognized technically using an indicator called intermittency.

2.2. PQ issues in conventional power systems

Any non-linearity in the loads or even system-dominating devices is often the major factor encouraging the related PQ difficulties in traditional power systems with big centralized generating units, overhead transmission/distribution lines, and passive consumers. Motor overheating, transformer saturation, system resonance, capacitor overload, protection malfunction, light intensity change, generator and turbine shaft damage, production loss, discomfort, and headaches are only some of the side effects of poor PQ [49].

2.3. PQ issues in modern power systems

The extensive use of distributed energy resources (DERs) in recent decades has coincided with an expansion in the use of interfaces based on power electronics. Power electronic devices have been operated as rigid non-linear loads alongside traditional power grids, however, their dispersion is less [50]. In the context of EVs, the global trend toward reducing pollutant emissions, in conjunction with DERs, revitalizes the concept of the electrified car. Thus, it can be argued that the nature of electrical demands has changed in addition to the innovation in generating technologies. It seems that non-linearity in power output and consumption is becoming increasingly common in today's power grids. Smart electronic household gadgets are a driving force that has system operators fretting about PQ problems [51]. Newer alternatives, such as adjustable speed drives (ASDs) and light-emitting diodes (LEDs), have a detrimental effect on PQ indices [52]. High-voltage direct current lines, improved power line communications, and the growing preference for subterranean connections alter traditional power grids' character. Research on the origins, causes, and techno-economic and even environmental consequences of PQ difficulties becomes more important when economic losses become a key constraint. More investigation is needed into the potential for innovative and unanticipated results from PQ problems arising from advancements in the current system design.

2.4. The PQ issues in the conventional electrical networks using EVs

The PQ may be affected by EVs since they are a novel component that connects to existing electrical networks. Voltage and frequency swings, power losses, phase imbalance, and harmonics are the typical metrics used to assess the PQ of an electrical network. The effects of EVs on PQ problems, including the difficulties and solutions, are discussed below.

2.4.1. Voltage profile

Network voltage issues, such as voltage loss and voltage oscillations, might be exacerbated by the charging of EVs. The effects of recharging EVs on the power grid have been the subject of several studies. Since the availability of EVs is unpredictable, the Monte Carlo simulation method

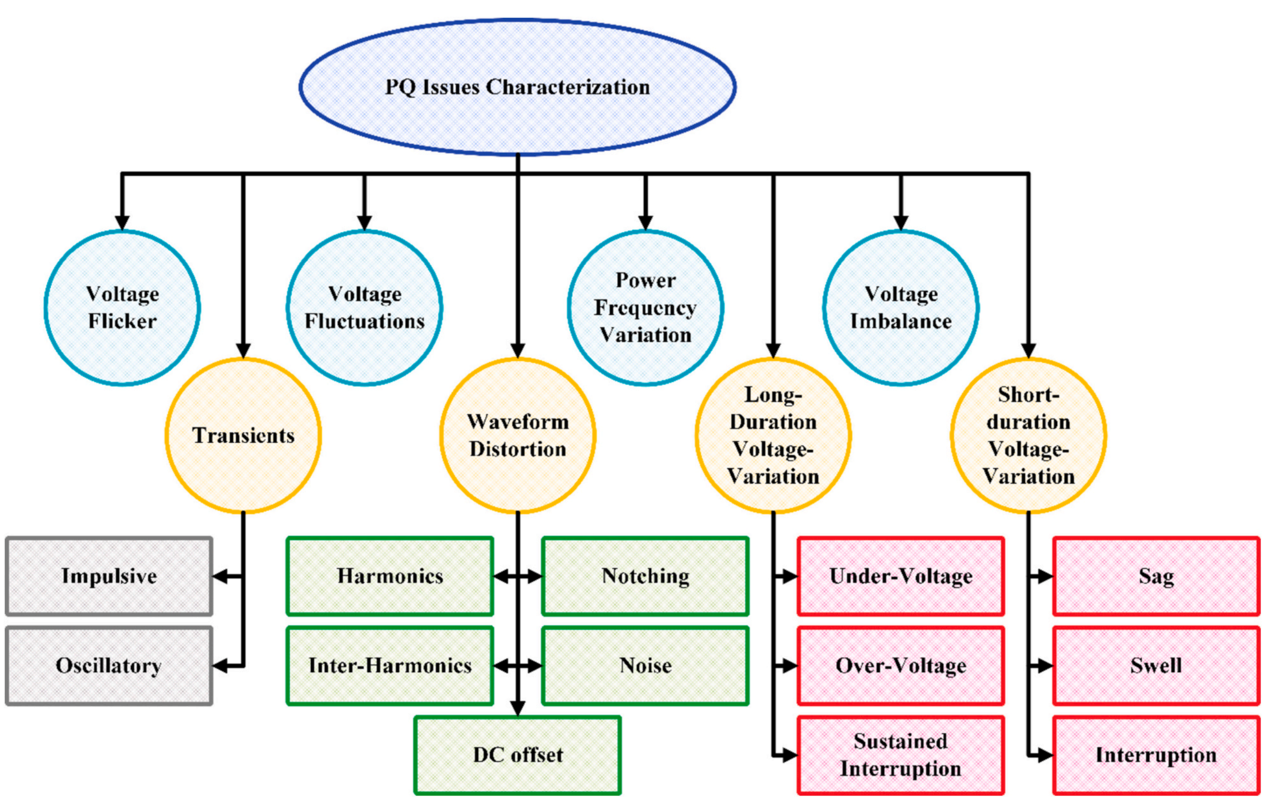

Fig. 3. PQ issues characterization.

was used to examine the effect of EV charging on the power grid's voltage [53]. Depending on factors like the quantity of EVs, the nature of the network, and the charging capabilities of the EVs, these effects may be either substantial or negligible. The research in [54] shows that low EV adoption has negligible effects on an urban distribution network's ability to handle the charging power of such cars. Research in [55] found that with 50 % penetration of EVs, network voltage variations exceed the normal threshold, in contrast to the findings in [56]. Six EVs equipped with fast-changing technology were found to exceed the network's standard voltage level in [57]. Many studies have used voltage control devices and methods to keep network voltages within the acceptable range. To reduce voltage fluctuations in the network, the tried-and-true techniques of tap-changing [58] and optimally installing capacitor banks may be used [59]. The voltage profile of a network may be improved by the control of EV charging stations. Masoum et al. [60] looked at synchronizing the charging of EVs as a smart load management control approach. The findings demonstrated that voltages are effectively regulated by coordinated charging of EVs using a realistic price and a time zone priority mechanism [61].

The voltage of the network may be controlled using the EV charger's decoupled active and reactive power regulation technique. The reactive power control may inject reactive power into the grid to sustain the network voltage [62], while the active power control regulates the functioning of EV charging. The bus voltage may be controlled by injecting reactive power, as shown by the model developed by Yong et al. [63]. Yong et al. [64] developed and deployed a prototype of a three-phase off-board EV charger that can regulate the network voltage within the allowed range by injecting reactive power while keeping the DC-link voltage constant. Distribution and transmission service providers may now consider EV charging control for voltage profile management.

2.4.1.1. LV distribution networks. Peak load voltage drop and PV active power injection-caused voltage increase are the primary issues. Marra et al. [65], by modelling a residence with rooftop PV and an EV, suggested the coordination between EV loads and the PV system to address the voltage increase. The findings of a simulation of a house equipped with rooftop PV and an EV prove the method's viability [66]. Furthermore, the coordination technique was put to the test in [67] by using real-world PV and EV data on an Australian distribution network. The voltage issue caused by EVs and PVs in LV networks may be reduced, however, by using the smart loads with back-to-back converters, as suggested in [68]. Even though two converters are needed, the findings demonstrate that smart loads with back-to-back converters can adjust the bus voltage [69].

2.4.1.2. MV distribution networks. The voltage control of a rapid charging station with a distributed EMS was investigated by Garca-Trivio et al. [70] and Torreglosa et al. [71] looked into a decentralized EMS of a charging station that used model predictive control (MPC) to regulate the bus voltage, and their findings supported the viability of the proposed technology to control the voltage in this way without requiring a communication interface.

2.4.1.3. Transmission network. End-user devices, such as EVs, were analyzed by Bayat et al. [72] to determine their contribution to voltage management on the grid. This research takes into account both active and reactive support groups, the latter of which is used to manage the voltage on the transmission bus. Using EV aggregators, wind and solar units, and diesel generators, Rana et al. [73] studied a modified droop control approach for MG frequency regulation. An EV aggregator may adjust charging and discharging speeds for EVs and SoC caps to maintain a constant SoC level [74] When the grid is experiencing voltage ride-through circumstances, EV converters may inject active and reactive power to keep things running smoothly. Active power injection from EVs during renewable energy transients may help ease grid stress. Falahi et al. [75] demonstrated that under ride-through situations, EVs provide ideal assistance for reactive and active power control.

2.4.2. Phase unbalance

Single-phase EV charging in power grids may lead to power losses and voltage violations due to the system's imbalanced operation. Due to the unknowns of EV charging rates and connection sites, the effect of EV charging/discharging on voltage imbalance in a residential low voltage (LV) distribution grid has been assessed using the Monte Carlo simulation approach in [76] EVs were shown to have a negligible effect on the voltage balance at the feeder's onset, but to raise the voltage imbalance factor at the feeder's end [77]. The imbalance index of a network may be reduced using voltage regulators [78]. The PQ is enhanced by using energy storage units, feeder capacitors, and DSTATCOM to deal with voltage imbalance and fluctuations [79]. Phase reconfiguration is another strategy for lowering the voltage imbalance factor [80]. The cost-effectiveness of a phase reconfiguration to lessen the imbalanced effects of EVs on an LV distribution system is evaluated in [81]. A phase reconfiguration strategy using the time-of-use tariff was shown to mitigate the unbalanced load caused by EVs [82]. Management of EV charging and discharging may also help alleviate the phase imbalance issue. To maintain a steady voltage, the charging and discharging states, connection locations (phases a, b, or c), and charging and discharging power rates must be chosen optimally. According to research presented in [83], the voltage imbalance factor may be considerably improved by synchronizing the charging and discharging of EVs.

2.4.3. Harmonics

Voltage and current harmonics are injected into the network by non-linear power electronic equipment such as rectifiers in EV chargers [84]. Low EV penetration and sluggish charging rate do not affect network PQ in terms of harmonic distortion, as shown by Kim et al. [85]. However, the widespread use of EVs and rapid charging times might cause significant voltage and current harmonic distortion [86]. In addition, Deilami et al. [87] discovered that the charging of randomly selected EVs might result in voltage harmonic deviations over the permitted threshold. Harmonics from EV chargers may be reduced or eliminated using tried and true methods [88]. In [89], the study focuses on power factor correction techniques specifically designed for EV chargers to enhance grid stability and efficiency. In [90], the research explores the implementation of shunt active power filters in EV charging stations to mitigate harmonic distortion and improve power quality. However, current harmonic amplification is likely to occur when using a shunt active power filter [91]. The ability of EVs to either absorb or inject harmonic currents into the network has been the subject of several research publications, such as [92]. Harmonic and reactive power auxiliary service sectors are open to EVs as well [93]. Wind generators as harmonic current sources may provide the common harmonic of EVs, as shown by Misra and Paudyal [94].

2.4.4. Power loss

The power flow in a network is affected by the addition of EVs to the system. More energy is lost as it travels through the electrical grid and its many components as a consequence of the rising current. The effect of EV integration on power losses has been the subject of a large body of literature [95]. High EV adoption with unmonitored EV charging has been shown to increase power losses in distribution networks [96]. When a high number of EVs are integrated, the power losses of a distribution transformer might rise by as much as a factor of three, as shown by Masoum et al. [97]. The negative effect of EV integration on power losses in a network may be reduced by the coordination of EV charging and discharging. Coordination of EV charging and discharging in residential areas is recommended in [98] to reduce peak loads and system losses. Clement-Nyns et al. [99] employed a stochastic programming approach to find a coordinated charging pattern that minimizes power losses. According to [100], reducing power losses by 10 % is possible with load management of EVs. Based on the availability of EVs, Luo and Chan [101] presented a real-time scheduling strategy for charging to minimize power losses or voltage drops in LV home distribution networks. Another method for lowering network power losses is to provide the load required by EVs from nearby DGs [102]. The electricity required to charge all of these EVs can be met exclusively by green energy. Coordinating the unpredictability of EVs with the variability of renewable energy sources is possible [103]. Managing EV charging in tandem with renewable sources yields optimum power losses for home distribution networks [104].

2.4.5. Frequency

Generation and load in electric power networks must be balanced in real-time, or else the grid frequency will differ from its nominal value [105]. More power output would be needed to keep the grid frequency within the allowed range if a heavy charging demand from EVs was placed on the system [106]. Uncertainties also exist concerning when exactly EVs will leave and return. As a result, there will likely be rising demand-side uncertainty for power systems. The grid's demand and generation may be balanced with the use of load curtailment and demand-side management (DSM) systems. Coordinated management of EVs improves power system stability [107]. Aggregators for EVs may take part in the energy and related services sectors in significant numbers. The EVs' ramping capability is substantially greater than gas turbines, and the method is cheaper than traditional ESSs.

3. Plugin electric vehicles (PEVs) and their impacts on power grids

The widespread adoption of PEVs is revolutionizing the transportation sector, but it also presents new challenges and opportunities for power grids. As the number of PEVs grows, they become both a substantial load and a valuable resource for grid management. The impact of PEVs on power grids can be broadly categorized into technical, economic, and regulatory aspects, as illustrated in Fig. 4. Further details on these impacts are discussed in the following subsections.

3.1. PEV charging and storage characteristics

As manufacturers compete in various markets with varied manufacturing costs, each electric car has its own set of charging characteristics. The Chevrolet Volt, Ford Fusion Hybrid, and Toyota Prius are well-known hybrid EVs, while the Nissan Leaf, BMW i3, and Tesla Model S are well-known purely electric cars [108]. The average daily mileage travelled is difficult to pin down since it varies depending on where the data is collected. The most frequent distance travelled by American households in 2001's National Household Travel Survey (NHTS) was between 25 and 30 miles. According to a study conducted by the Australian Bureau of Statistics, the average daily mileage for a passenger automobile is 23.45 miles [109]. Other authors [50] determine the SoC at a distance of 60 miles. Data from "The EV Project" cars and charging stations was gathered for research conducted by ECOtality and the Idaho National Laboratory [110]. Over 10,000,000 miles were driven in PEVs in 2011 and their data was evaluated. The cars averaged 30.3 miles per day, with a median of 26.8 miles travelled, and were charged 1.05 and 0.99 times per day driven, respectively. While it's obvious that nations have different maximum speeds, it's also true that users in urban areas have different driving habits, with some needing to charge their PEVs twice a day and others just once. 82 % of PEV owners reportedly charge their vehicles at home. Using a battery with an SoC >85 % for extended periods affects battery life, therefore this might become a future issue. Users' driving habits, battery size and chemistry, system-on-chip (SoC), and utility connection (supply voltage, permissible current, and number of phases) all influence the total power demand to the grid [111]. Most PEVs are designed with a single-phase, 230 V/16 A (or 120 V/15 A) connector for home charging in mind [112]. To fully charge the batteries overnight, most users would likely consider charging at 3.7 kW. Fig. 5 depicts a charging station for PEVs integrated with various RESs like solar, wind, and fuel cells [113]. The system appears to manage power flows ranging between 200 and 450 V DC with a power capacity of 20-80 kW. The EMS's role is to optimize resource usage, ensuring efficient energy management between the grid, storage systems, and EV charging infrastructure.

3.2. Vehicle to grid (V2G)

Some PEVs may use vehicle-to-grid (V2G) technology to contribute to the grid by switching their power flow in the other direction during peak demand. The vehicle may be brought up to the required SoC for its next usage thanks to the concept's frequency and voltage regulation [114]. The V2G has the potential to significantly shorten the lifespan of

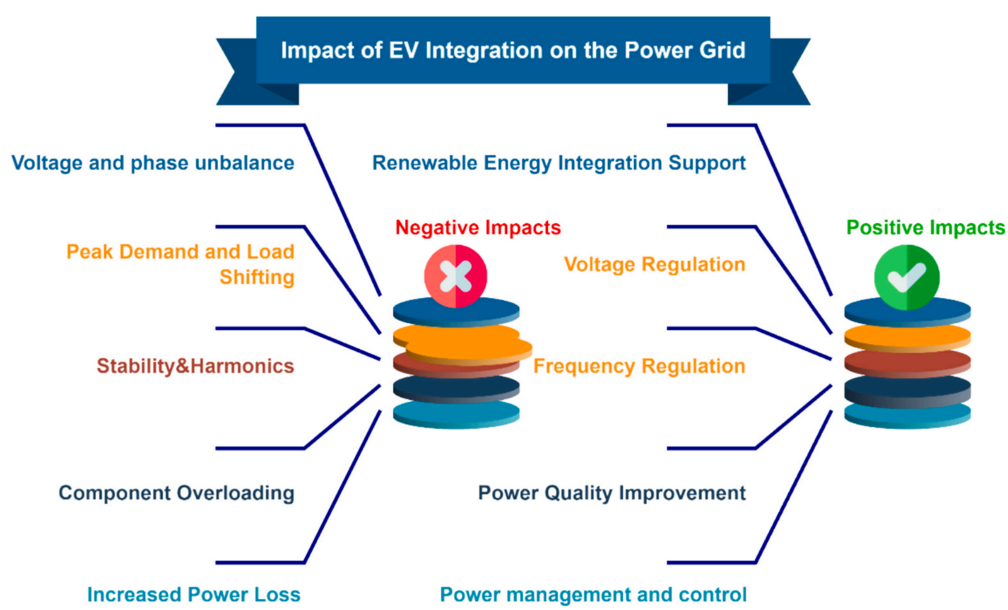

Fig. 4. Impacts of EV integration on the power grid.

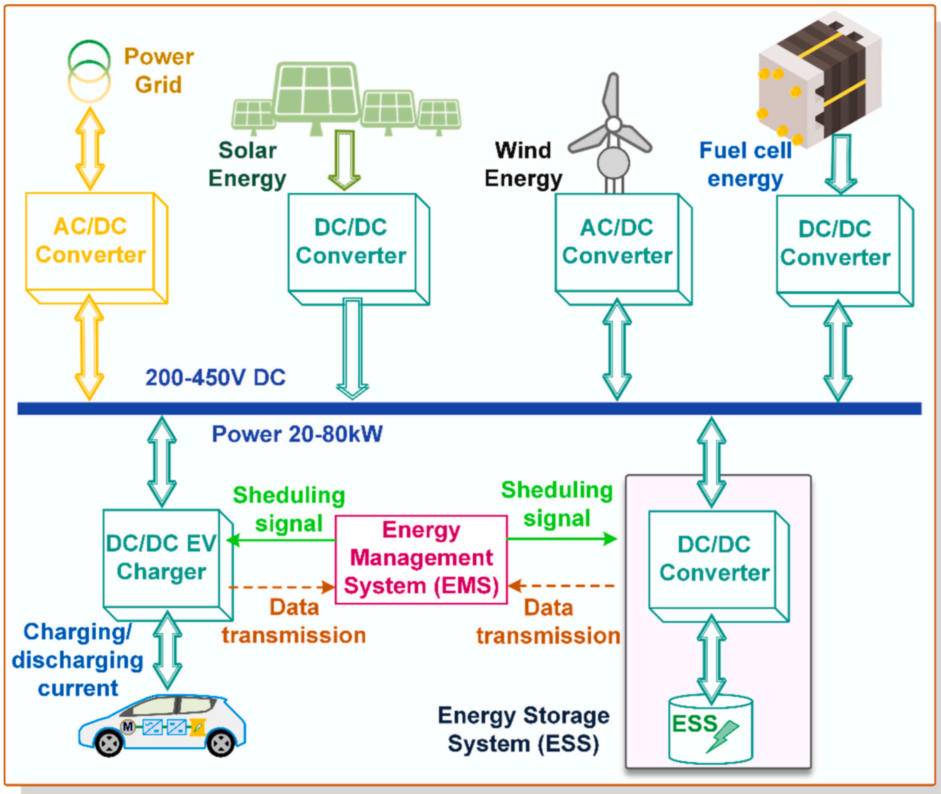

Fig. 5. Schematic of an EV charging station integrated with renewable energy sources and ESS.

batteries, which is a function of the depth of discharge and the frequency of cycling [115]. Battery degradation costs are hard to predict since battery technology is still in its infancy. It is clear that V2G technology is costly and more complex to adopt, but that it ultimately aids in the more effective distribution of power demand. In [116], the author presents a rule-based algorithm for a 400 kVA medium to low voltage distribution system. To assess the system's average power rating, it was fed 96 homes with charging currents ranging from 5 to 32 A in 5 A increments. The authors created four different scenarios by varying the SoC, the arrival time, the PEV, and the home's power profile. In scenario 1, when the visitor arrived at 15:30, the residential load peaked at 7.9 kVA, requiring a 32 A charging current. The voltage profile of the distribution system was afterwards computed using a Matlab/Simulink study. The system voltage was lowered from 0.92 to 0.88 during the colder months, while the home voltage dropped from 0.99 to 0.965 p.u. This voltage discrepancy exceeded the standard 10 % threshold of various regulations. Finally, they developed a linear voltage control plan using V2G to guarantee the PEV is fully charged when the user needs it, based on the quasilinear growth of the voltage profile slope. In [117], an optimization method for agents is devised; these agents compete to increase their profits. Authors claim that EVs can control frequency or act as a spinning reserve. Power distribution parameters are estimated at each stage of the simulation to determine which buses equipped with EVs will have the most impact on reducing wait times. The authors indicate that a wind turbine, solar panels, microturbine, fuel cell generator, and one battery were all part of the electric system. Other sources of electricity generation included fossil fuels and nuclear fission. At any given time of day, nine EVs were networked together in various clusters. The data shows that in moderate circumstances of power congestion in feeders, EVs' power output, or just slowing their charge pace, may alleviate the problem. They determine that reactive power regulation must be included in the algorithm to significantly lessen traffic congestion.

3.3. Harmonic distortion and transformer life reduction

Current and voltage waveforms in distribution systems are particularly vulnerable to harmonic distortion due to the nonlinear characteristics of electronic devices. The significance of these effects may increase with the rate of PEV adoption and the power factor. Since residential loads fluctuate throughout the day, and PEVs are typically charged at specific times, harmonic distortion is a dynamic issue. One potential disadvantage of nighttime charging is that harmonic cancellation, which occurs when a large number of PEVs are connected to the grid, may be diminished when most PEVs are fully charged in the morning, especially when no other household appliances are in use. Preliminary research utilizing a Monte Carlo simulation indicates that the total harmonic distortion for current (THD_i) remains approximately constant at around 49 % when the number of PEV chargers exceeds seven. In another study, in [118], the authors employed the Central Limit Theorem to investigate a community power grid where 36 PEVs charge at 20 kWh over a five-hour period [119]. The results showed a voltage distortion (THD_v) of 5 % and a current distortion (THD_i) ranging from 43.7 % to 49 %. Compared to the previous research, these findings suggest that current distortion could be substantial and may interfere with the operation of other electronic devices in the vicinity. More recent work has introduced the application of derating $K-$ Factors for managing load and ensuring PQ control in [120].

The harmonic derating factor (K) is calculated based on the rms (root mean square) load current for each harmonic order h and the rated rms load current of the transformer I^1_{rms}. The equation is:

$$K = \sum_{h=1}^{H} \frac{\left(I^h\right)^2 h^2}{\left(I^1_{rms}\right)^2} \tag{1}$$

where H is considered the highest harmonic order. The factor K accounts for the impact of harmonics on the transformer's load current, with higher harmonic currents contributing more significantly to heating due to the h^2 term. The derated rms current $I_{derated}$, which is the effective current the transformer can safely carry after considering harmonics and other losses as:

$$I_{derated} = \sqrt{\frac{1 + P_{CE-R}}{1 + K\left(\frac{\left(I_{rms}^{1}\right)^2}{\sum_{h=1}^{H}\left(I^{h}\right)^2}\right)P_{CE-R}}} \tag{2}$$

where P_{CE-R} is core loss ratio, which is the power loss in the transformer core due to eddy currents and hysteresis. The transformer's derated apparent power capacity $kVA_{derated}$ can be determined using the derated rms current from Eq. (2) and the rated kVA

$$kVA_{derated} = kVA_{rated} \times I_{derated} \tag{3}$$

Finally, the percentage drop in the transformer's kVA rating is given by Eq. (4):

$$\%Derating = (1 - I_{derated}) \times 100\% \tag{4}$$

Example Scenario: In the case of PEVs connected to a 250 kVA, 23 kV/415 V transformer, the following scenarios are considered using 1.3 kW chargers. Depending on the harmonic content of the load currents from the PEVs, the transformer may need to be derated to prevent overheating. The equations above help calculate the reduced capacity and quantify the derating percentage based on the harmonics introduced by the PEV loads. Three scenarios were considered, all using 1.3 kW charges:

i) Heavy PV charging at peak load (120 PEVs).
ii) Smart load control charging (2).
iii) A significant number of PEVs charging during off-peak hours.

THD_i was 19.1 % with a 4.9 % transformer derating in instance 1, 17.9 % with no transformer derating in case 2, and 29.9 % in *Case iii.*

The "hot-spot" temperature inside the windings of a power transformer reflects the effects of overloading. In [121], a mathematical model was presented to carry out this analysis based on this assumption. According to the research presented here, the insulation deterioration that occurs over time is directly proportional to the winding temperature. The test was first performed on a more robust transformer (50 kVA) with an oil-time constant of 411.4 min and then on a second, less powerful transformer (200 min). To do this, they used a typical Austin, Texas, family and factored in the PEV contribution of the Chevrolet Volt and the Nissan Leaf. The findings demonstrate that the less robust transformer's life is shortened the most by uncontrolled charging. These same authors suggest, in a later piece, combining house energy management systems (HEMS) with transformer energy management systems (TEMS) to regulate the hot spot temperature of the transformer without affecting residential load. The results show that regulated charging significantly lengthens the lifespan of transformers. Lifespan rises from 24 years to 47 years, depending on the transformer and PEV examined, as compared to the previously referenced scientific work. Another research [122] discovered a quadratic connection between current THD_i and reduced transformer life, suggesting that the life of the transformer would not be adversely impacted if THD_i is kept at between 25 and 30 %. In [123], a probabilistic model is described. The likelihood of an individual distribution transformer becoming overloaded was determined using a binomial distribution. According to the authors, the system under review was "a distribution network in Denver, Colorado with 75,000 distribution transformers of varying capacities and 550,000 customers across 400 feeders." With the introduction of two charging tiers (1.2 kW and 3.8 kW), market penetration went from 10 % to 30 %. The primary limitation was that transformers couldn't be overloaded by >1.8 p.u. before being replaced. The findings indicated that under the most cautious, moderate, and aggressive scenarios, 3.64 %, 8.58 %, and 15.8 % of transformers, respectively, would need to be replaced. The authors concluded by outlining an optimization framework for cutting down on transformer replacement expenses. When six PEVs were charging at once, the findings showed that the transformer could be overloaded by 150 %, and the authors calculated that a 25 % increase in load might increase the winding temperature by 10.1C. Harmonic distortion in contemporary PEVs like the Nissan Leaf has been drastically decreased. Although several approaches have been used in the past to analyze the effects of PEVs on transformers, all of them have reached the same conclusion: that unregulated charging may overload them and significantly shorten their life. To extend the life of a transformer, TEMS and HEMS are essential.

3.4. Impact on supply-demand balance

According to [124], researchers in Perth, Australia, ran a simulation study. The authors accounted for 800,000 PEVs, dividing them among substations in each zone based on the number of customers connected to each substation. From 2010 to 2019, the city is expected to generate 4950 MW, with a spare capacity of between 136 MW and 242 MW. Two important factors emerged from their analysis of plug-in EVs (PEV) addition implications on sub- and transmission networks and generating capacity.

i) On a typical day, available power ranges from 1087 MW to 1473 MW, which accounts for 80 % of the peak demand. This capacity could support approximately 572,000 plug-in PEVs.
ii) Without additional generation, 41 % of PEVs' load must be moved to off-peak hours on a typical day, and 93 % of this load must be moved on the yearly peak day.

To incentivize off-peak pricing, they determined a variety of tariff structures and load control technologies were required. If this doesn't happen, the predicted generating capacity may be exceeded by a 100 % penetration of PEVs.

Another investigation [125] of a standard distribution network operating at 33 kV and dropping to 400/230 V. These most recent substations only have one of their four feeds modelled. Each 400 V feeder served one hundred residential customers with PEV capability. The authors modelled residential load profiles for both the summer and winter seasons in the United Kingdom, considering three different billing scenarios. Unregulated pricing increased peak demand by 18 % for every 10 % of market penetration, and complete market penetration might cause generation to surpass projections. Comparing the baseline case to the regulated charging situations, the peak demand was found to be reduced by 25 %. If electricity companies don't implement management techniques to reduce peak loads in anticipation of PEV adoption, the resulting price hikes might be substantial. A more effective approach is to combine energy management systems (EMSes) like TEMS and HEMS to charge during off-peak hours and lower peak loads. The utility and the customer would both gain from this. Utilities must factor in PEVs into future grid expansion plans. Blackouts caused by overloaded transformers, distribution, and transmission lines would cost the company a lot of money to fix.

3.5. Impact on voltage regulation

The IEEE 34-node test feeder with each phase of a 100 kVA transformer was modelled in detail [126]. With no PEVs present, the highest load measured was 69 kVA. Two simulation programs were used to find the optimal balance between power generation and power loss for penetration levels of 0 %, 10 %, 20 %, and 30 % for PEVs. Node voltages were determined in a deterministic program utilizing a common load profile with a flat voltage profile and the backwards-forward sweep technique. In the end, the optimal charging profile was determined employing quadratic optimization. To ensure the batteries could be charged to their full capacity in a reasonable amount of time given their starting SoC, some restrictions were imposed. Each node in the network had one of 2000 possible profiles chosen at random by stochastic software. All voltages were calculated following the deterministic code's specifications. The discrepancies between the two models were small enough to warrant the conclusion that everyone could share a single load profile. During the winter evenings (18-21 h), a 10.3 % voltage deviation would occur in one of the nodes, which violates the mandatory Belgian standard EN50160, which allows for a maximum of 10 % voltage deviation 95 % of the time. An 18 % increase in demand is predicted by 2040 [127] based on a study of the energy infrastructure in Ada County, Idaho. They discovered that a voltage drops below 0.96 p.u. would be present if the load increases as proposed, and so they concluded that a time-of-day incentive plan, in addition to the systematic replacement of underrated devices, could lessen the strain placed on the power grid by the charging of PEV's batteries. According to [128], an analysis was conducted using a typical UK distribution system. There were 384 customers for every electrical substation. To determine the voltage, drop that would result in a penetration level of 50 % to 100 %, they modelled the PEVs as a load with actual and reactive power consumption. Authors discovered that even at modest penetration levels, statutory voltage breaches occurred at the far end of the network.

3.6. Transient stability impact

Effective coordination between PEV charging and the electrical grid is necessary to prevent transitory disruption. During periods of low demand, PEVs may take advantage of cheap power rates to top up their batteries. Eventually, when more people start using power, the cost of it will go up. As PEVs begin discharging to the grid, the resulting shift in load might cause an undesirable voltage and frequency transient. The same thing would happen if electric cars that have been discharging abruptly because of the step fluctuation in power prices suddenly began charging. In [129], the authors apply a small-signal stability study to the New England 39-bus system, modelling PEVs as CPL allowed generators to quickly raise output to 7106.05 MW, whereas modelling them as CIL allowed them to sustain a maximum penetration of 7138.16 MW. These findings are important because, when energy prices fluctuate, a greater number of PEVs considered as CIL may be efficiently dispatched. Researchers in [130] also regarded a PEV fleet to be a potential generator. After simulating the effects of a three-phase malfunction on the 24-bus Reliability Test System 96 (RTS-96), they found that the SVSI increased when the PEVs were treated as a source rather than a load. However, the potential effect of an increase in short circuit current on circuit breakers was not addressed. When the PEV has the potential to provide electricity to the grid, this evaluation is crucial for V2G.

To prove the value of combining V2G operation with superconducting magnetic energy storage (SMES), a transient stability study of the power grid was conducted [131]. The main benefit of SMES is a shorter charge/discharge time, but their expensive price means they can only store a small quantity of energy. An infinite bus was fuelled by a synchronous generator (SG) linked to the main grid through a double-circuit transmission line. The generator terminal bus was used to link the SMES unit to the larger power grid. A thyristor-based SMES and a SMES controller made up the SMES unit. Each PEV has its own DC/AC power converter so that it can plug into the grid. The PEV and SMES controllers were in constant contact with the grid operator. They demonstrated an active-reactive power regulator that uses turbine generator speed variation to regulate active power and voltage variation to regulate reactive power. They looked at three scenarios, each with a different number of PEVs: 5000, 10,000, and 50,000. In identical situations, the voltage dropped to 0.85 p.u. and steadied at around 0.75 s when a single-phase ground fault occurred. In the end, they determined that both SMESs and PEVs may improve the power grid's transient stability, but that SMESs contribute more to the system overall. As was previously mentioned, the transient stability of the grid is at risk in two extreme scenarios. To begin, only efficient generating technologies add to the extra cost of the system while demand is low, therefore prices are low. A spike in energy use during peak hours might drive up prices because it forces the activation of less efficient power facilities. Right now, PEVs will begin discharging into the grid, causing a transitory event that will have consequences depending on the extent to which PEVs are integrated into the grid. The second scenario involves a precipitous price drop, the polar opposite of the first. Right now, PEVs are beginning to charge, creating a similar momentary phenomenon. To reduce the effects of load changes on the power grid's stability, they suggested a wide area controller (WAC) architecture. The results showed that the system's stability could be restored in around 5 s after a 3-phase failure for 10 cycles at one of the buses. Since PEVs may cause abrupt power fluctuations due to changes in loading circumstances, transient stability may be crucial if energy prices fluctuate throughout the day. Pay-as-bid pricing may act as a counterbalance to this demand reaction [132].

3.7. Integration of renewable sources with PEVs

Stochastic driving patterns, an optimization model to lower charging expenses, and an agent-based electricity market equilibrium model were all used in a study [133] conducted for the German setting, with the latter two being used to predict the volatility of power prices. The authors considered a 2030 scenario in which wind and solar energy production are intermittent but can be balanced by PEVs. There are expected to be 12 million PEVs on the road by 2030, with estimates placing the installed capacity of onshore wind, offshore wind, and solar at 37.8 GW, 25 GW, and 63 GW, respectively. One of their primary contributions is the possibility of a domino effect brought about by automated systems that detect price signals, resulting in peaks in either demand for energy or production. They suggest that using price elastic demand bids to allocate PEVs charging during low demand periods might help the system mitigate this impact. In addition, electricity from German offshore wind farms is likely to be used at night, which helps charge PEVs then and therefore integrating PEVs with intermittent renewables. In another study [134], the same authors use an agent-based simulation model to contrast the German 2030 scenario with a case study from California. A total of 12 million PEVs were planned for Germany, while 6.8 million were projected for the state of California. The ratio of fleet power to energy was also calculated to be 0.44 for both California and Germany. Both scenarios had 47 % of energy production based on RES, with Germany at 162 % and California at 97 %. This difference was due to the assumed differences in the capacity factors for wind and photovoltaic (PV) generation in the two countries.

The study found that PEVs in California are more efficient if charging stations are conveniently located near where cars are kept during the day and when using solar production. In Germany, only 43 million cars were registered in 2013, according to KBA [96], and without population growth, this number would not expand much by 2030. This suggests that the quantity of PEVs estimated in the prior research may be an optimistic approach. Reaching 12 million PEVs by 2030 would mean a penetration of 28 %. Due to the intermittent nature of electricity provided by wind and solar, it is anticipated that PEVs linked to the power grid would be able to supply the necessary energy backup at this level of penetration. If this occurs, less money will be put into developing alternative energy sources. Interactions between physical factors like solar irradiance, wind speed, and the SoC and smart calculations and judgments are what make up a cyber-physical energy system (CPES). Using a previously published work, [134] successfully integrated renewable energy sources with grid-capable cars by combining an electrical and a thermal infrastructure that interacts with communication devices from utilities and markets. In this concept, the electricity grid and its consumers are in constant dialogue with one another to better serve everyone's requirements while cutting down on wasteful spending and harmful emissions. PEVs equipped with

V2G and RES with CPES, the authors argue, might serve this function. By contrasting conventional generation with RES and PEV cars using particle-swarm optimization for recharging and CPES, they examined a sustainable integrated electrical and transportation infrastructure with 50,000 PEVs. Even though a sizable financial commitment is needed to implement this smart grid concept, the results revealed that marginal costs and emissions will be greatly decreased.

Incorporating PEVs will help with renewable energy distribution, but how that is accomplished will vary from nation to country based on environmental factors. In locations with greater solar irradiation, PEVs might benefit from daytime charging, while in others, where wind energy is more likely to be abundant at night, PEVs would be better served by overnight charging. More economic models are needed to estimate and reduce the potential costs to the electricity system associated with integrating this technology. Recent studies have started to explore the implications of integrating plug-in hybrid EVs (PHEVs) into power systems, focusing on both the small-signal stability of the grid and the advantages of V2G operations. Das and Aliprantis [135] conducted a small-signal stability analysis of power systems integrated with PHEVs, identifying potential impacts on grid stability and offering insights into system performance under various conditions. Meanwhile, El Chehaly et al. [136] examined the applications and benefits of V2G mode in PHEVs, highlighting its potential to enhance grid reliability and efficiency while providing auxiliary services such as load balancing and voltage regulation.

3.8. Micro-grid interaction with charging PEVs

In [137], the authors provide the results of research conducted on a British Distribution Network. Deterministic results indicated that under minimum load with high PEV penetration (71 %), the distribution transformer would be overloaded at medium (33 %) and high penetration levels, and at maximum load for all penetration levels, power losses could reach an 8 % and 10 % at minimum and maximum loading conditions, respectively. Among the several scenarios given by the probabilistic model to improve the distribution network, the integration of mGen in all single-family homes with an average power rating of 1.1 kW stands out as the most promising. Findings demonstrated that winter is harsher on the network, predicting voltage statutory infractions for medium and high penetration. The chance of voltage violations at high penetration levels would drop from 100 % to 60 % if mGen was 100 %. However, at low (12.5 %) and medium penetration levels, the likelihood of transformer overloading in the winter is reduced by mGen. Power losses may be reduced by roughly 1 % with mGen, too. The authors believe that low-level voltage violations may be eliminated with substantial penetration of mGen sources, and the chance of transformer overloading can be lowered from 85 % to 5 % with smart regulation of battery charging. In a separate investigation, researchers considered how a microgrid (MG) may be implemented in a low-voltage residential system [138]. The authors' MG considered a micro-turbine, a fuel cell, a wind turbine, and five PV arrays for its power generation. There were three distinct groups of customers served by the network's three feeders: a residential area, a small workshop, and a commercial sector. The uncertainty of each battery's SoC upon return home was calculated using a random charging time profile and three different penetration levels (2, 4, and 10 PEVs) with a battery capacity of 7.5 kWh and a SoC of 50 % during departure. Both regulated and uncontrolled EV charging situations were taken into account. At medium and high penetration levels, especially during the winter, the MG would be unable to provide all of the demand if the PEVs' charging was left unrestrained. Because rates were cheaper at night, that's when most people choose to charge their devices. As a result, the MG's peak load was lowered across the board, and charging needed very little, if any, additional power during peak hours from the grid.

In the not-too-distant future, micro-networks will be useful because they can improve existing electricity grids. Local generation has the potential to eliminate peaks caused by the charging of PEVs, which would significantly reduce voltage fluctuations, transformer overload, and power losses. Furthermore, the DC MGs may lessen energy waste caused by converting direct current (DC) from PV panels to alternating current (AC) and then back to DC for use in charging PEVs and other DC-powered devices. Distributed generation in micro-grids has a drawback in the accumulated uncertainty on their power production, hence new methodologies are being developed that take possibilistic and probabilistic uncertainties into account simultaneously [139].

4. BESS typologies in EV charger integration

Before addressing the main topic, a brief review of various EV charging topologies will be presented. Fig. 6 shows a block diagram of various EV charging systems. EV-Level 1 and Level 2 chargers are essential for residential and commercial charging needs. Faddel et al. [140] propose a fuzzy logic-based autonomous controller for residential distribution systems, optimizing EV charging under various grid conditions to enhance efficiency and adaptability. Wang et al. [141] investigate network-level energy consumption for EVs, considering vehicle and user heterogeneity, providing insights into the impact of charging patterns on grid performance. Hemmatpour et al. [142] focus on voltage and energy control in distribution systems, examining the coordinated charging of EVs to maintain grid stability and improve energy management, especially in the presence of flexible loads like EVs. EV-Level 1 chargers use standard 120-volt AC outlets found in homes, offering slower charging rates, typically adding 2 to 5 miles of range per hour. On the other hand, EV-Level 2 chargers operate on 240 volts AC, commonly installed at homes, workplaces, and public stations, providing faster-charging rates of about 10 to 60 miles of range per hour, depending on the vehicle and charger specifications [143]. EV-Level 3 chargers, or DC fast chargers, are designed for rapid charging at public stations, delivering high-voltage DC power directly to an EV's battery [144]. They can charge up to 80 % capacity in approximately 20 to 30 min, significantly faster than Level 1 and Level 2 chargers [145]. Level 3 chargers use connectors such as the combined charging system (CCS) and Tesla Supercharger, depending on the vehicle's compatibility. Feng et al. [146] propose a bi-level decomposition algorithm for real-time automatic generation control commands, enabling large-scale EVs to participate effectively in frequency regulation, thereby enhancing grid stability during fast charging operations. García-Triviño et al. [147] analyze the control and operation of power sources in an MV DC MG, showcasing its application in an EV fast-charging station equipped with photovoltaic and battery energy storage systems to optimize energy usage and charging efficiency. Regarding charging topologies, unidirectional chargers facilitate one-way energy flow from the grid to the EV, common in Level 1 and Level 2 chargers where the vehicle solely receives power. In contrast, bidirectional chargers, also known as V2G chargers, enable EVs not only to charge but also to discharge energy back into the grid [148]. This capability supports grid stability and peak load management, allowing EVs to contribute stored energy during peak demand or low renewable energy generation periods, enhancing overall grid efficiency and resilience [149]. Furthermore, typical charging topologies for EVs are presented in Fig. 7.

The integration of EV chargers into the electric power grid represents a pivotal step toward sustainable transportation infrastructure [150]. As the adoption of EVs accelerates globally, the demand for efficient and reliable charging solutions becomes increasingly paramount [151]. The BESS has emerged as an integral component in addressing the challenges associated with integrating EV chargers into existing grid infrastructures [152]. By leveraging the capabilities of BESS, various topological solutions have been developed to enhance grid stability, manage peak demands, and optimize energy utilization in the context of EV charging [153]. This review explores the diverse typologies of BESS-based solutions tailored for facilitating large-scale integration of EV chargers into the electric power grid. It examines centralized and distributed BESS

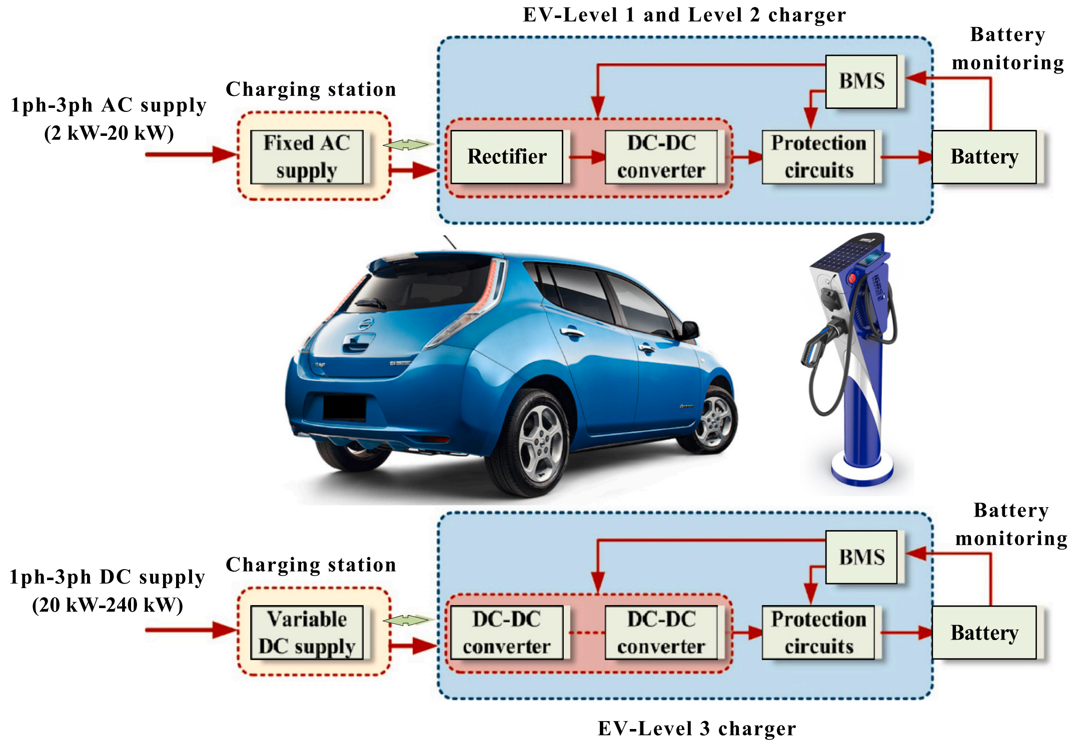

Fig. 6. Block diagram of various EV charging.

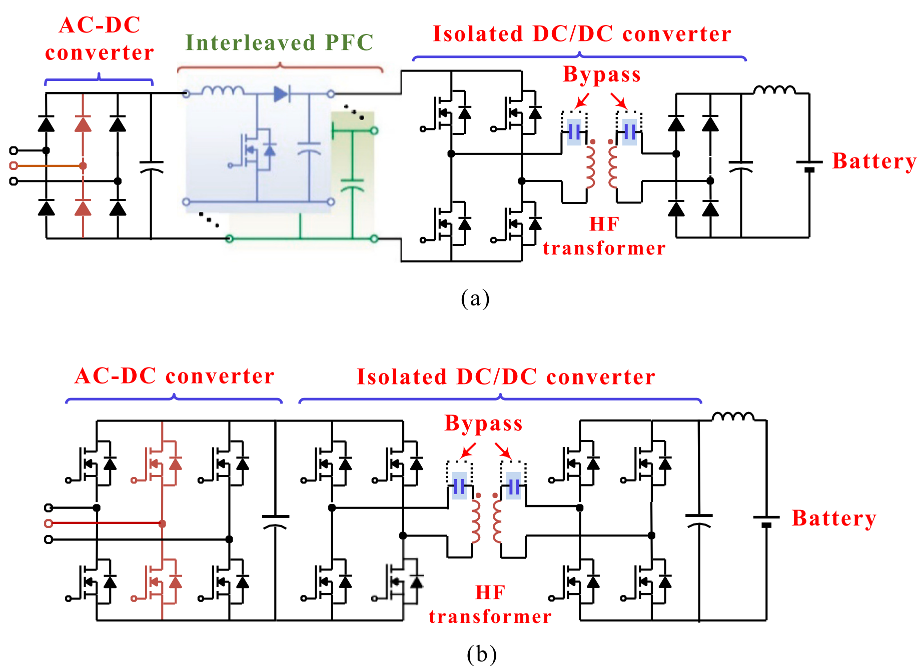

Fig. 7. Typical charging topologies for EVs. a) unidirectional charger and b) bidirectional charger.

configurations, hybrid ESSs (HESS), V2G technologies, and smart grid integration strategies. Each of these solutions offers unique advantages and challenges, influencing their applicability and effectiveness in supporting the growing demand for electric mobility. Wu et al. [154] provide an overview of the hierarchical operation of EV charging stations in smart grid integration, emphasizing the potential for coordinated energy management to enhance grid reliability. Ma et al. [155] review grid-tied modular BESSs, discussing their configurations, advanced control strategies, and performance, which are critical for supporting EV charging infrastructure. Liu et al. [156] offer an extensive overview of batteries and battery management systems for EVs, focusing on advancements in battery technology and control methods to improve energy efficiency and lifespan. Hilton et al. [157] make a case for integrating ESSs at high-rate EV chargers to facilitate solar energy utilization, proposing an optimized approach to enhance sustainability and reduce grid dependency. By comprehensively evaluating the characteristics and operational dynamics of BESS-based solutions, this analysis aims to provide insights into optimizing EV charger integration strategies while advancing the broader goals of clean energy transition and grid modernization. The topology system solution based on BESS for EV charger integration includes four parts, as presented in Fig. 8. In the following, the BESS configuration for the mentioned challenge is presented in Fig. 9.

4.1. Centralized BESS (CBESS)

4.1.1. Definition and characteristics of CBESS

The CBESS are large-scale energy storage facilities strategically positioned within the electric grid infrastructure [158]. These systems are notable for their substantial storage capacities, ranging from several megawatt-hours (MWh) to hundreds of MWh, tailored to diverse applications. They are centrally controlled and managed, typically by grid operators or utility companies, ensuring coordinated operation and efficient dispatch of stored energy [159]. Integrated directly into critical grid points like substations or distribution centers, The CBESS provides essential ancillary services, enhancing overall grid stability. Moreover, the CBESS exhibits technological diversity by employing various battery chemistries such as lithium-ion and storage technologies like capacitors, allowing customization to meet specific operational demands and objectives [160].

4.1.2. Application of CBESS in integrating EV chargers with the grid

The CBESS is pivotal in integrating EV chargers with the grid by providing essential functionalities. They enable efficient peak load management by storing surplus electricity during off-peak periods and releasing it during peak demand, thus mitigating grid strain caused by simultaneous EV charging [161]. Moreover, the CBESS enhances grid stability through frequency regulation, voltage support, and reactive power control, which is crucial for maintaining a reliable electric supply amidst variable demand and renewable energy integration. Additionally, the CBESS supports fast-charging stations by delivering high-power outputs when required, ensuring rapid and consistent charging without compromising grid stability [162].

4.1.3. Benefits and challenges of using CBESS for EV charger integration

The utilization of centralized battery ESSs (CBESS) for integrating EV chargers offers significant benefits alongside notable challenges [163]. Benefits include improved grid reliability and efficiency through optimized energy utilization and reduced peak demand charges. CBESS also facilitates cost savings for EV charging providers by minimizing operational expenses associated with peak power demand. Moreover, their scalability enables flexibility in infrastructure planning to accommodate evolving demand patterns [164]. However, challenges such as high initial costs for installation and maintenance, complexity in integration with existing grid infrastructure, and regulatory compliance requirements pose significant considerations. Addressing these challenges effectively is essential to harnessing the full potential of CBESS in supporting sustainable and resilient EV charging infrastructures [165].

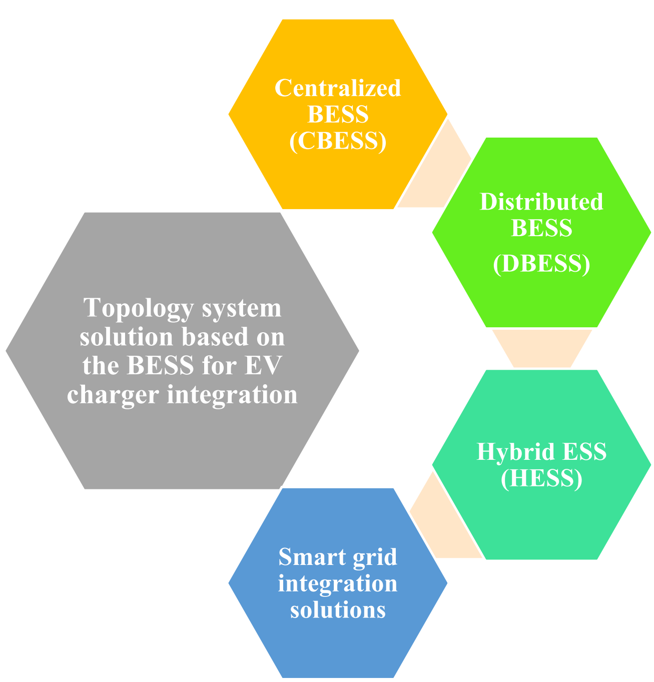

Fig. 8. Schematic diagram of the topology system solution based on BESS for EV charger integration.

4.2. Distributed BESS (DBESS)

4.2.1. Definition and characteristics of DBESS

The comparison between CBESS and DBESS strategies is presented in Table 2. The DBESS are decentralized units that store electrical energy across various locations within the electric grid [166]. These systems are characterized by their modular design and localized deployment, allowing for flexibility in placement and operation. The DBESS typically have smaller storage capacities compared to centralized systems, ranging from kWh to several MWh and are often integrated at distribution levels or near consumption points to manage localized energy needs efficiently [167].

4.2.2. Role of DBESS in supporting EV charger integration

The DBESS plays a crucial role in supporting EV charger integration by providing localized energy management capabilities [168]. They facilitate peak load shaving by storing excess electricity during periods of low demand and releasing it during peak charging times, thereby reducing strain on local distribution networks and improving grid stability [169]. The DBESS also enhances the reliability of EV charging infrastructure by ensuring consistent power supply, especially in areas with fluctuating grid conditions. Barker et al. [170] present an ANFIS-driven power extraction and control strategy for PV-BESS integrated EV charging stations, demonstrating improved efficiency and control in managing energy flow between renewable sources, batteries, and EV chargers. Zhao et al. [171] propose a distributed state-of-charge and power balance estimation method for aggregated battery energy storage systems, specifically designed for EV aggregators, which ensures optimal power distribution and enhances the scalability of EV charging infrastructure.

4.2.3. Advantages and challenges associated with DBESS

Utilizing DBESS offers several advantages alongside inherent challenges. Advantages include enhanced grid resilience through localized energy management, which supports reliable EV charging operations even during grid disturbances [172]. The DBESS also contributes to cost savings by optimizing energy consumption and reducing peak demand charges for EV charging providers. Furthermore, their modular design facilitates easier scalability and integration into existing infrastructure, promoting widespread adoption of EVs. However, challenges such as coordination complexities in managing multiple distributed units, the potential for increased operational costs due to decentralized maintenance, and regulatory uncertainties regarding grid interactions can hinder widespread deployment [173].

4.3. Hybrid ESS (HESS)

4.3.1. Overview of HESS combining different storage technologies

The HESS integrates multiple storage technologies, such as batteries, capacitors, or supercapacitors, to leverage their respective strengths in energy storage and delivery [174]. By combining these technologies, HESS can enhance operational flexibility and efficiency compared to single-storage systems. This hybrid approach allows for better

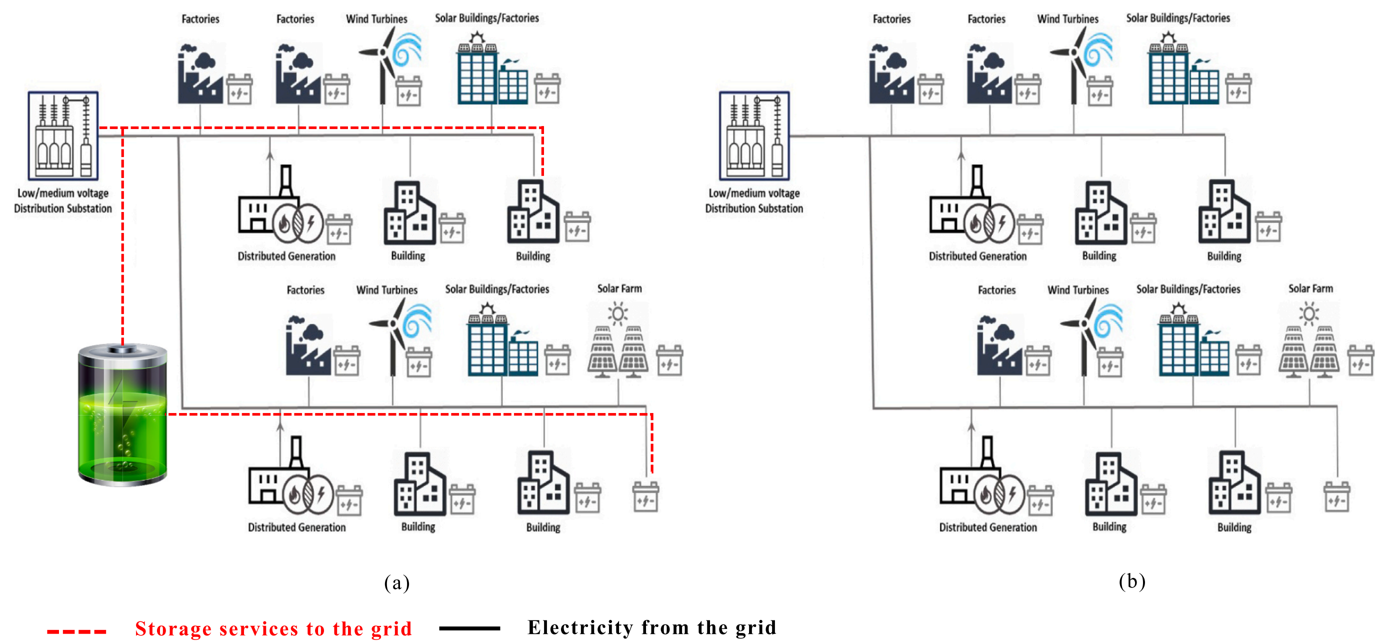

Fig. 9. The BESS connection schematic; a) CBESS and b) DBESS.

Table 2
Comparison of CBESS and DBESS strategies.

Parameter	CBESS		DBESS	
	Without storage	With storage	Without storage	With storage
Additional cost	x	x Investment on storage	x	✓ Investment on storage
Storage strategy	x	x Provision of storage to the grid	x	✓ Optimization of own consumption
Leverage to reduce electricity bill	✓ Reduced cost grid-level	✓ Reduced cost grid-level	Not available	✓ Reduced cost by use of storage onsite
Revenues from storage aggregation	x	x	x	✓ Yes
System-level benefits	x	✓ Load shaving ✓ Load leveling ✓ Ancillary service ✓ Reserve capacity ✓ T&D deferral	x	✓ Possible load leveling ✓ Possible load shaving

management of energy flows, optimized charging and discharging cycles, and improved overall performance in diverse operating conditions [175].

4.3.2. Application of HESS in optimizing EV charger integration

HESS is applied to optimize EV charger integration by offering tailored energy management solutions. These systems can adaptively balance power demands from EV chargers with varying grid conditions and user requirements. HESS enables efficient peak shaving by storing surplus energy during off-peak periods and supplying it during peak demand, thereby reducing strain on the grid and minimizing operational costs for EV charging providers [176]. Moreover, the combination of different storage technologies in HESS allows for rapid response times and enhanced reliability in delivering consistent power to EV chargers, ensuring uninterrupted service even during fluctuating grid conditions or sudden surges in demand.

4.3.3. Performance benefits and challenges of HESS in this context

Utilizing HESS for EV charger integration offers notable performance benefits alongside certain challenges. Benefits include enhanced energy efficiency through optimized storage and utilization strategies, which contribute to cost savings and reduced environmental impact [177]. The HESS also improves grid stability by providing fast-response capabilities and ensuring reliable power supply for EV charging infrastructure. However, challenges such as complex system integration, compatibility issues between different storage technologies, and higher initial investment costs for hybrid systems can pose barriers to widespread adoption [178].

4.4. Smart grid integration solutions

4.4.1. Role of advanced controls and communication in EV charger integration

Advanced controls and communication technologies play a pivotal role in EV charger integration within smart grids [179]. These solutions enable real-time monitoring and management of charging processes, optimizing energy flow based on grid conditions and user preferences. By utilizing sophisticated algorithms and data analytics, smart grid integration systems can prioritize charging schedules, balance load distribution across the grid, and dynamically adjust charging rates to minimize peak demand. Moreover, enhanced communication protocols facilitate seamless interaction between EV chargers, grid operators, and EMSs, ensuring efficient utilization of grid resources and improving overall system reliability. Deng et al. [180] explore the application of a

HESS in fast charging stations, highlighting its role in stabilizing the grid and improving charging efficiency. McDonough [181] investigates the integration of inductively coupled power transfer with a HESS, proposing a multiport power electronics interface to enhance energy transfer efficiency in battery-powered EVs. Song et al. [182] optimize a HESS in EVs using a dynamic programming approach, focusing on improving energy management and extending system lifespan.

4.4.2. *Strategies for enhancing grid stability and managing peak loads*

Strategies for enhancing grid stability and managing peak loads in the context of EV charger integration revolve around proactive management of energy flows and demand response capabilities. Grid operators can implement predictive modelling and forecasting algorithms to anticipate charging patterns and optimize grid resources accordingly [183]. Demand-side management strategies, such as time-of-use pricing incentives and smart charging protocols, encourage users to shift charging activities to off-peak hours, thereby reducing stress on the grid during peak periods. Additionally, deploying ESSs and integrating renewable energy sources into the grid further enhances stability by providing additional capacity and reducing dependency on fossil fuel-based generation during high-demand periods [184]. Finally, a summary of features and challenges for BESS typologies in EV charger integration is presented in Fig. 10.

5. Energy management

Haze, environmental degradation, and energy shortages are just some of the problems that have sprung up in recent years. According to the U.S. Department of Energy, traditional internal combustion engine cars waste about 40 % of fuel energy as heat via exhaust emissions, while only 15 % is used to operate the vehicle and its related components. This results in substantial waste and significant environmental contamination. On the other hand, the EVs may achieve a conversion efficiency of 75 % or more. In other words, running cars and their accessories account for >75 % of total energy use. In addition, the EVs have drawn rising attention over the past decade all over the globe due to their low emission, low pollution, etc. properties. The United States, the European Union, China, and other nations and regions have all adopted regulations to help push the widespread adoption of EVs. The question of how ESSs might be made better to accommodate the high energy and power needs of EVs has received the least amount of attention among these concerns. However, with today's technology, it's challenging for a single ESS to fulfil both the energy and power needs of a vehicle without diminishing the vehicle's lifespan. Therefore, integrating two or more ESSs into a hybrid-ESS might be a suitable approach to overcome the aforementioned issue by making use of each ESS's strengths while avoiding its weaknesses [185]. There is a large variety of features and capabilities available in an EV's ESS. The rated power, charge/discharge rate, power density, energy density, self-discharge rate, reaction time, energy storage efficiency, cycle life, etc. are all key indications [186]. Depending on one's desired level of performance, an appropriate ESS may be selected [187]. There are notable differences between these ESSs. The HESSs are built from many on-board energy storage sources that must work together to handle difficult driving situations. To coordinate the distribution of power among various power sources, HESSs need suitable topologies and EMSs. In addition, by fairly dispersing the power output, the lifespan of the HESSs can be extended, system efficiency can be increased, and system economics can be bolstered. There is a tight relationship between the study of topologies and that of EMSs when it comes to HESSs [188].

5.1. *Energy management strategy*

The foundation of the HESS control approach is figuring out how to allocate the power of the battery packs and the UC packs in various system states to maximize system efficiency and lifespan while fulfilling the power need. With the right management plan in place, a battery/UC hybrid ESS may maximize the benefits of both technologies. The goal of the control strategy is to maximize power efficiency, dynamic performance, and battery life by allocating power between the input and

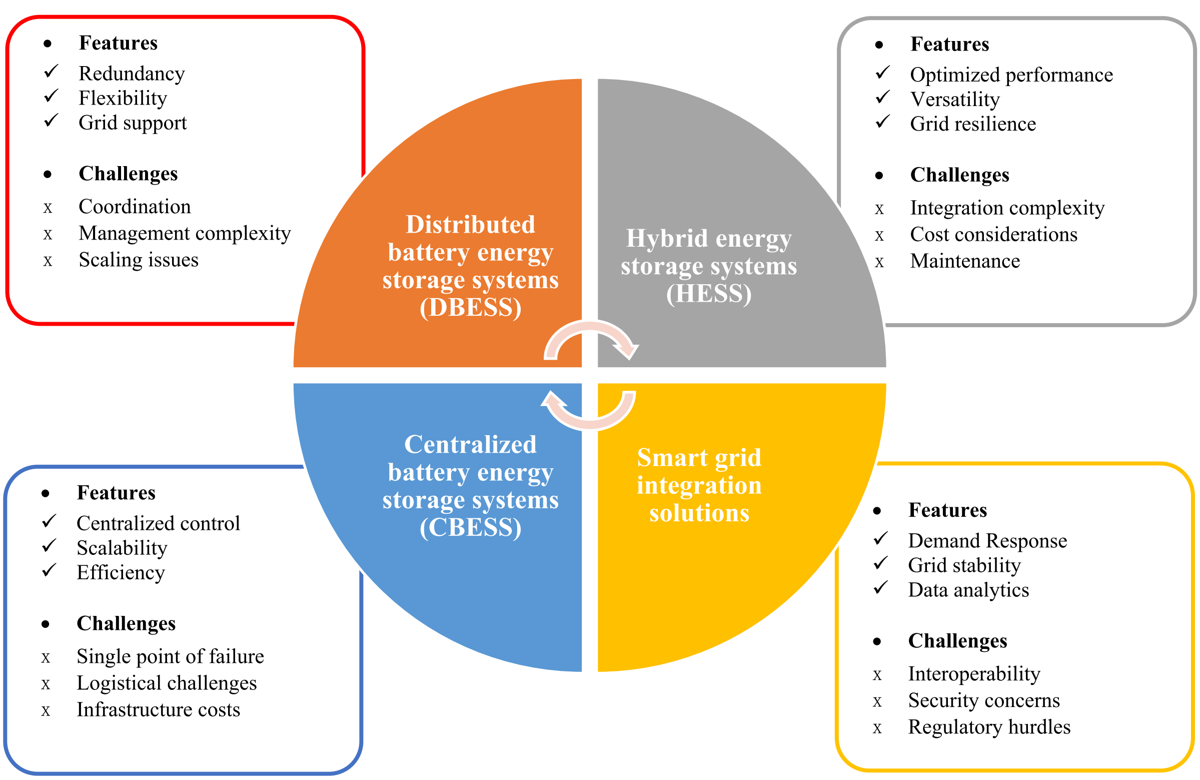

Fig. 10. Summary of features and challenges for BESS typologies in EV charger integration.

output based on the characteristics of the two power sources. The battery must not only provide average demand power and low-frequency power, but the management approach also mandates a decrease in the battery's charge-discharge rate and current surge [189]. The control approach requires both rapid power surges and sustained high frequencies from the UC. When used to increase the high-power charge-discharge capability of HESSs, UC may be seen as acting as a power buffer device. Fig. 11 depicts a status diagram for power distribution in a partially operational HESS.

Currently, rule-based control techniques and optimization-based control strategies comprise most of the HESS EMS research literature. The deterministic rule control method, fuzzy logical control (FLC), and wavelet transform (WT) are the most common types of rule-based EMS [190]. Dynamic programming, genetic algorithms, model predictive control, particle swarm optimization, and linear programming are all examples of optimization-based control systems [191]. It's also important to note the new research into intelligent algorithms like machine learning. Researchers in the field of HESS energy management are also using intelligent algorithms. As shown in Fig. 12, the HESS control techniques examined here fall into one of three broad classes.

5.1.1. Rule-based control strategy

Heuristics and empirical experience-based rule-based control techniques are now the most popular in usage. These approaches have the benefits of being easy to implement and manage, being very resilient and reliable, and requiring little in the way of computer resources [192]. The rule-based control technique can't be modified in practice, which leads to subpar performance in various contexts. Due to its limited capacity, the UC's prior system power distribution and SoC have a direct impact on future system control [193]. In theoretical studies of HESSs, the rule-based control technique is usually combined with other methods. Its most common uses are in conjunction with other control techniques, such as a comparison to optimum control or a combination of control strategies.

5.1.2. Fuzzy logical control

Based on concepts from fuzzy set theory, fuzzy linguistic variable, and fuzzy logical inference, fuzzy logical control (FLC) is a sort of control algorithm. Defining the parameters of the membership function and the fuzzy rule is crucial to the success of the control approach. The fundamental characteristics of FLC are that the fuzzy controller design does not need a precise mathematical model of the controlled objects, nor does it require knowledge of the explicit mathematical connection between the controller's input and output. FLC offers high flexibility and resilience, and its design may be based on the researcher's prior knowledge of the controlled item. Furthermore, it may be broken down further into the classic fuzzy approach, the adaptive fuzzy strategy, and the forecasting fuzzy approach. When it comes to controlling HESSs, FLC is superior to deterministic rule control strategies because of how well it adjusts to changing situations. Since FLC relies on past results, it is often used in tandem with other control procedures by scientists. The authors in [193] suggested utilizing a Markov chain to foresee the power consumption of the system. Based on the forecast and the actual demand power value, the algorithm refined the fuzzy control impact. The modelling and experimental findings validate the viability and efficiency of this approach. Song et al. [194] presented a comparative study on energy management strategies for EVs with hybrid ESSs. The authors evaluated the performance of different strategies, including rule-based, optimization-based, and fuzzy logic-based approaches, and discussed their advantages and disadvantages. The study provided valuable insights into the design and implementation of EMS for hybrid EVs, highlighting the importance of optimizing energy storage and release to improve vehicle performance and efficiency. In contrast, Han et al. [195] proposed a novel EMS based on a frequency-varying filter for battery-supercapacitor hybrid systems in EVs. This study explored the potential of frequency-varying filters to optimize energy storage and release in hybrid systems, demonstrating the effectiveness of this approach in improving the overall efficiency and performance of EVs. Wang et al. [196] developed a fuzzy logic-based power management strategy for HESSs, integrating Markov random prediction to optimize energy management and minimize energy losses. The study highlighted the potential of fuzzy logic and Markov random prediction to improve the efficiency and reliability of HESSs in EVs, providing a valuable contribution to the development of advanced EMSs. Gao et al. [197] presented an optimal fuzzy logic-based EMS for battery-supercapacitor HESSs in EVs. The authors designed a fuzzy logic-based controller to optimize energy storage and release in hybrid systems, demonstrating its effectiveness in improving the overall performance and efficiency of EVs. The study showcased the potential of fuzzy logic-based approaches to enhance the efficiency and reliability of hybrid ESSs. Lastly, Zhou

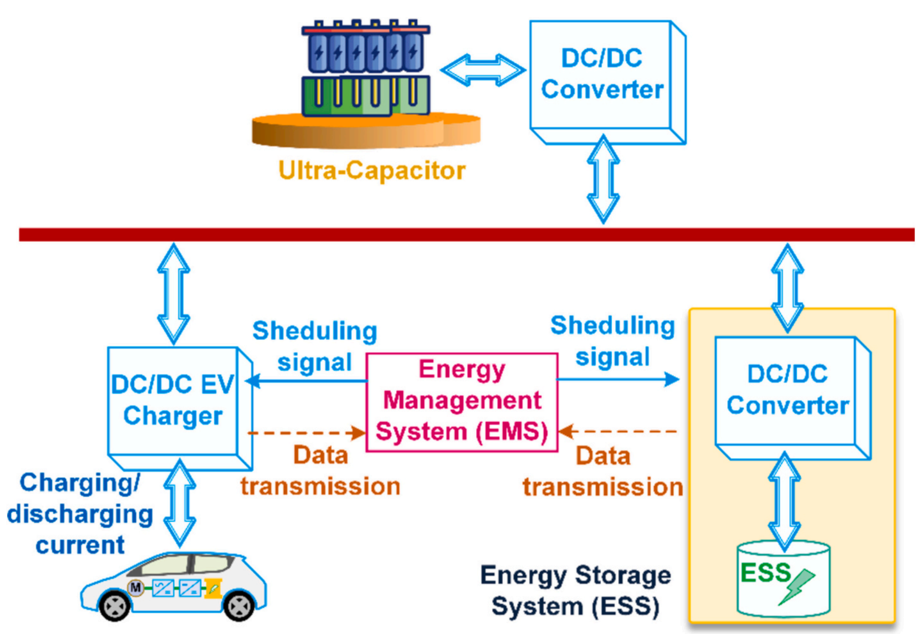

Fig. 11. EV charging station with ESS and ultra-capacitor integration for enhanced power management.

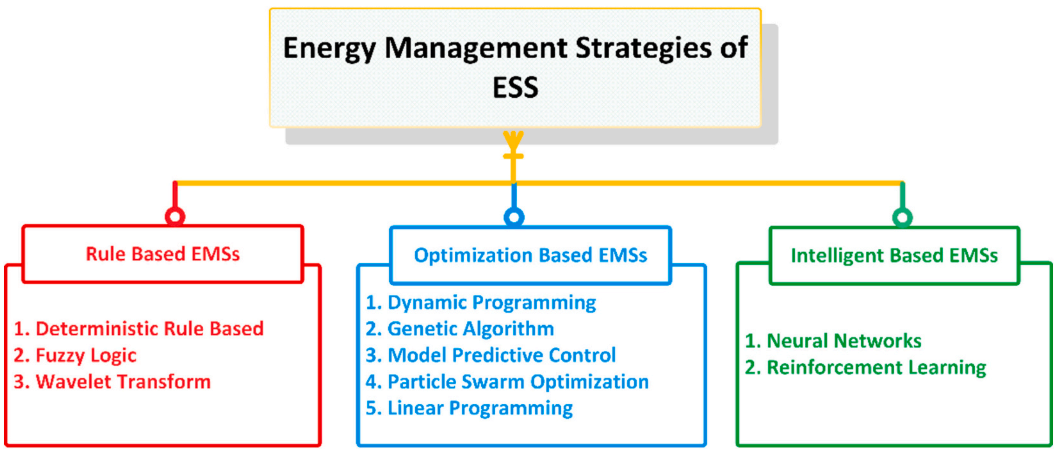

Fig. 12. Classification of ESS control techniques.

et al. [198] proposed an adaptive fuzzy logic-based EMS for EVs. The authors developed an adaptive fuzzy logic controller to optimize energy management in hybrid ESSs, demonstrating its potential to improve the efficiency and reliability of EVs. The study highlighted the importance of adaptive energy management strategies in enhancing the performance and sustainability of EVs, providing a valuable contribution to the development of advanced energy storage technologies.

5.1.3. Wavelet transform

Since the Wavelet transform (WT) can analyze signals locally in both the temporal and frequency domains, it finds widespread application in the field of signal processing. Due to its distinct benefits, the WT algorithm has seen widespread use in the area of energy management in recent years [199]. There may be more than one basis function in a wavelet transform. The Haar wavelet function is one of the most popular basis functions because of its simplicity and utility. Other popular base functions include the Morlet wavelet function, the Daubechies wavelet function, and the Meyer wavelet function. The WT algorithm has been used to separate the high-frequency and low-frequency components of the demand power. The authors in [200] employed discrete WT as a time-frequency filter to regulate HESS by combining it with the power prediction method. For completely active HESS power distribution, Erdinc et al. [201] proposed a wavelet-fuzzy logic-based EMS for a fuel cell/battery/ultra-capacitor hybrid vehicular power system. This approach combines wavelet analysis with fuzzy logic to optimize energy management and improve the overall efficiency of the system. The strategy aims to effectively allocate energy between the different power sources, minimizing energy losses and enhancing the system's reliability. In contrast, Ibrahim et al. [202] developed an EMS for battery/ultra-capacitor HEVs using a nonlinear autoregressive neural network. This approach leverages the capabilities of neural networks (NNs) to predict energy demand and optimize energy storage and release, resulting in improved system efficiency and performance. Meanwhile, Zhang and Deng [203] presented an adaptive EMS for EVs based on driving cycle identification and wavelet transform. This strategy uses wavelet analysis to identify driving patterns and optimize energy management, accordingly, adapting to changing driving conditions to minimize energy consumption and improve overall system efficiency.

5.2. Optimization-based control strategy

A real-time control application is very unlikely to benefit from an optimization-based control technique due to its high computational complexity. However, shortly, it may be implemented online with the optimization of control algorithms, and it can lead to the formulation of rules or other optimal control techniques. Researchers have put in a lot of time and effort into perfecting optimal control for HESSs in recent years. The power loss of a HESS is often regarded as an optimization goal function among the many uses of the optimization control algorithm. The total power loss is broken down into three main components as:

$$P_{ESS-loss} = P_{Bat-loss} + P_{UC-loss} + P_{DC/DC-loss} \tag{5}$$

where $P_{Bat-loss}$ is battery loss, $P_{UC-loss}$ is ultracapacitor loss and $P_{DC/DC-loss}$ is DC/DC converter loss.

The total power loss $P_{ESS-loss}$ of the HESS is the sum of the individual losses from the battery, ultracapacitor, and DC/DC converter. Minimizing these losses is typically an important objective in the design and control of HESS, as it improves the system's overall efficiency and extends the lifetime of the energy storage components. Optimization algorithms are often applied to minimize these losses by adjusting how power is distributed between the battery and ultracapacitor, managing the operating points of the DC/DC converter, and balancing efficiency against performance requirements [204]. The primary focus of this part is a comparison and analysis of the research algorithms for best practices in HESS energy management. Particle swarm optimization, which is often used for PHEVs or fuel cell HEVs, is not examined in this research since it is not widely used for HESSs.

5.2.1. Dynamic programming

The best control input for a deterministic system may be calculated using DP and an appropriately crafted optimization objective function. DP is superior to other optimization control theories because of its ability to perform global optimization on complicated linear and nonlinear systems with many states and inputs. DP is often employed in HESS control due to its global optimality. The authors in [205] utilized DP to improve system control by incorporating a battery lifetime degradation model; this reduced system expenses and increased battery lifespan compared to a rule-based control method. The authors in [206] suggested a battery lifetime model to get the ideal battery and UC pack parameter values and the best system management approach based on DP for a HESS applied to a Series Plug-in HEV, to extend the battery's useful life. The authors in [207] suggested a battery lifetime degradation model under various temperatures and discharge depths and improved the HESS power distribution under different states using the DP method because of the decline in battery performance and lifespan attenuation at low temperatures. In addition, various rule control systems and optimization procedures for training and education may benefit from DP's HESS optimum outcomes [208]. To implement the best control strategy in real-time across a variety of operational settings, the authors in [209] derived a rules-based control strategy from the DP technique. From the optimum results achieved by DP under multi-conditions, The authors in [210] retrieved suboptimal rules, and the optimized rule control technique has clear benefits. The authors in [211] employed DP-optimized findings to successfully train an online-applicable neural networks model. Future HESS EMSs will have useful references thanks to this optimization training strategy. Additionally, DP may be used to assess energy-based HESS management algorithms and compare various HESS architectures [212]. The authors in [213] built and released a general DP toolbox that can be executed in Matlab because of the widespread use of DP in optimum system control. Due to the need for knowledge about the future system state when using DP in a HESS control application, this rule is best utilized for comparative purposes and not in real time. Moreover, DP has to go through a lot of data, which results in a hefty computation overhead, particularly in the presence of various states and inputs. The calculation grows exponentially when the variables are too big and the computing grid is too thin, a situation known as a “dimensional disaster”.

5.2.2. Genetic algorithm

The natural selection theory and genetic mechanism in Darwin's biological evolution theory provide the basis of the genetic algorithm (GA), a computing model that replicates the biological evolution process. It's a way to find the best answer by mimicking how evolution works. Generalized additive models are very flexible and resilient, able to handle nonlinear, multi-model, and multi-objective function optimization issues. The following are some of its features:

i) GA begins its search with a predefined set of strings; this gives it broad coverage and the ability to choose the global optimum. To prevent local optimization,
ii) GA may process numerous persons in parallel. Third, GA does not need a continuous differentiable since it employs the fitness function as the optimization target. The domain may be chosen at will, and the range of possible uses is enormous.
iii) In GA, the chance of an individual's survival is decided by their fitness, and the search direction is selected automatically.
iv) GA is capable of self-organization, -adaptation, and -learning. GA is often utilized in the EMS of HESSs since it is a sort of global optimization technique. The authors in [214] suggested a GA-based real-time control method that limits the battery's charge-discharge cycles. The authors in [215] proposed an optimum fuzzy control method based on GA and got excellent results since the FLC depends too much on experts' expertise and has poor performance in system control. Researchers optimized the daily energy usage and battery deterioration costs of light-rail cars using GA, which included the introduction of battery lifespan costs. It was shown to have a cost-cutting effect of 13.9 % on operations [216]. The multi-objective and nonlinear issues of the system have led to GA's employment in parameter matching and optimization of several energy sources. However, there are situations where GA struggles, namely with multi-object and nonlinear optimization problems. However, it is classified as a stochastic algorithm, which might provide sub-optimal results in real-world situations.

5.2.3. Model predictive control

This technique was used in HESS control applications to bridge the gap between global optimization and real-time management. The success of model predictive control (MPC) hinges on two factors: how well predictions are made and how well the control method is optimized. Researchers have devised a HESS control strategy that utilizes predictions of driving circumstances and system demand power to increase the control efficiency of a HESS and maximize the real-time and resilience of the system control strategy. In HESS control, MPC is used in conjunction with other methods, like the Markov process to predict the vehicle information in a limited time domain, and then an optimization algorithm, like quadratic programming, the DP algorithm is used to optimize the power distribution in the control system. Power allocation and prediction for HESSs was conducted using the MPC toolbox in MATLAB. Usually, it is important to construct a complicated nonlinear system model and develop the DC-DC model to enhance the precision of system control [217]. Validation of complicated models requires a high-performance test rig due to their computational complexity. Many academics have used a linear system model to simplify the MPC method calculation, which is not surprising given MPC's versatility and depth of complexity. The authors in [218] suggested utilizing numerous low-order MPC models to regulate individual HESS components, this approach would inevitably lead to worse prediction and control. The authors in [219] developed a strategy for reducing the computational burden of MPC algorithms by using non-uniform sample periods for various prediction scenarios. Multiple articles used different ways to control multiple power sources. The authors in [220] presented a hierarchical control mechanism for a HESS to minimize the decline in battery life and maximize system efficiency. To balance the load on a HESS, the authors in [221] integrated the rule-based method with MPC. Fig. 13 illustrates a MG system incorporating renewable energy sources such as wind turbines and solar panels, a BESS for storing excess energy, and EV charging stations. The system employs an MPC strategy to optimize energy flow and utilization. The MPC predicts future system behavior and makes control decisions to maximize the utilization of renewable energy, minimize reliance on the grid, optimize EV charging schedules, and maintain grid stability by providing ancillary services like frequency regulation and voltage support. The BESS plays a crucial role in mitigating the intermittency of renewable energy sources and enabling grid-independent operation. The MPC aims to achieve these objectives while minimizing operational costs and maximizing energy efficiency. Fig. 13 highlights the power flows between these components, controlled by the MPC algorithm to achieve the desired outcomes.

5.3. Artificial intelligence-based control strategy

Algorithms based on AI will play a significant role in system control in the future. Pattern recognition of complicated pictures [222] has been accomplished using cross-modal subspace learning algorithms, which also have reference value in vehicle condition prediction and energy management. AI algorithms have been used for HESSs by researchers. Basic AI algorithms include NNs, hence NNs and reinforcement learning methods are included together. These algorithms are the future of HESS-focused intelligent algorithms.

5.3.1. Neural networks

By modelling the properties of human neural activity, NNs achieve a similarity to human computational and cognitive processes. When used, NNs perform best when trained with a large amount of data. Learning NNs is essentially an inductive learning method. The internal adaptive algorithm continually adjusts the weight across neurons, causing weight distributions to converge to a stable range based on the repeated learning of a large number of occurrences. Training NNs optimally requires a large sample size. First, NNs have a high degree of parallelism; second, they play a non-linear global role; third, they have great fault tolerance and associative memory; and fourth, they are highly adaptable and capable of learning. In addition to being able to quickly process system control, NNs also perform well in nonlinear situations. Controlling systems, recognizing patterns, making predictions, and optimizing processes all make use of them to varying degrees. When utilizing an NN for a HESS, researchers must first gather a large number of high-quality control data sets. Once the NN has been trained, the remaining portions of the data sets are utilized to ensure it has been correctly applied. Many studies have been conducted employing NNs for HESS optimization based on this principle. To achieve real-time application of optimized data and real-time verification [223], the authors in [224] trained an NN controller using HESS power distribution data based on a DP method. The authors in [225] improved productivity by 3.3 % by using data-trained NNs to replace the PI feedback system's rules. The authors in [226] successfully implemented an NN for system control to enhance the

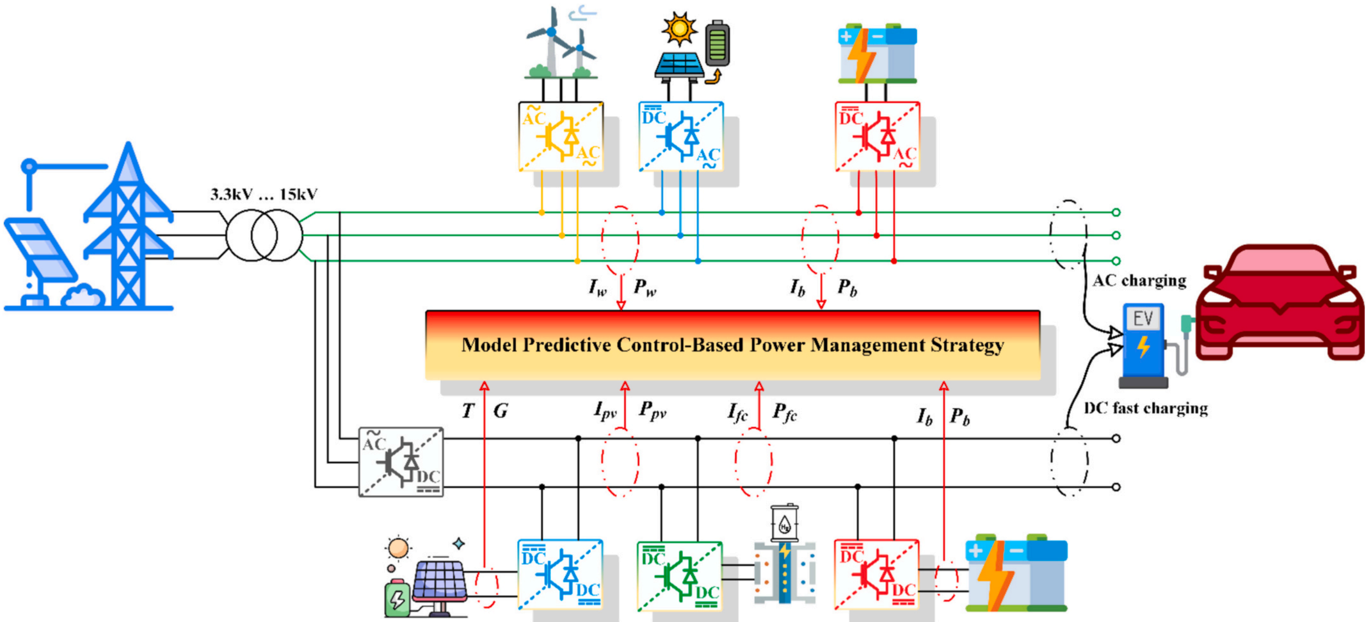

Fig. 13. BESS and EV charging with MPC for MG power management.

transient performance of HESS power distribution. In addition, NNs have a significant impact on velocity forecasting [227]. There is a clear correlation between the volume and quality of training, as well as the usefulness of the preexisting NN models, and the results. It's important to quantify the effects of many variables on NN development and training. Further, Kalogirou's [228] provides an overview of the use of artificial neural networks in renewable energy systems, highlighting their potential to improve the efficiency and performance of these systems. In contrast, Jui et al. [229] present a survey of recent machine learning approaches for optimal energy management strategies in HEVs, demonstrating the growing interest in using advanced algorithms to optimize energy consumption and reduce emissions. Wang et al. [230] propose a novel EMS for HEVs that combines computer vision and deep reinforcement learning, enabling the system to learn from real-time data and adapt to changing driving conditions. Similarly, Li et al. [231] develop a deep reinforcement learning-based EMS for series HEVs, which utilizes history cumulative trip information to optimize energy consumption and improve vehicle performance.

Fig. 14 illustrates an RL-based framework for optimizing the scheduling of a BESS integrated with a PV system. The system's power balance involves four key components: the BESS, the PV system, the residential building load, and the external grid connection [232]. Before training the RL agent, a mathematical model is developed to ensure that the sum of all power flows equals zero, maintaining system balance. This model is built using a database comprising PV generation, electricity load profiles, pricing data, and BESS specifications. The RL framework comprises an agent that interacts with an environment, which simulates the dynamics of the energy system. The agent's state includes crucial

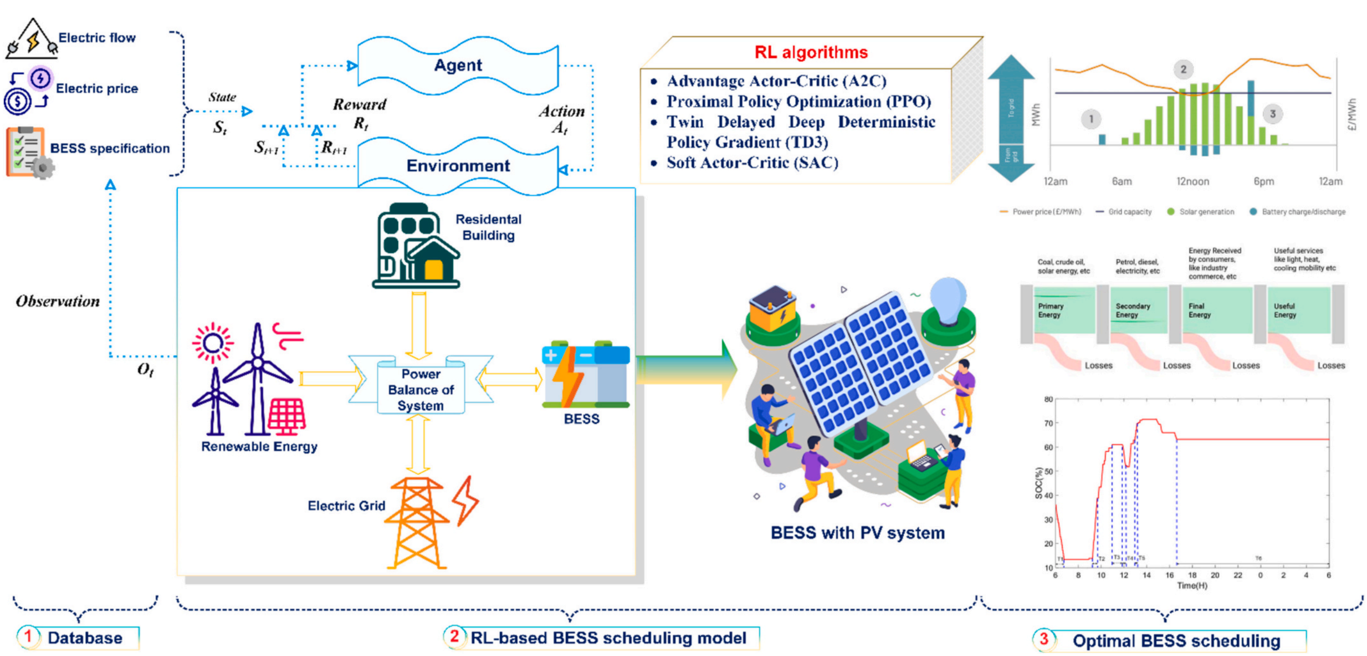

Fig. 14. RL-based energy management for optimizing BESS scheduling.

parameters such as the time of day, PV generation, residential load, BESS SoC, and electricity prices for buying and selling at each timestep. Since the purchase price of electricity is higher than the sale price, the framework focuses on maximizing the self-sufficiency rate (SSR) to minimize dependency on grid electricity and reduce operational costs. The reward function is designed to promote SSR maximization while also minimizing peak load, reflecting the assumption that higher SSR leads to greater economic benefits. The RL agent continuously trains and improves its scheduling decisions by interacting with the environment and optimizing the reward. Various RL algorithms, such as advantage actor-critic (A2C), proximal policy optimization (PPO), and soft actor-critic (SAC), are used for training. The performance of the trained RL model is validated through comparison with other optimization methods [233]. This approach highlights the framework's ability to adapt to real-world uncertainties, dynamic energy profiles, and operational conditions, ensuring robust and efficient BESS scheduling [234]. Fig. 14 also depicts key power flows and the interaction of system components, emphasizing the role of RL in achieving optimal energy management for residential applications [235].

5.3.2. Reinforcement learning

As computing, operations research, and robotics continue to progress, so do the applications of new intelligent algorithms. Future system control will likely make extensive use of clever algorithms. Among them, reinforcement learning (RL) has been successfully used in HESS EMSs. In the 1950s, the authors in [236] proposed the RL algorithm. Since significant progress has been made in the mathematical foundations of RL, it has emerged as a leading research area in the field of machine learning [237]. The RL algorithm is now popular in the domains of automated control for complex systems. RL is the process of directing a system by monitoring and evaluating its present behavior to arrive at the best possible choice via trial and error in the face of uncertainty about the system's structure and characteristics [238,239]. The efficiency of the proposed real-time EMS is shown by contrasting the simulation results of the RL algorithm with those of the DP method. The authors in [240] account for both battery life and temperature fluctuations in HESS EMSs using the RL algorithm that accounts for forgetting variables. The findings demonstrate that in comparison to a rule-based control technique, the RL-based algorithm is 16.8 % more effective at minimizing energy loss. A hybrid ESS (HESS) that makes use of fuel cells and batteries also employs RL [241]. The study of EMSs for HESSs has made considerable strides in recent years. There has to be more testing and real-world use of the current crop of innovative algorithms. However, many EMSs' designs only assumed that the future route information was provided when in fact it was not. Under normal situations, HESS performance may be greatly improved by focusing on EMS optimization. However, since the actual circumstances are unknown, many innovative algorithms are not usable in real-world settings.

6. Challenges and opportunities

6.1. The impact of ESS and the power grid on large-scale EV chargers

The integration of stationary ESS plays a critical role in addressing challenges posed by large-scale EV chargers, particularly at high-capacity charging plazas equipped with direct current fast charging (DCFC) stations. ESS solutions mitigate the strain on the power grid, stabilize demand fluctuations, and optimize the operation of EV charging plazas. By leveling the power demand of EV charging plazas, ESS can significantly decrease the required connection power, reducing the reliance on grid infrastructure during peak usage. ESS systems absorb excess energy during low-demand periods and supply power during high-demand intervals, ensuring smooth and consistent grid interaction. This functionality not only stabilizes grid voltage but also minimizes power quality disturbances, such as sudden voltage sags and frequency variations, caused by fast charging stations [242]. The sizing of ESS is a crucial consideration, as its capacity directly influences its effectiveness in supporting large-scale EV chargers. Studies show that a relatively small ESS capacity can substantially reduce the required connection power, even for large charging plazas with multiple DCFC stations. However, the ESS requirements are inversely proportional to the charging plaza size and grid connection power, indicating that larger plazas or those with higher connection power need proportionally smaller ESS capacities for the same level of demand reduction [243].

The power grid also plays a vital role in facilitating the operation of large-scale EV chargers. An adequately designed grid connection, coupled with advanced grid management techniques, enhances the performance and reliability of EV charging plazas. Smart grid integration and demand-response strategies allow real-time optimization of power flow, enabling dynamic adjustment of energy supply to match fluctuating demand [244]. These strategies reduce stress on the grid while maintaining efficient and reliable charging services for EV users. The temporal resolution of EV charging data significantly impacts the accuracy of ESS sizing and performance assessment. Averaging intervals in charging power time series data, ranging from 1 s to 1 h, can distort the results, leading to underestimation of ESS capacity requirements and utilization rates [245]. High-resolution data is therefore essential to ensure precise ESS specifications and optimal performance, particularly for large-scale EV charging applications. By leveraging ESS and advanced grid integration, EV charging plazas can achieve higher operational efficiency, reduced dependency on grid upgrades, and enhanced charging reliability. These solutions collectively support the transition to widespread EV adoption while mitigating the challenges associated with large-scale EV charger deployment [246].

6.2. Technical challenges in EV charger integration

The integration of EV chargers into the power grid presents several technical challenges. One of the most significant issues is grid capacity limitations. The existing grid infrastructure in many regions is not designed to handle the additional load that large-scale EV charger deployment brings, especially during peak hours when many EVs are charging simultaneously. This increased demand can lead to voltage instability, power outages, and PQ issues such as voltage sags, harmonic distortions, and flicker. Furthermore, harmonic disturbances from EV chargers, particularly fast chargers, can negatively affect other connected loads, resulting in decreased PQ and equipment lifespan. Another technical challenge is ensuring grid reliability. As more EVs are integrated into the grid, managing the intermittent nature of renewable energy sources becomes critical. Without proper EMSs, the power supply might become unreliable, leading to potential disruptions in electricity delivery [247].

6.3. Economic challenges

The high installation costs associated with EV chargers, particularly fast-charging stations, are a major economic barrier to widespread adoption. These costs include not only the hardware but also the infrastructure upgrades required to support the increased load, such as transformer upgrades, new substations, and enhancements to distribution lines. Moreover, there are ongoing operational costs, including maintenance, energy supply, and demand response systems to mitigate PQ issues. For utilities and governments, the cost of upgrading the grid infrastructure to support EV chargers can be substantial. From a consumer perspective, cost parity between EVs and conventional vehicles remains a concern. While the price of EVs has been decreasing, the upfront cost is still higher than traditional internal combustion engine vehicles. Without sufficient incentives or subsidies, the economic attractiveness of EVs may be limited, slowing down the demand for EV chargers [248].

6.4. Regulatory and policy challenges

On the regulatory front, policy frameworks need to evolve to support the large-scale integration of EV chargers into the grid. Grid codes and standards for EV chargers, including PQ requirements, interoperability, and safety protocols, are still in development in many regions. A lack of uniform standards can lead to compatibility issues between different types of chargers and vehicles, hindering widespread adoption. Moreover, governments must implement incentives for renewable energy integration with EV charging infrastructure. Policies promoting the use of renewable energy sources to power EV chargers, such as solar-powered EV charging stations, are critical to reducing the carbon footprint of EVs. However, the regulatory environment in many regions is still catching up to these innovations, delaying the broader adoption of green charging solutions [249,250].

6.5. Opportunities in EV charger integration

Despite the challenges, significant opportunities exist for advancing EV charger integration into the grid. One of the most promising areas is the advancement of smart grid technologies. Smart grids, which integrate real-time monitoring, distributed energy resources (DERs), and advanced communication technologies, can help manage the increased load from EV chargers more efficiently. By using demand-side management (DSM) and real-time optimization, smart grids can shift EV charging to off-peak hours, reduce strain on the grid, and improve PQ. The V2G technology also offers a substantial opportunity, allowing EVs to act as distributed storage units that can feed energy back into the grid during times of high demand. The BESS represents another critical opportunity. By coupling EV chargers with BESS, utilities can mitigate the intermittency of renewable energy sources like solar and wind, providing a buffer during periods of high demand. This integration also helps address PQ issues, as BESS can smooth out voltage fluctuations and provide backup power during grid disturbances. Additionally, policy support for renewable energy and sustainability initiatives is growing globally. Governments are increasingly recognizing the need to promote clean transportation and reduce greenhouse gas emissions. As part of this shift, many regions are implementing EV charging incentives, subsidies for renewable energy-powered EV stations, and carbon credit programs to make EV infrastructure investments more attractive for businesses and consumers [251,252].

Finally, innovation in EMS offers another avenue for addressing the challenges of EV charger integration. With the development of intelligent EMSs, incorporating machine learning, real-time optimization, and predictive algorithms, utilities can better balance load demand, manage PQ, and improve overall system reliability. These advancements not only support the large-scale adoption of EV chargers but also contribute to the efficient operation of the power grid as a whole.

6.6. Intelligent energy management strategy

The control performance of EMSs for hybrid EVs (HEVs) can be enhanced through intelligent methods, though several issues remain. A significant factor affecting EMS performance is the driving cycle. Since the driving cycle influences the control outcomes of all existing EMSs, incorporating driving cycle identification or prediction into the strategy could enhance HEV performance. However, forecast information from vehicle-mounted sensors or navigation systems often contains uncertainties and disruptions, making accurate driving cycle predictions challenging. Additionally, algorithms designed for driving cycle recognition or prediction can increase the computational burden on the system. Therefore, there is a need for a simple, practical, effective, and resilient algorithm for recognizing or predicting the driving cycle. To further optimize performance, integrated multi-objective and coordinated optimization are crucial. The ultimate goal of HEV energy management is to create commercially viable, high-performance vehicles that require EMSs combining multiple objectives such as energy conservation (fuel economy), environmental protection (emissions), safety (fault tolerance and component durability), and comfort (drivability). While some strategies consider additional performance metrics like emissions and drivability, they are often treated as penalty terms in the optimization problem and largely overlooked. To meet the multifaceted requirements of HEVs, future EMSs must prioritize not only energy efficiency but also environmental friendliness, passenger safety, and driving comfort. In addition to optimization, powertrain modelling errors and their impact on control performance should be carefully studied. While convex optimization has proven to be an efficient strategy for powertrain dimensioning, energy management control, engine on/off control, and gear-shifting control in HEVs, alternative practical methods of energy management also need exploration [253,254].

6.7. Computational complexity and optimization performance

A major challenge in the development of EMSs is finding a balance between computational complexity and optimization performance. Currently, many EMSs reduce the computational burden at the cost of optimization performance, resulting in only short-term fixes rather than permanent solutions. One potential avenue for overcoming this challenge is cloud computing, which can help maintain the optimality of an energy management plan while managing computational complexity. Until new real-time optimization algorithms are developed, it is important to simplify existing optimization methods. Research is needed to determine whether this simplification should focus on optimization issues, algorithm implementation, or powertrain models—or possibly all three. The goal is to find methods that reduce computation without sacrificing control performance [255,256].

6.8. Fair and trustworthy assessment system

Each approach to energy management has its benefits and drawbacks. To develop the most appropriate EMS for a specific HEV and its performance goals, a fair and trustworthy assessment system is essential. This system would evaluate different energy management methods, providing a clear understanding of their effectiveness and trade-offs. In addition to evaluation, establishing an appropriate assessment mechanism is critical to bridging gaps in current EMS research. A standardized, transparent framework for comparing different strategies would facilitate the development of more efficient and effective EMSs, contributing to the advancement of HEVs and their integration into the broader energy ecosystem [257].

7. Conclusions and future research opportunities

The integration of EVs into modern power grids presents remarkable opportunities but also significant challenges, particularly concerning PQ and load management. This review synthesizes current research, offering a comprehensive and innovative analysis of the pivotal role of the ESSs in enabling large-scale EV charger integration while addressing associated PQ challenges. A central contribution of this review is the detailed comparative evaluation of various ESS typologies—BESS, HESS, and DESS—each demonstrating distinct advantages in mitigating PQ issues such as harmonic distortion, voltage regulation, and peak demand control. Compliance with IEEE-519 standards is highlighted as essential for preserving grid reliability and maintaining high PQ standards amid the rising deployment of EV chargers. This review explores the various impacts of the PEVs on power grids, highlighting key contributions. It analyzes PEV charging and storage, showing how their charging patterns and energy storage can improve grid stability and efficiency. This review paper emphasizes the potential of V2G technology, which allows bidirectional power flow to support grid functions such as stabilization, energy balancing, and ancillary services. It also addresses ways to reduce harmonic distortion from PEV charging, protecting transformer performance and lifespan. Strategies for managing large-scale PEV integration, including predictive and adaptive control, are discussed. The study presents new approaches to improving grid recovery after disturbances and evaluates the integration of renewable energy with PEVs for more sustainable systems. Lastly, this review paper introduces models for PEV interaction with MGs, boosting energy resilience and grid flexibility. These contributions provide a roadmap for tackling modern power grid challenges.

The paper highlights the crucial role of advanced EMSs in optimizing EV-grid integration and improving system efficiency. These EMSs fall into three main categories: rule-based EMSs, which rely on fixed rules, fuzzy logic, and wavelet transforms; optimization-based EMSs, using methods like dynamic programming, genetic algorithms, MPC, and particle swarm optimization; and intelligent EMSs, which apply neural networks and reinforcement learning for adaptive and predictive control. These strategies are vital for effectively managing and coordinating energy flows in EV-grid systems. As electric mobility continues to advance, V2G technology emerges as a transformative solution for enhancing grid resilience and stability, fostering a sustainable energy future. This study underscores the importance of ongoing innovation and strategic collaboration among utilities, policymakers, researchers, and technology developers to address the technical, economic, and regulatory challenges associated with EV charger integration.

The future of EV integration relies on advancements in scalable ESS technologies with higher energy density and longer lifespans, driven by research into new materials like solid-state and flow batteries. Intelligent grid management systems will leverage AI and machine learning (ML) for real-time optimization and enhanced cyber-resilience. Improved EV-grid interaction models will explore innovative vehicle-to-everything (V2X) paradigms, expanding beyond traditional V2G applications to include vehicle-to vehicle (V2V), vehicle-to-home (V2H) and vehicle-to-building (V2B) scenarios. These models will enable EVs to function as distributed energy resources, contributing to peak load management, demand response, and grid stability. Economic and environmental considerations, including lifecycle cost analyses and supportive policies, are crucial. Blockchain technology may facilitate energy trading and peer-to-peer (P2P) energy exchange in EV networks. Interdisciplinary collaboration between researchers, policymakers, and industry stakeholders is vital to overcome challenges and ensure the successful integration of EVs into a reliable and sustainable power grid. This research provides a visionary roadmap for future innovations, highlighting the need for interdisciplinary collaboration between researchers, policymakers, and industry stakeholders to overcome the technical, economic, and regulatory challenges associated with EV integration into modern power systems.

CRediT authorship contribution statement

Doğan Çelik: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Muhammad Adnan Khan:** Writing – original draft, Methodology, Formal analysis. **Nima Khosravi:** Writing – original draft, Formal analysis. **Muhammad Waseem:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Hafiz Ahmed:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

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

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Data availability

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

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