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Smart Grid–Based Charge Scheduling of Electric Vehicles: A Comprehensive Review

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Abstract: The rapid penetration of electric vehicles (EVs) presents significant challenges and opportunities for modern smart grids. Uncoordinated EV charging can lead to increased peak demand, voltage deviations, and accelerated aging of distribution infrastructure, whereas coordinated charge scheduling can enhance grid reliability, reduce operational costs, and facilitate renewable energy integration. This paper presents a comprehensive review of EV charge scheduling strategies within smart grid environments. Various control architectures, including centralized, decentralized, and hierarchical approaches, are examined along with their corresponding optimization objectives such as cost minimization, peak load reduction, loss mitigation, and user comfort maximization. The review covers mathematical formulations based on deterministic, stochastic, and robust optimization, as well as emerging data-driven and reinforcement learning-based techniques for real-time scheduling under uncertainty. Bidirectional vehicle-to-grid (V2G) operations and their role in providing ancillary services are also discussed. Furthermore, commonly used datasets, simulation tools, and performance metrics for evaluating charging strategies are summarized. Finally, key challenges related to scalability, user behavior modeling, uncertainty management, and cyber security are highlighted, and future research directions toward intelligent, flexible, and user-centric EV charging frameworks are identified.

Keywords: Electric Vehicles (EVs), Smart Grid, Charge Scheduling, Smart Charging, Vehicle-to-Grid (V2G), Optimization Techniques, Reinforcement Learning, Demand Response, Renewable Energy Integration, Distribution Networks.

I. INTRODUCTION

The global transition toward sustainable transportation has led to the rapid adoption of electric vehicles (EVs) as a promising solution for reducing greenhouse gas emissions and dependence on fossil fuels. Advancements in battery technology, supportive government policies, and declining costs of electric drivetrains have significantly accelerated EV penetration across residential, commercial, and public charging infrastructures. While this transition offers substantial environmental and economic benefits, it also introduces new operational challenges for power systems, particularly at the distribution level[1].Uncoordinated EV charging, especially during peak demand periods, can result in excessive load growth, voltage fluctuations, increased power losses, and overloading of transformers and feeders. Such impacts may compromise grid reliability and necessitate costly infrastructure upgrades. Conversely, the integration of EVs within smart grids presents a unique opportunity to enhance system flexibility through intelligent charge scheduling. By leveraging advanced communication, control, and automation technologies, smart charging strategies can shift and regulate EV charging demand in response to grid conditions, electricity prices, and renewable energy availability[2].

Charge scheduling of EVs aims to optimally determine charging power levels and time slots while satisfying user requirements such as energy demand and departure time constraints. Over the past decade, a wide range of scheduling approaches has been proposed, including centralized optimization, decentralized and distributed control, and hierarchical architectures involving aggregators. These approaches typically pursue objectives such as minimizing charging costs, reducing peak demand, improving voltage profiles, mitigating power losses, and maximizing user comfort[3]. Furthermore, the emergence of bidirectional vehicle-to-grid (V2G) technology enables EVs to act as distributed energy resources capable of supplying power back to the grid, thereby supporting frequency regulation and other ancillary services.Recent research has also focused on addressing uncertainties inherent in EV charging, such as stochastic arrival and departure times, variable state-of-charge requirements, and intermittent renewable generation. To handle these challenges, advanced techniques including stochastic and robust optimization, game theory, model predictive control, and data-driven methods such as reinforcement learning have been increasingly explored. These intelligent approaches enable real-time adaptation and scalability, which are essential for large-scale EV integration in future smart grids[4].

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Despite significant progress, several challenges remain unresolved, including scalability to large EV fleets, user participation and incentive design, cyber security and privacy concerns, and the economic feasibility of V2G operations considering battery degradation[5]. Therefore, a comprehensive review of EV charge scheduling techniques is essential to consolidate existing knowledge, compare methodologies, and identify research gaps.In this context, this paper presents a systematic review of EV charge scheduling in smart grid environments.[6]

II. BACKGROUND

An electric power system operates through three fundamental functional layers: generation, transmission, and distribution. Electrical energy is produced at generation units and transported over long distances through the transmission network before being delivered to consumers via the distribution system, which comprises substations, feeders, and transformers. The transmission network is supervised and regulated by an Independent System Operator (ISO), responsible for maintaining system stability, reliability, and balance between power supply and demand. The increasing integration of distributed energy resources, including renewable generation and energy storage systems, has introduced new challenges in power flow control and system coordination [7]. These developments have accelerated the transition from conventional power grids to smart grids, which combine electrical infrastructure with advanced communication and information technologies. Smart grids employ intelligent sensors and control devices at the physical layer to enable real-time monitoring, while higher-level decision-making is supported through data analytics and automation platforms to enhance system efficiency and responsiveness[8].

In the existing literature, smart grids are generally described using three conceptual frameworks: the Internet-based model, the active network model, and the microgrid model. The Internet-based model relies on information and communication technologies to establish real-time connectivity among grid components, enabling rapid adaptation to variations in electricity demand, generation availability, and market prices. The active network model focuses on strengthening interactions between generation and consumption points, allowing end users to modify their load profiles based on real-time pricing signals and demand-side management programs, thereby improving supply–demand coordination[10]. The microgrid model conceptualizes the smart grid as an interconnected network of intelligent microgrids, where each microgrid is capable of locally generating, distributing, and managing electricity for a defined group of consumers. These microgrids can operate independently or exchange power with the main grid, enhancing overall system reliability and operational flexibility[11].

The deployment of smart grid technologies offers several advantages, including improved reliability and efficiency in power generation, automated system operation and maintenance, enhanced utilization of existing network assets, and increased resilience against disturbances. Additionally, smart grids support predictive maintenance strategies and self-healing mechanisms that enable rapid detection and mitigation of system imbalances. The integration of renewable energy sources is also facilitated, contributing to environmentally sustainable power system operation[12].Demand response mechanisms play a crucial role in achieving the objectives of smart grids. By providing consumers with real-time information on electricity prices and availability, demand response programs encourage the shifting of flexible loads to off-peak periods, resulting in economic benefits for users. Simultaneously, these programs alleviate peak demand stress on the grid, reduce the likelihood of congestion and overloads, and enhance the ISO's ability to efficiently manage system operations[13].

III. CLASSIFICATION OF CHARGE SCHEDULING ALGORITHMS FOR ELECTRIC VEHICLES IN SMART GRIDS

Charge scheduling algorithms for electric vehicle (EV) charging in smart grid environments are designed to optimally manage charging demand while satisfying grid constraints and user requirements. Based on control architecture, decision-making strategy, uncertainty handling, and operational objectives, these algorithms can be broadly classified into several categories[14].

A) BASED ON CONTROL ARCHITECTURE

I. CENTRALIZED SCHEDULING ALGORITHMS

In centralized approaches, a central entity such as a utility operator or an aggregator collects charging requests and system information from all EVs and determines an optimal charging schedule for the entire system. These methods often rely on deterministic or mixed-integer optimization techniques to minimize objectives such as total charging cost,

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peak demand, or power losses. While centralized algorithms can achieve globally optimal solutions, they face challenges related to scalability, communication overhead, and user privacy.

II. DECENTRALIZED SCHEDULING ALGORITHMS

Decentralized algorithms distribute decision-making among individual EVs or local controllers. Each EV independently determines its charging behavior based on local information or price signals broadcast by the grid operator. Game-theoretic models and price-based demand response strategies are commonly used in this category. Decentralized approaches improve scalability and privacy but may lead to suboptimal system-wide performance if coordination is limited.

III. HIERARCHICAL SCHEDULING ALGORITHMS

Hierarchical approaches combine centralized and decentralized strategies by introducing multiple control layers, such as grid operator, aggregator, and EV levels. The upper layers set system-level objectives or constraints, while lower layers optimize individual charging decisions. This structure offers a balance between optimality, scalability, and privacy preservation.

B)BASED ON OPTIMIZATION METHODOLOGY

I. DETERMINISTIC OPTIMIZATION-BASED ALGORITHMS

These algorithms assume known EV arrival times, departure times, and energy requirements. Linear programming (LP), quadratic programming (QP), and mixed-integer linear programming (MILP) are widely used to minimize charging costs or peak loads. Although computationally efficient, their performance degrades when system uncertainties are high.

II. STOCHASTIC AND ROBUST OPTIMIZATION ALGORITHMS

To address uncertainties in EV behavior and renewable energy generation, stochastic and robust optimization techniques are employed. Stochastic methods model uncertainties using probability distributions, while robust optimization ensures feasible solutions under worst-case scenarios. These approaches enhance reliability but often increase computational complexity.

C) BASED ON INTELLIGENCE AND LEARNING CAPABILITY

I. RULE-BASED AND HEURISTIC ALGORITHMS

Rule-based methods rely on predefined charging rules, such as time-of-use pricing or priority-based scheduling. Heuristic algorithms, including greedy methods and metaheuristics, provide near-optimal solutions with reduced computation time. However, they lack adaptability to dynamic grid conditions.

II. ARTIFICIAL INTELLIGENCE AND LEARNING-BASED ALGORITHMS

Recent research has increasingly adopted artificial intelligence techniques, particularly reinforcement learning (RL) and deep reinforcement learning (DRL), to enable adaptive and real-time EV charge scheduling. These algorithms learn optimal charging policies through interaction with the environment and can effectively handle uncertainty and large-scale systems. Multi-agent RL frameworks are especially suitable for decentralized EV charging scenarios.

D) BASED ON POWER FLOW DIRECTION

I. UNIDIRECTIONAL CHARGING (G2V) ALGORITHMS

Unidirectional scheduling focuses solely on grid-to-vehicle (G2V) charging. The objective is to manage charging demand without allowing power flow from EVs back to the grid. These algorithms are simpler and widely adopted in current EV charging infrastructures.

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II. BIDIRECTIONAL CHARGING (V2G) ALGORITHMS

Bidirectional algorithms enable vehicle-to-grid (V2G) operation, allowing EVs to supply energy back to the grid during peak demand or frequency regulation events. While V2G-based scheduling enhances grid flexibility and reliability, it introduces challenges such as battery degradation, user acceptance, and complex market participation mechanisms.

E) BASED ON TIME HORIZON

I. OFFLINE SCHEDULING ALGORITHMS

Offline algorithms generate charging schedules using historical or forecasted data. These methods are suitable for planning purposes but lack adaptability to real-time system variations.

II. ONLINE AND REAL-TIME SCHEDULING ALGORITHMS

Online scheduling algorithms operate in real time using rolling horizon optimization or learning-based control. They continuously update charging decisions based on real-time grid conditions, EV arrivals, and price signals, making them suitable for highly dynamic smart grid environments.

Table no 1 Summary of Classification of EV Charge Scheduling Algorithms

Classification Basis	Algorithm Type	Key Features	Limitations
Control Architecture	Centralized	Global optimality	Scalability, privacy
	Decentralized	Scalable, privacy-preserving	Suboptimal coordination
	Hierarchical	Balanced performance	Implementation complexity
Optimization Method	Deterministic	Computationally efficient	Sensitive to uncertainty
	Stochastic/Robust	Handles uncertainty	High complexity
Intelligence Level	Heuristic	Fast, simple	Limited adaptability
	AI/RL-based	Adaptive, scalable	Training complexity
Power Flow	G2V	Simple, mature	Limited flexibility
	V2G	Grid support	Battery degradation
Time Horizon	Offline	Planning-oriented	Not adaptive
	Online	Real-time control	High data dependency

IV. UNIDIRECTIONAL CHARGING PARADIGM (G2V)

Unidirectional charging, commonly referred to as **Grid-to-Vehicle (G2V)** charging, allows electric power to flow only from the power grid to the EV battery. This paradigm represents the most widely deployed charging mode in current EV infrastructures. The primary objective of G2V scheduling is to determine optimal charging times and power levels such that user energy requirements are satisfied while minimizing adverse impacts on the power grid.In smart grid environments, unidirectional charging is often coordinated using time-of-use pricing, demand response programs, or centralized and decentralized scheduling algorithms[15]. These methods aim to reduce peak demand, flatten load profiles, and lower charging costs without allowing EVs to actively support grid operation. Due to its simplicity, lower hardware requirements, and minimal impact on battery life, G2V charging is considered highly reliable and economically feasible for large-scale deployment[16].

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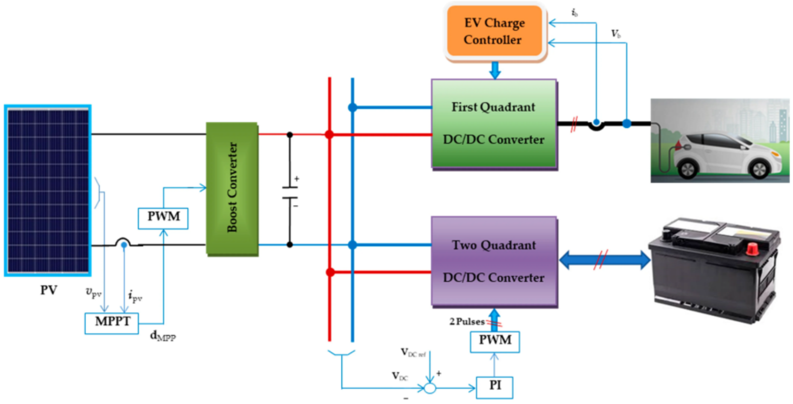

Fig. 1 proposed unidirectional charging method

However, unidirectional charging limits the flexibility of EVs as grid assets, as they cannot provide ancillary services such as frequency regulation or peak load support.

V. BIDIRECTIONAL CHARGING PARADIGM (V2G)

Bidirectional charging, known as Vehicle-to-Grid (V2G), enables electric power to flow both from the grid to the EV and from the EV back to the grid[17]. In this paradigm, EVs act as distributed energy storage units capable of supplying electricity during peak demand periods or grid disturbances. V2G technology significantly enhances grid flexibility and supports advanced services such as peak shaving, frequency regulation, voltage support, and renewable energy balancing.

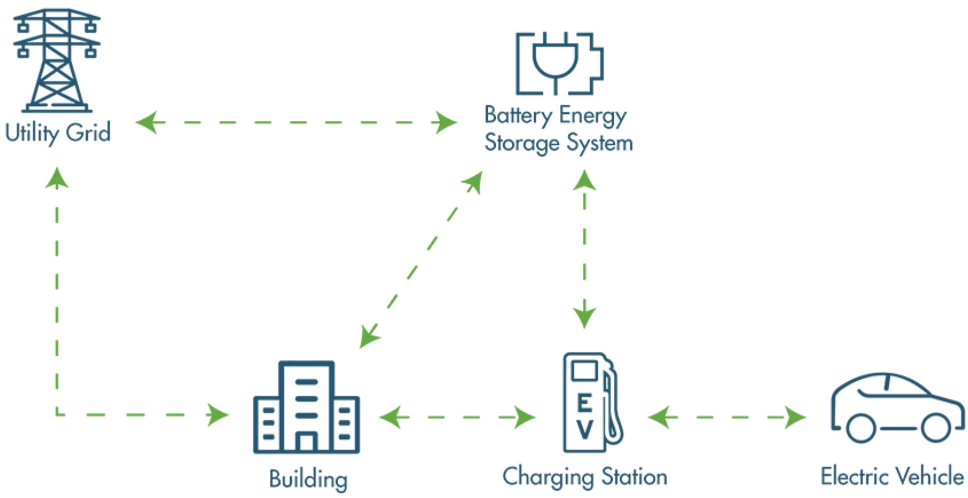

Fig. 2 proposed unidirectional charging method

Charge scheduling under the V2G paradigm is more complex, as it must simultaneously consider user mobility needs, battery state-of-charge constraints, grid requirements, and economic incentives. Optimization-based, game-theoretic, and reinforcement learning approaches are commonly used to manage bidirectional power exchange effectively. Despite its advantages, V2G adoption faces several challenges, including increased battery degradation, user acceptance issues, regulatory barriers, and the need for advanced power electronics and communication infrastructure. Consequently, the practical deployment of V2G remains limited compared to unidirectional charging.

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TABLE NO 2 : COMPARISON OF CHARGING PARADIGMS

Aspect	Unidirectional (G2V)	Bidirectional (V2G)
Power flow	Grid → EV	Grid ↔ EV
Infrastructure complexity	Low	High
Battery degradation	Minimal	Higher
Grid support capability	Limited	High
Scheduling complexity	Moderate	High
Commercial maturity	Widely deployed	Emerging

VI. OPEN ISSUES AND RESEARCH DIRECTIONS

Despite significant progress in the development of charge scheduling algorithms for electric vehicles in smart grid environments, several technical, economic, and operational challenges remain unresolved. Addressing these open issues is essential to enable large-scale, reliable, and user-centric EV integration[18,19].

A) SCALABILITY AND COMPUTATIONAL COMPLEXITY

One of the major challenges in EV charge scheduling is scalability. As EV penetration increases, scheduling algorithms must handle thousands or even millions of charging requests in real time. Centralized optimization-based approaches often face computational bottlenecks and communication overhead, limiting their applicability to large-scale systems. Future research should focus on scalable distributed and hierarchical frameworks, including decomposition techniques, multi-agent systems, and graph-based learning methods, that can efficiently manage large EV fleets without compromising system performance.

B) UNCERTAINTY MODELING AND FORECASTING

EV charging behavior is inherently uncertain due to variability in arrival times, departure times, driving patterns, and state-of-charge requirements. In addition, renewable energy sources introduce further uncertainty into the grid. Although stochastic and robust optimization methods have been proposed, they often rely on accurate probabilistic models and incur high computational costs. Future research should explore data-driven uncertainty modeling, hybrid learning–optimization approaches, and probabilistic forecasting techniques to improve the robustness and reliability of charging schedules.

C) USER BEHAVIOR AND INCENTIVE MECHANISMS

Most existing scheduling models assume rational and cooperative user behavior, which may not reflect real-world conditions. User preferences, convenience, and willingness to participate in smart charging or vehicle-to-grid programs significantly influence algorithm effectiveness. Designing fair, transparent, and incentive-compatible pricing and reward mechanisms remains an open research problem. Future studies should incorporate behavioral economics, user-centric utility models, and adaptive incentive schemes to improve participation and acceptance.

D) VEHICLE-TO-GRID INTEGRATION AND BATTERY DEGRADATION

While vehicle-to-grid (V2G) technology offers substantial benefits such as peak shaving and ancillary service provision, concerns regarding battery degradation, warranty limitations, and user compensation remain largely unresolved. Existing models often oversimplify battery aging effects. Future research should integrate accurate battery degradation models into scheduling algorithms and develop economically viable compensation frameworks that balance grid benefits with battery health and user satisfaction.

E) REAL-TIME IMPLEMENTATION AND COMMUNICATION CONSTRAINTS

Practical deployment of real-time EV charge scheduling requires reliable, low-latency communication between EVs, aggregators, and grid operators. Communication delays, packet losses, and cyber-physical constraints can significantly affect scheduling performance. Future research should investigate resilient control strategies that remain effective under imperfect communication, as well as edge-computing and fog-computing architectures to reduce latency and improve responsiveness.

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F) CYBER SECURITY AND PRIVACY PROTECTION

The exchange of sensitive user and system data in smart charging infrastructures raises serious cybersecurity and privacy concerns. Unauthorized access, data manipulation, or cyberattacks can compromise grid stability and user trust. While some privacy-preserving algorithms have been proposed, comprehensive security-aware scheduling frameworks are still limited. Future research directions include secure communication protocols, privacy-preserving optimization, federated learning, and blockchain-based transaction mechanisms for EV charging systems.

G) INTEROPERABILITY AND STANDARDIZATION

The lack of unified standards for communication, control, and data exchange among EVs, charging stations, aggregators, and grid operators hinders large-scale deployment. Ensuring interoperability across different manufacturers and platforms remains a challenge. Future work should align scheduling strategies with emerging standards and develop platform-independent solutions that support heterogeneous EV and charging infrastructures.

H) INTEGRATION WITH MULTI-ENERGY SYSTEMS

Future smart grids are expected to operate as integrated energy systems involving electricity, heat, gas, and transportation sectors. Most existing EV scheduling studies focus solely on the electrical domain. Research opportunities exist in developing coordinated scheduling frameworks that jointly optimize EV charging with renewable generation, energy storage systems, and other flexible loads in multi-energy systems.

VII. CONCLUSION

The rapid growth of electric vehicles presents both challenges and opportunities for modern smart grids, making effective charge scheduling a critical research area. This paper has presented a comprehensive review of EV charge scheduling strategies in smart grid environments, highlighting various control architectures, optimization formulations, and intelligent scheduling techniques. Centralized, decentralized, and hierarchical approaches were discussed alongside deterministic, stochastic, and learning-based methods, emphasizing their respective strengths and limitations. The review also examined unidirectional and bidirectional charging paradigms, underscoring the potential of vehicle-to-grid technologies to enhance grid flexibility and support ancillary services. Furthermore, commonly used datasets, simulation tools, and performance metrics were summarized to provide practical guidance for researchers. Despite significant advancements, several challenges remain, including scalability, uncertainty management, user behavior modeling, cyber security, and battery degradation concerns associated with V2G operations. Future research should focus on developing scalable, real-time, and user-centric scheduling frameworks that effectively integrate advanced optimization, artificial intelligence, and data-driven approaches. Addressing these challenges will be essential to enable reliable, efficient, and economically viable EV charging infrastructures, thereby facilitating the sustainable integration of electric vehicles into next-generation smart grids.

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