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TOPICAL REVIEW

# Optimization Schedule Schemes for Charging Electric Vehicles: Overview, Challenges, and Solutions

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**ABSTRACT** Electric vehicles represent a global endeavor towards environmentally friendly transportation, and such a green transition is promoted worldwide, being deployed in many regions nowadays. As the number of electric vehicles has been increasing rapidly for more than a decade, how to meet the need for charging their batteries appears as an important research topic, having received remarkable attention in both industry and research community. Uncoordinated charging of many electric vehicles may lead to congestion at charging stations and unbalanced load of the power supply grid. To address this problem, optimized charging schemes which consider available energy resources and user requirements are required. This paper offers an overview of state-of-the-art charging solutions covering two main categories of approaches, namely, centralized and decentralized charging. In addition to addressing the potential challenges that arise in charging schedule optimization, we cover various optimization techniques that have been proposed for optimizing charging schedules. Furthermore, this paper analyzes the current solutions and identifies their limitations and gaps. Open research issues are identified and several potential research topics are suggested.

**INDEX TERMS** Battery charging, charging scheduling, electric vehicles, optimization techniques, optimal charging schemes.

## I. INTRODUCTION

In recent years, Electric Vehicles (EVs) attracted intensive attention from governments, citizens, researchers, policy-makers, and industries [1]. This surge in attention is attributed to various factors, including concerns about climate change, advancements in battery technology, and growing governmental incentives promoting the green shift towards sustainable transportation. Moreover, many studies on various aspects of EV technologies, e.g., on vehicle design, manufacturing, operation, charging, and impact on the environment, have been published [2]. Recent advancements in battery technology increased the drive range of EVs, by developing high-capacity lithium-ion batteries [3]. Also, the development of fast charging infrastructures have reduced the charging time (the time it takes for an EV to recover the energy consumed). These advancements make EVs more environmentally sustainable and convenient.

Another major factor driving the promotion of EVs is their potential to reduce greenhouse gas emissions and dependency on fossil fuels. The transportation sector is a significant contributor to global emissions, with several types of vehicles. The integration of EVs with Renewable Energy Systems (RESs) could reduce carbon dioxide emissions up to 70%, compared to conventional vehicles [4]. For instance, the Photovoltaic (PV) technology provides a sustainable and

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renewable energy source by converting sunlight directly into electricity. PV can be integrated with EV charging systems to harness solar energy for charging EVs. This integration not only reduces reliance on traditional grid electricity generated from fossil fuels but also improves our living environment by reducing carbon dioxide emissions.

Along with the popularity of EVs, a societal challenge has emerged, which is how to optimize charging schedules in order to balance the demand of EV charging with grid capacity [5]. First of all, it is essential to ensure the stability of the grid in a high number of EVs condition [6]. From another perspective, it is important to implement smart charging schemes that oversee and regulate charging processes. These schemes could be developed based on various criteria, including time of day, energy prices, renewable energy availability, charging network characteristics, real-time specifications, and energy providers' policies. The joint consideration of these criteria escalates the complexity of the problem and underscores the multicriteria nature of the optimization algorithms [7].

Another challenge arises from the limited distance range of EV autonomy when compared to traditional vehicles. This limitation serves as motivation to enhance battery technology to effectively increase the range of EVs [8] and to develop faster-charging infrastructures. In the meantime, it is necessary to deploy more widespread and accessible Charging Stations (CSs) to increase the convenience of EVs owners to facilitate their long-distance journeys. Another challenge stems from user behavior, which can significantly impact the load on the power grid. For instance, when a certain number of users choose to charge their EVs, particularly during peak hours, substantial demands on the grid may be generated [9]. Additionally, distinct charging patterns observed in home and public settings can influence the design of efficient charging strategies and schemes.

In the realm of charging EVs, various survey papers on the optimization of charging strategies have been published. For instance, the study in [10] examined scheduling algorithms for charging EVs in smart grids. A power and communication system has been designed for bidirectional flows of electricity and information. The authors categorized their work based on unidirectional and bidirectional charging, centralized and decentralized scheduling, and the consideration of mobility aspects. Another study conducted in [11] compared different approaches based on factors such as Real-Time Pricing (RTP), Time of Use (TOU), Critical Peak Pricing (CPP), and Peak Time Rebates (PTR) to offer a comprehensive analysis of EV charging and scheduling under dynamic pricing systems. The study also tackled challenges linked to uncoordinated charging and highlighted the potential benefits of coordinating charging activities through dynamic pricing.

The study in [12] focused on coordinating charging and discharging activities of EVs, considering the state where the EVs are connected to the grid. The authors addressed various challenges associated with charging/discharging control with respect to system performance, such as power quality deterioration, overloading, and power loss. Their work introduced a novel multistage hierarchical approach for regulated charging and discharging, however, limited to aggregated energy management. Moreover, a comprehensive overview of EV technology, charging methods, EV standards, and optimization techniques was presented in [13]. The study explored the essential characteristics of EVs and Hybrid Electric Vehicles (HEVs), followed by an examination of various EV charging methods such as Battery Swap Stations (BSS), Wireless Power Transfer (WPT), and Conductive Charging (CC). The authors suggested several opportunities for future research in the realm of EV technologies and their integration with energy systems.

However, existing research primarily explored general EV charging methods and focused on standard EV charging scheduling under dynamic prices strategies, and energy flow management. Complementarily, this article offers a comprehensive overview related to EV charging schemes, with a focus on user demands within existing charging infrastructure. The paper highlights the impact on the power grid and emphasized the need of optimal charging schemes. This study discusses multiple aspects associated with EV charging demands such as charging modes, charging patterns (i.e., public, home, or mobile), centralized and decentralized charging systems, and EV types. Furthermore, this article presents a critical review on existing optimization techniques for charging scheduling, insightfully analyzes existing solutions, and identifies their limitations and gaps. Moreover, we shed light on potential research directions relevant to this topic, aiming at helping other researchers and engineers to develop more efficient, sustainable, and user-friendly EV charging schemes.

The remainder of this article is organized as follows: Section II introduces EV types and Section III explains charging modes. After elaborating charging patterns in Section IV, Section V addresses the coordination of EV charging. Then, Section VI examines several optimization techniques for charging scheduling. Section VII summarizes various Machine Leaning (ML) techniques and discusses their applicability for charging optimization. Section VIII is dedicated to scheme comparison, gap observation, and research direction recommendation. Finally, Section IX concludes this study.

## II. TYPES OF ELECTRIC VEHICLES

Four main types of EVs are categorized in the literature [14]: Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs), Hybrid Electric Vehicles (HEVs), and Fuel Cell Electric Vehicles (FCEVs).

BEVs operate solely on battery power, resulting in zero tailpipe emissions [15]. The batteries of BEVs can be recharged by plugging the vehicle into external CSs, either at home or through public CSs (refer to Section IV). BEVs present a lower running cost and reduced environmental impact compared to the other types of EVs. However, they have a very limited range and long charging time [4].

PHEVs have both a battery and an internal combustion engine, providing additional power when the battery is depleted. PHEVs can operate in the all-electric mode for a certain distance before switching to the hybrid mode when the battery's charge diminishes or specific driving conditions necessitate it. In the all-electric mode, a vehicle relies only on electric power, whereas in the hybrid mode, both the battery and internal combustion engine collaborate to propel the vehicle. This adaptability allows PHEVs to accommodate short journeys emission-free and switch to hybrid mode for more extended trips or when the battery's capacity is exhausted [16], [17]. However, they have higher running costs and carbon emissions compared to BEVs.

HEVs are equipped with an internal combustion engine and an electric motor. The electric motor is powered by a battery, recharged through regenerative braking and the internal combustion engine. Unlike PHEVs, HEVs are not typically charged externally; instead, they are designed to be self-sufficient in terms of power. HEVs provide enhanced fuel efficiency and lower emissions compared with traditional vehicles. However, they offer lower levels of electric drive compared to BEVs and PHEVs [18].

Another type of EV is FCEVs that utilize hydrogen to generate electricity to power the electric motor. The sole emission from FCEVs is water vapor, making them zero-emission vehicles. However, FCEVs are not yet widely available and the infrastructure for producing, transporting, and storing hydrogen is still in its early stage [19].

The types of EVs available on the market vary according to the regions and the manufacturers [20]. These available types of EVs offer a spectrum of benefits, such as reduced carbon emissions and lower running costs, among others. However, the decision on which type of EV to purchase hinges on factors like driving habits, budget, and the accessibility of charging infrastructure (refer to Table 1).

**TABLE 1. Different types of electric vehicles.**

| Type | Budget | Driving Habits | Charging Station | Examples | Ref. |
|---|---|---|---|---|---|
| BEV | High | Short to medium daily commutes, occasional longer trips | Home or public CSs | Tesla Model S, Nissan Leaf, BMW i3 | [4], [14], [15] |
| PHEV | Moderate to high | Short daily commutes, occasional longer trips | Home or public CSs | Toyota Prius Prime, Chevrolet Volt, Ford Fusion Energy | [14], [16], [17] |
| HEV | Low to moderate | All driving habits | No charging needed | Toyota Camry Hybrid, Honda Accord Hybrid, Ford Escape Hybrid | [17], [18] |
| FCEV | High | All driving habits | Hydrogen refueling stations | Toyota Mirai, Honda Clarity, Hyundai Nexo | [17], [19] |

## III. CHARGING MODES FOR EVs

There are four main modes of charging based on the Deltrix Chargers classification [21]:

1) Charging mode 1: This mode is the slowest form of charging for an EV. It involves using a standard home plug to connect the EV to the power grid. Charging an EV battery in mode 1 can take several hours or even require an overnight. However, one advantage of this gradual charging process is that it generates less heat and imposes less stress on the EV battery [22].
2) Charging mode 2: This mode also uses a home plug for charging EVs. It incorporates a specialized cable equipped with built-in shock protection against risks from both Alternative Current (AC) and Direct Current (DC), enhancing the safety of the charging process.
3) Charging mode 3: It is the most popular charging method among EV users. It can be implemented both at home and at public CSs. Like mode 2, it provides shock prevention against both AC and DC currents. In mode 3, the EV user does not need to use a specific cable for charging; instead, the necessary connecting cables are provided at the stations.
4) Charging mode 4: Often referred to as fast charging mode, it involves the use of CSs that convert AC power to DC, allowing direct charging for EVs. Typically, fast charging mode is notable for its efficiency; an average EV battery takes about 30 minutes to an hour to be fully charged. The charging rates supported in this mode vary, ranging from 5 kW units up to 50 kW and 150 kW. Future standards may even extend this range to 350 kW and 400 kW. However, these higher charging rates can generate significant heat, which may impact the battery's lifespan. Therefore, a special cooling system is often required to manage this heat effectively.

However, the selection of an appropriate charging mode depends on various factors, such as EV battery capacity, current charging status, required driving range, user preferences, and the availability of charging infrastructure.

## IV. CHARGING PATTERNS

There are three primary charging patterns based on the type of CS: home charging, public charging, and mobile charging.

### A. HOME CHARGING

Home charging, also referred to as Electric Vehicle Supply Equipment (EVSE), appears as the most convenient and cost-effective method for EV owners. This approach enables them to charge their vehicles overnight, taking the advantage of typically lower electricity rates during that time [23]. Furthermore, home chargers can be installed in a garage or outdoors, offering a reliable and secure charging solution. Particularly, it is suitable for daily commuting and short trips.

### B. PUBLIC CHARGING

Public charging constitutes an essential aspect of EV infrastructure, particularly for owners planning long trips or those lacking access to home charging [24]. Public CSs are typically located in public areas such as parking lots, shopping centers, or along major roads [25]. They can provide either charging mode 3 or mode 4 (refer to Section III), depending on the capabilities of a CS. Thus, the utilization of public CSs can vary significantly based on several factors, including location, day of the week, time of day, and user requirements. For instance, CSs at workplaces are often utilized throughout the work hours, e.g., from 9 am to 5 pm, as employees can plug in their EVs when they arrive at work and let them charge throughout the day. Shopping centers and commercial CSs typically experience peak power consumption in the midday to early evening hours, corresponding with the hours when people are most likely to be shopping or running errands. Furthermore, many CSs are deployed at highway rest stops or gas stations and provide charging mode 4 for longer trips. These CSs typically experience a distributed usage throughout the day but may also experience peak consumption during weekends or holidays when long-distance travel is more common.

### C. MOBILE CHARGING

Mobile charging, also referred to as on-the-go charging, emerges as a trend for EV transport, by offering a portable charging solution for EV owners at remote locations where the availability of home and public CSs are limited. These mobile CSs can be mounted on a trailer or truck and are suitable for public events, construction sites, and emergency scenarios where home and public CSs are not available [26]. Note that this flexible charging pattern is typically not used in traditional stations that are based on fuel oil.

## V. EV CHARGING STRATEGIES

EV battery charging is typically performed through two charging strategies: uncoordinated and coordinated.

### A. UNCOORDINATED CHARGING

This strategy refers to a random charging behavior, where EV owners can charge their vehicles at any type of CS and at any time as they prefer. The problem with uncoordinated charging is that it can lead to overloaded transformers, power outages, and increased electricity costs. Moreover, it can result in battery degradation and shortened battery lifespan due to frequent charging and discharging. According to [27], uncoordinated charging can introduce high variability in electricity demand, posing a challenging task for grid operators to balance supply and demand.

### B. COORDINATED CHARGING

This type of charging involves planned and managed charging schemes that are applicable to optimize and manage EV charging operations, such as mitigating grid stress, enhancing energy efficiency, and minimizing costs [28]. These schemes also consider various factors in their management, e.g., grid capacity, electricity demand, renewable energy availability, and user preferences. Generally, coordinated schemes can be implemented using two types of charging systems: centralized or decentralized charging. There are also hybrid charging systems that combine both centralized and decentralized approaches, e.g., those investigated in [29], [30], and [31]. However, discussing hybrid approaches is beyond the scope of this article.

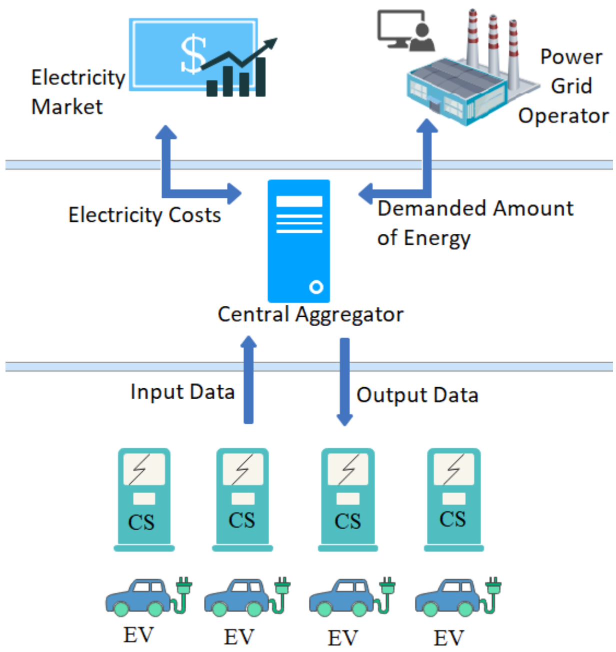


**FIGURE 1.** The architecture of a centralized system for EV charging.

#### 1) CENTRALIZED SCHEMES FOR COORDINATED CHARGING

Following centralized schemes, a central entity coordinates the charging of EVs within a specific geographic area, such as a neighborhood in a city [32]. The central entity in this charging system, know as an aggregator, communicate with both EV users and grid operators. It obtains and transmits demands as well as performs system configuration and coordinates other operations. To achieve this, the aggregator first collects charging information from EV owners, such as the identity (ID) number of an EV, the EV's battery capacity, the State of Charge (SOC), and the arrival time at a CS. Then it executes an algorithm to optimize charging schedules based on the collected data, by taking into account the overall power demand and electricity prices in the market. The aggregator submits these schemes to the grid operator for approval. From the perspective of a business model, the aggregator and the grid operator are regarded as independent of each other but they are cooperating entities. The role of the grid operator is crucial and the operator should ensure that the adopted scheme aligns with the stability and efficiency of the power grid, considering factors such as grid load, peak demands, and the balance between supply and demand.

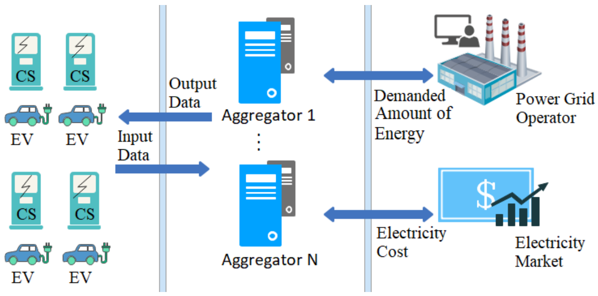


**FIGURE 2.** The architecture of a decentralized system for EV charging.

To keep this balance, the grid operator may execute some kind of admission control for new charging requests, based on the current grid status. If a charging schedule scheme is not acceptable, the grid operator will reply to the aggregator to revise the scheme, or to wait until the grid resource conditions allow to execute this scheme.

With such an approach, a negotiation procedure would be involved and consequently, the complexity of the overall handshake overhead will be significantly high. The charging scheme (output data transmitted from the aggregator to EV owners and/or CS operator) may include information such as the amount of electricity to be supplied from CSs to EVs, the assignment of the EV to a most appropriate CS, charging mode preference, and charging patterns (e.g., home, public, or mobile charging).

However, the specific features of the scheme and the data involved may vary based on factors such as the algorithm used, system configuration, and optimization objectives. This variability arises because the nature of the EV charging problem faces multiple criteria. Figure 1 presents a simplified high-level architecture of a centralized charging system, showing the primary functional units responsible for implementing system management and control. Note that Figure 1 does not illustrate the power flows or communication links between EV users, CSs, and the aggregator. Several optimized charging schemes that are applied in centralized systems are available in [33], [34], [35], [36], [37], and [38].

### 2) DECENTRALIZED SCHEMES FOR COORDINATED CHARGING

In the decentralized charging approach, an incentive-based strategy is introduced where the charging schedules of EVs are affected indirectly by electricity prices [39]. The EV owners play an active role in making their charging decisions, utilizing information provided by the aggregator, such as current electricity prices and the availability of CSs in the area managed by that aggregator. The primary objective of adjusting electricity prices is to motivate EV users to charge their vehicles during off-peak hours, thereby reducing the load on the grid during periods of high demand. Similar to a centralized approach, each aggregator collects user information or, even predicts the charging demand of EVs for the next period of time. This information is used to find an optimal charging scheme. The aggregator cooperates with the grid operator to align the charging prices with the conditions of the electricity market and the status of the power grid. As a result of this pricing strategy, EV owners make a charging schedule based on their personal preferences, aiming to minimize the charging cost.

Figure 2 presents a simplified high-level architecture of a decentralized charging system. For decentralized charging, multiple aggregators manage the charging of EVs across a large region, where each one coordinates local charging within a small geographic area. Each aggregator communicates with the grid operator and EV owners. These aggregators also communicate with each other to ensure the stability and reliability of the power grid [40]. Several optimized charging schemes that are applied in decentralized systems are available in [41], [42], [43], [44], [45], [46], and [47].

**TABLE 2.** Centralized versus decentralized charging: A comparison.

| System nature | Centralized | Decentralized |
|---|---|---|
| **Capacity** | High, serves many vehicles at a time | Lower, serves fewer vehicles at a time |
| **Flexibility** | Less, due to fixed locations | High, can adapt to user patterns |
| **Scalability** | Requires significant expansion for growth | Easily scalable with demand |
| **Risk of Congestion** | Higher at peak times | Lower, distributed across many locations |
| **Computational Complexity** | High if the number of EV is large | Distributed computational complexity |
| **Failure Impact** | Prone to failure problem affecting the entire system | Distributed nature offers more resiliency |
| **Infrastructure Investment** | Significant investment | Lower investment required |

### 3) CENTRALIZED VERSUS DECENTRALIZED CHARGING

As summarized in Table 2, both centralized and decentralized charging systems discussed above have their advantages and disadvantages. A centralized charging system may be applied to large-scale or small-scale communities, particularly suitable for high-density urban areas or commercial hubs. In a centralized system, the central aggregator comprises many CSs and can handle a large number of vehicles simultaneously. However, such a system faces a real-time response problem, especially during peak hours. The time needed to collect data from EVs and to perform computation corresponding to the number of EVs is lengthy. Additionally, a sole aggregator in the system represents a single point of failure, raising security concerns. Furthermore, significant investment in infrastructure is needed to build a large network interconnected CSs, managed from a central aggregator. This approach demands substantial financial input for hardware, software, and network capabilities to handle the scale and complexity of the system. Traditional centralized energy systems face various challenges like scalability, grid capacity, and inconvenience for EVs that are far away from a CS. These constraints can limit the popularity of centralized charging in meeting the growing demand for EV charging.

On the contrary, decentralized systems offer flexible and scalable charging options as multiple aggregators are distributed at various locations (e.g., home, work, and public sites). Through multiple smaller aggregators, the demand for electricity is spread out, potentially reducing the strain on the power grid and range anxiety. However, decentralized approaches are more complex compared with centralized approaches. They require more geography information, such as current number of EVs in the region of interest, electricity prices, and the availability of CSs by a specific aggregator, and such information needs to be continuously updated. A decentralized system can handle fewer number of EVs compared with a centralized system. For instance, a home CS or a charger located at a public parking lot typically supports one or few vehicles simultaneously. In general, decentralized systems require lower infrastructure investment. The cost is often distributed among different stakeholders based on their demands, including homeowners, businesses, grid operators, and local governments.

## VI. CLASSICAL OPTIMIZATION TECHNIQUES FOR EV CHARGING

In this section, we discuss and review classical optimization techniques used to optimize charging schemes for EVs, classified into three categories, namely, linear programming, dynamic programming, and heuristic algorithms.

### A. LINEAR PROGRAMMING

Linear Programming (LP) stands out as a widely employed optimization technique. It formulates a problem model as a linear set of equations and aims at optimization, where both the objective function and constraints adhere to linearity. This characteristic is algebraic and applies to both the problem and the algorithm [48]. LP has been proved to be effective in optimizing charging schedules that encompass multiple EVs, CSs, and power grids. For example, the study in [49] developed an LP model for EV charging/discharging scheduling based on real-world datasets collected at the parking lots of the University of Deusto, Spain. The objective of that study was to decrease power consumption of parking lots during peak hours using a peak-to-valley strategy. EVs are charged during periods of low power demand (valley filling) and discharged during periods of high-power demand (peak shaving). The LP algorithm was validated through MATLAB simulations, demonstrating the model's effectiveness in energy management and its potential for cost savings, especially during peak power demand.

On the other hand, the emerging Vehicle-to-Grid (V2G) technology has also attracted increasing attention [50]. The V2G concept enables EVs to feed their redundant power back into the grid (discharging) or other vehicles, instead of merely drawing power from the grid (charging). This capability of EVs provides a valuable source of distributed energy storage [51]. If the V2G technology is involved in a charging system, it would require additional coordination among EV owners/users, aggregators, and grid operators to manage the bidirectional flow of energy. As mentioned earlier, the PVs systems also provide RESs for EV charging. If PVs are involved in an EV charging system along with V2G, it would add another level of complexity in terms of scheduling and energy management. The study in [52] developed a model that integrated EVs with PV power and aimed to increase the PV power self-consumption by using smart EV charging strategies and the V2G technology. The model was implemented in a microgrid placed in a neighborhood in Utrecht, Netherlands, where the emulation involved 31 kW of PV with solar energy, three households, and two EVs. Three charging methods were evaluated to reveal their impact on PV self-consumption and peak demand reduction, including a real time control method, a real time control with V2G method, and an LP method. The results indicated that the LP method was more effective than the others, as it led to increased self-consumption from 49% to 62%-87% and reduced peak demand (ranging from 27% to 67%). These methods contribute to grid stability by decreasing peak demand and enhancing PV self-consumption, showing the potential for more efficient utilization of renewable energy in real-world microgrids. Their study also provides insight into the effects of these charging strategies on EV battery degradation.

Moreover, Mixed-Integer Linear Programming (MILP) represents a type of LP model that extends the capabilities of traditional LP by accommodating integer decision variables. The study in [53] utilized MILP to formulate the scheduling of EV charging and discharging. The charging system has been integrated with other energy sources, such as PV generated power, V2G, and dynamic electricity prices. Through simulations conducted based on the datasets collected in Austin, TX, USA, a significant reduction in the energy cost of EV charging from PV is demonstrated, in comparison with immediate and average rate charging policies. The findings of their study indicate that integrating various smart applications for EV charging provides a sustainable and cost-effective approach to manage the charging of an EV fleet in workplaces or public places with PV installations. Moreover, the incorporation of V2G technology offers ancillary services, enhancing grid stability.

Furthermore, it is also feasible to apply LP to dynamic systems under certain circumstances, by solving a series of LP problems to optimize a system based on varying parameters over time. For instance, the study in [54] introduced a novel approach for EV charging optimization, by integrating energy storage and considering the dynamics of electricity prices. The authors of [54] employed a MILP model along with a heuristic algorithm based on LP to address the scheduling problem. The results demonstrate a noteworthy enhancement in aggregator revenue, averaging 80.1% with the optimal charging scheme, and a further increase of 7.8% when energy storage is utilized. Their finding illustrates that optimized EV charging within existing electricity market structures can yield commercial benefits for aggregators.

### B. DYNAMIC PROGRAMMING

Dynamic Programming (DP) is a widely used optimization technique in mathematics and computer science for solving complex optimization problems. However, no standard mathematical formulation of the DP problem exists. Instead, DP involves a problem-solving method where the problem is decomposed into smaller subproblems and solved recursively [55]. DP leverages the fact that optimal solutions to these subproblems contribute to efficiently resolving the larger problem. It is worth noting that dynamic programs can be equivalently formulated as linear programs. As a result, LP can serve as an efficient alternative to the functional equation approach in solving such problems, when it is combined with DP, helps to characterize the polyhedral structure of discrete optimization problems. Additionally, DP ensures global optimality for a solution in general nonlinear optimization problems with nonconvex constraints. It is particularly well-suited for dynamic systems, such as optimizing charging schedules involving multiple EVs, CSs, and power grids, where the charging rate of each EV may vary over time.

The study in [56] formulated the problem of online charging scheduling as a finite-horizon DP problem, with a continuous state space and action space. It involves estimating statistical information about future arrivals of plug-in EVs. The authors proposed to adopt a Model Predictive Control (MPC) algorithm to address dynamic EV arrivals and charging requirements. The approach avoids the high complexity associated with solving a DP problem. Therein, three distinct algorithms were employed to oversee the charging process, namely, Sample Average Approximation (SAA), heuristic online Average (AVG), and online Expected Load Flattening (ELF). The evaluation was conducted under varied traffic patterns to simulate real-life scenarios, including light, moderate, and heavy load conditions. Their findings indicate that the proposed ELF algorithm closely approximates the optimal solution that is achieved by the SAA algorithm. It adeptly manages EV charging schedules and proves suitable for systems with fluctuating numbers of EVs and charging demands, making it applicable in diverse real-world scenarios.

Moreover, [57] proposed an optimal scheduling method integrated with DP to minimize the costs of battery replacement during the entire service life of Electric Bus Fleets (EBFs). The developed method considered the differences in workload and battery capacity degradation models for calculating battery capacity loss and the number of battery replacements. The results indicate that the proposed method reduces battery replacement costs by 20% in comparison with an uncoordinated scenario, showcasing its effectiveness in optimizing EBF scheduling and its contribution to overall cost-effectiveness. Their approach can be potentially extended to large-scale urban transit systems, further enhancing the sustainability and economic efficiency of EBF operations.

### C. HEURISTIC ALGORITHMS

Heuristic optimization algorithms employ approximate methods to find solutions for complex problems, especially when the problem is too large or complex. These algorithms have been proven beneficial in addressing charging scheduling problems. A few examples of heuristic algorithms utilized for charging scheduling optimization, as explained in [58], include Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Ant Colony Optimization (ACO). For instance, the study in [59] proposed an optimal charging scheduling scheme considering that EVs were parked at home (static). The objective of their study was to minimize charging costs and actual charging duration for EVs while adhering to the constraints related to the status of a CS. The results show the proposed method that is based on PSO exhibits superior performance in minimizing charging costs and duration compared with other methods such as Arrival Time-based Priority (ATP) and State of Charge-based Priority (SBP). The authors claim that PSO is favorable in cases when a trade-off between charging duration and cost needs to be considered.

The study in [60] utilized PSO for EV charging scheduling at parking lots, incorporated with V2G. The authors considered factors such as EV battery lifetime, distribution network, and local transformer loading. Their proposed method was compared with a traditional charging scheme where an aggregator provided EVs with full-capacity charging at the maximum power rate. Their study incorporated real-world data including the activities at a parking lot and electricity prices. According to their results, EV charging management and cost reduction in parking lots were effectively achieved through the proposed method. That study demonstrates how the V2G technology can be seamlessly integrated into parking lots efficiently to enhance energy management.

Furthermore, the study in [61] developed a GA to introduce an intelligent scheme for coordinating the charging of EVs. The scheme considered electrical parameter constraints such as thermal line limits, voltage limits, load on transformers, and parking availability patterns. A real-life simulation was conducted on a low-voltage residential distribution network in Madrid, Spain, involving 100 individual EVs. Three scenarios of EV penetration were considered: a low level (5%), a medium level (20%), and a high level (50%). The results indicate a flattening in the load profile, peak load shaving, and prevention of the aging of power system elements. This approach fits well in smart grid systems, contributing to better management and lifespan extension of power system components by optimizing the load profile.

The study in [62] introduced a Genetic Algorithm-based Emergent Charging Scheduling (GECS) scheme to address routing and scheduling optimization problems for EVs, when there is a sudden demand for rapid charging in a high-density area. The GA is incorporated with the scheduling policies of Earliest Deadline First (EDF) and Nearest Job First (NJF) to streamline the multiobjective optimization process. While

EDF prioritizes the minimum recharging deadline time, NJF focuses on the minimum recharging path from an EV to a CS. The results therein reveal that the proposed scheme minimizes the average distance and waiting time for emergent EV charging. This approach is particularly suitable during peak hours when the density of EVs is high and EVs need to obtain enough energy to reach their destinations.

Moreover, [63] introduced a charging scheme based on ACO to schedule EV charging within a CS. The study considered power constraints such as maximum contracted power and maximum power imbalance. The experimental setup utilized a real-world benchmark configuration, emulating a charging system with three lines, representing a CS and 180 charging units (also referred to as charging points), each line connected with 60 charging units. The results demonstrate that ACO outperforms other methods, including First Come First Serve (FCFS), Latest Starting Time (LST), Earliest Due Time (EDT), and GA, in terms of minimizing total charging delays for EVs. The approach in [63] contributes to grid stability by efficiently managing the charging load and avoiding peak hours, particularly beneficial for optimizing charging schedules at CSs with multiple lines and high EV traffic.

## VII. APPLYING MACHINE LEARNING FOR EV CHARGING OPTIMIZATION

The ML algorithms can analyze and interpret large datasets, identify patterns, and make predictions or decisions based on the patterns discovered. ML algorithms are not predetermined but are discovered by a machine through its learning process and based on its prior experiences. In the context of EV charging, ML algorithms may also be developed for the purpose of optimizing charging schedules. Through training based on historical charging data, ML algorithms can predict future charging patterns, potentially improving the efficiency and reliability of charging processes. Moreover, these techniques facilitate intelligent decision-making, adapting to dynamic grid conditions in accordance with user preferences. In this section, we first revisit various categories of ML techniques and explore their applicability to EV charging, then explain the interpretability of ML algorithms as well as its importance for designing optimal EV charging schemes.

### A. A REVISIT OF ML TECHNIQUES AND THEIR APPLICABILITY TO EV CHARGING

#### 1) SUPERVISED LEARNING

Supervised Learning (SL) algorithms are firstly trained, using labeled data. Particularly, they are effective in scenarios when historical data are available. Various supervised ML algorithms exist, including Support Vector Machines (SVMs), Naive Bayes (NB), K-Nearest Neighbors (KNN), Neural Network (NN), and Random Forests (RF). RF is an ensemble method that relies on multiple decision trees. According to [64], several studies have revealed that RF can produce more stable and accurate results than SVMs in load prediction, indicating its effectiveness in forecasting electrical load. In general, SL algorithms can be applied to EV charging, from learning of instances to predicting optimal charging schedules.

#### 2) UNSUPERVISED LEARNING

Unsupervised Learning (UL) algorithms make decisions without requiring labeled data to train the model. UL algorithms autonomously identify patterns and structures in unlabelled data, without human supervision. These algorithms group data based on similarities and/or differences, useful in applications like customer segmentation. UL algorithms also comes with drawbacks, such as algorithm's complexity and the potential for predicting faulty outputs when utilizing unlabeled data.

UL algorithms are applicable to identifying suitable EV charging schemes and these types of algorithms are particularly useful in scenarios when the availability of historical labeled data is scarce or unobtainable.

#### 3) SEMI-SUPERVISED LEARNING

Semi-Supervised Learning (SSL) integrates the concepts from both SL and UL, where data training undergoes a division into two segments: smaller portion with labeled data and larger portion with unlabeled data. This approach harnesses the labeled data to enhance the deduction of patterns in the unlabeled data, resulting in more precise outputs. Despite the advantages, SSL algorithms have a drawback. Namely, they may not produce consistent results per iteration.

SSL offers various benefits for EV charging scheme optimization, including forecasting energy demand, applying dynamic pricing models to manage demand and grid load, and predicting strategic station placement. SSL may also provide personalized charging recommendations to EV owners, such as suggesting the best time and location for charging based on their typical routes and schedules.

#### 4) REINFORCEMENT LEARNING

Reinforcement Learning (RL) involves learning from past experiences and improves the performance through a trial-and-error-correction approach. Unlike other learning algorithms that rely on initial training data, RL explores various options, aiming to refine itself with each iteration. This approach provides a versatile framework for decision-making, where the key components act as an agent and an environment. The agent interacts with the environment, triggering changes within it. These changes result from the agent's actions and external factors that are beyond the agent's control. The agent observes the state (s) of the environment, often an incomplete view, and must make decisions based on this information. The main objective is to maximize cumulative rewards obtained from the environment.

RL can be instrumental in implementing demand response strategies. An RL algorithm can learn to adjust charging rates or suggest charging times to EV owners based on grid conditions, promoting energy conservation during peak hours. RL can also be adopted to develop algorithms that schedule charging times for EVs in a way that minimizes grid stress and/or maximizes cost efficiency. Such an algorithm can dynamically adjust schedules based on current grid load and electricity prices.

#### 5) DEEP LEARNING

Deep Learning (DL) algorithms rely on the concept of NNs, which comprises interconnected nodes (neurons) that are arranged into multiple layers. The input layer manages the input data, hidden layers uncover patterns within the data, and the output layer presents the results. The input data traverses each layer, establishing a sequential learning path for the model. Various types of DL networks exist, including modular, recurrent, and convolutional neural network.

The study in [65] developed four DL algorithms to forecast EVs charging demand: Gated Recurrent Units (GRUs), Long-Short-Term Memory (LSTM), Recurrent Neural Networks (RNNs), and Artificial Neural Networks (ANNs). The study tackled various problems linked to the growing adoption of EVs and its potential ramifications on distribution networks based on the datasets collected from two public charging stations in Morocco. The results indicate that the GRU model exhibits superior performance in estimating EV power charging demand.

#### 6) DEEP REINFORCEMENT LEARNING

Deep Reinforcement Learning (DRL) combines RL and DL taking their benefits to solve complex problems. While the RL part defines the objective, the DRL component offers problem-solving mechanisms. DRL algorithms are widely adopted today in various domains, thanks to their ability to handle high-dimensional input data and learn optimal strategies through trial and error-correction.

DRL algorithms have also exhibited applicability in EV charging optimization. For instance, the study in [66] introduced an optimal charging scheme utilizing DRL for Fast Charging Station (FCS) selection and route planning for EVs in the smart grid. The approach considered constraints, such as charging availability and electricity price fluctuations, to minimize the overall EV charging overhead in terms of both time and monetary costs. It also relies on the integration of two technologies, namely, Software-Defined Networking (SDN) and Vehicular Edge Computing (VEC). The outcomes of the proposed DRL method showed a substantial reduction in charging overhead compared with conventional charging. It demonstrates the capability to manage charging demands in a dynamic urban environment, devising charging policies based on historical data to adapt to real-world conditions.

### B. INTERPRETABILITY OF ML ALGORITHMS

#### 1) A SUMMARY ON INTERPRETABILITY

The *interpretability* of ML algorithms is important, especially when human decisions have to be taken based on the results of a specific ML algorithm. *Explainability* is regarded as a similar term which is closely related to interpretability – Interpretable systems are explainable if their operations can be understood by human beings. However, there is no unique definition of ML interpretability. The work in [67] describes interpretability as *the degree to which a human can consistently predict the model's result*. Due to the interpretation subjectivity, interpretability is not a monolithic notion [68] implying that it has several dimensions. Interpretation itself can be formulated either in terms of low-level parameters or as input features used by a model.

ML low interpretability comes from the hidden behavior of the so-called black box ML models (e.g., Deep Neural Networks (DNN) and others) [69], where the internal ML logic and rationale are hidden to human users. Multilayer NNs typically operate as black boxes without exposing why specific features are selected during training; how the correlations in the training data are represented for feature extraction; and why a specific pathway in the network is selected over others [68].

In [69] and [70], an overview and a taxonomy of interpretable models and explanation methods based on different criteria were presented. The study in [71] presented an extensive and in-depth identification analysis, and provided an comparison of various ML interpretability methods, including *Pre-model, In-model, Post-model; Intrinsic, Post-hoc; Model-specific*, and *Model-agnostic*. When building an ML model, one has to decide which method is applicable, namely, before (premodel), during (in-model), or after (post-model) model development. Another criterion is intrinsic versus post-hoc. It is used to distinguish whether interpretability is achieved through the constraints imposed on the ML model complexity (intrinsic) or by applying methods that analyze the model after training (post-hoc). Another rather important criterion is model-specific versus model-agnostic. In the former case, each method is based on a specific model's internals (e.g., weights in a linear model). The model-agnostic methods can be applied to any ML model (black box or not). These methods rely on analyzing pairs of feature input and output. Such methods cannot have access to the model inner workings, such as weights or structural information. One can differentiate between explanation methods based on the results that each method produces: feature summary, model internals, data point, and surrogate intrinsically interpretable model.

The degree of interpretability is related to accuracy [72]. If two models lead to similar accuracy, additional criteria can be applied to select a model. In addition, there is a link between interpretability and usability of models. The work in [73] reveals that interpretability may assist in overcoming several bottlenecks of DL.

#### 2) INTERPRETABILITY OF ML ALGORITHMS FOR EV CHARGING OPTIMIZATION

The interpretability of ML algorithms is important for developing optimal EV charging schemes, given that many

ML-based solutions have been proposed recently, for predictions, optimizations and so on. On the other side, human users are involved in such systems and the rationale behind decisions should be explainable well enough.

When designing a public EV charging system which includes ML-based decisions, ML interpretability is needed to evaluate the system capabilities to meet the regulation requirements and the degree of assurance for safety guarantees. The amount of information for EV charging is increasing exponentially from both EV user and electricity grid sides. The study in [74] employed three ML algorithms to predict EV charging time, namely, Extreme Learning Machine (ELM), Feed Forward Neural Network (FFNN), and Support Vector Regression (SVR). Multiple ML parameters have been optimized by a Grey Wolf Optimizer (GWO), a meta-heuristic technique, to enhance prediction accuracy. The study also applied Shapley Additive Explanation (SHAP), an ML interpretation method, to overcome the low interpretability of ML algorithms, by monitoring the output of multiple variables and measure their impact on charging time. The results show that the A/C compressor, start SOC, and end SOC are the most important parameters in determining optimal EV charging time. The heater and the day of the week are two of the least sensitive input variables, whereas the lighting condition, season, and time of day are the medium critical input variables.

We believe that there is still a need for more exploration on the interpretability of ML models for developing optimal EV charging systems. Apart from prediction accuracy, the complexity of the models needs to be better understood on how they produce predictions. Although the interpretability evaluation can be performed at the human-level, application-level, or functional-level, the major areas of interest in EV charging systems are at the functional-level and then the application-level. Developing methods to interpret and understand the output of ML models will enhance the reliability and transparency of ML-based solutions for optimal EV charging.

## VIII. COMPARISONS, LIMITATIONS, AND POTENTIAL RESEARCH DIRECTIONS

In this section, we provide an analysis of existing research, addressing various aspects including charging optimization from a grid, a user, or both grid and user, perspective, the selection between centralized and decentralized systems. Additionally, we delve into factors such as computational complexity and computation time, pointing out the limitations and gaps of these existing studies. In addition, potential research directions are suggested.

### A. COMPARISONS AND DISCUSSIONS

#### 1) COMPLEXITY AND COMPUTATION TIME

The study in [49] focused on optimizing grid operation by reducing peak power demand and filling low-demand periods, commonly referred to as *peak to valley filling*. A decentralized scheme was proposed therein, considering that the developed model applied to a university campus. Although LP suffers from complexity, it offers more effective optimization within reasonable computation time. However, when the number of EVs or parking lots becomes larger, an LP based scheme leads to a significant increase in terms of complexity and computation time.

The study in [52] focused on grid operation optimization by implementing a microgrid energy system that controls EV charging patterns in a decentralized manner. Real-time algorithms, which are less complex than LP but less effective in optimizing self-consumption of PV energy, have been developed. Although no specific details about computation times were provided, the inherent complexity of LP suggests that potentially longer computation times are needed compared with real-time control algorithms. The model and control algorithms presented in that study considered both real-time and predictive data, making them suitable for both dynamic and static operations. The authors discussed also potential issues when scaling up the microgrid, noting that self-consumption and peak reduction might decrease when using the V2G technology. Scaling up the microgrid involves adding more components, such as extra households, solar panels, and EVs. The complexity of managing these additional elements in a larger system can lead to higher complexity when optimizing energy use, as balancing the energy demand of the additional components requires sophisticated control algorithms.

#### 2) ENERGY COSTS AND CHARGING EFFICIENCY

The study in [53] concentrated on optimizing energy costs and charging efficiency for both grid and EV fleet operations, by employing time of use (TOU) pricing and PV integration. Assuming that PV installation was performed at a workplace-owned parking lot, energy management control and EV scheduling were implemented through a decentralized system. Although no explicit detail on computational complexity and time was given in [53], it is well known that MILP is computationally intensive, especially when the number of EV fleets is large. In contrast, the study in [54] concentrated on maximizing the revenue of aggregator, which acts as a grid operator serving as the central controller to manage EV charging rates and energy storage operations. The MILP model offers an optimal solution with high computational complexity. On the other hand, the *LP rounding algorithm* provides solutions close to optimal in polynomial times with lower complexity. This exhibits its ability to solving large-scale problems and striking a balance between computational efficiency and optimization quality.

Furthermore, DP has been proven to be effective in addressing intricate problems such as optimal plug-in EV charging scheduling [56] and minimizing battery replacement costs [57]. However, solving DP problems can be computationally expensive due to the *curse of dimensionality*. In [56], a centralized MPC-based algorithm has been employed to mitigate such complexity with a focus on optimizing charging schedules for the power grid rather than for EV users. Given

**TABLE 3.** Summary of EV charging algorithms.

| Algorithm | Application in EV Charging | Advantages | Limitations | Computational Complexity |
|---|---|---|---|---|
| Linear Programming (LP) | Optimizing charging schedules considering multiple EVs, CSs, and power grids | Effective in multiscenario optimization, suitable for peak shaving and valley filling strategies | Can be complex in scenarios with a large number of variables | Variable; can be high in large-scale scenarios |
| Dynamic Programming (DP) | Online charging scheduling, managing dynamic EV arrivals and charging requirements | Effective for multistage decision problems, adaptable to changing conditions | Computationally expensive (curse of dimensionality), requires substantial computational resources | High due to recursive computations |
| Heuristic Algorithms (e.g., PSO, GA, ACO) | Scheduling charging of EVs in various settings like homes, parking lots, considering user behavior | Good at finding near-optimal solutions for large or complex problems, adaptable to different scenarios | Parameter tuning can be complex, may not always find the global optimum | Variable: lower than exact methods but can increase with problem size |
| Machine Learning (ML) Techniques | Predicting future charging patterns, optimizing charging schedules based on historical data | Adaptive to new data, can improve accuracy over time, suitable for dynamic systems | Requires large datasets for training, some models may be "black box" with low interpretability | Depends on the model; deep learning models can be computationally intensive |

that an MPC-based algorithm has a computational complexity level of $O(T^3)$, where $T$ is the total number of time stages, this complexity is regarded as low for handling such scheduling problems as it leads to manageable computation times.

The study in [57] focused on optimizing the operational efficiency of EBF from an operator's perspective for a centralized system. Despite of unknown computation complexity and times for their study in [57], DP is considered as complex but effective for solving multistage decision problems. On the other hand, the use of a *reverse order matching strategy* could increase complexity and computation time but ensure optimal results.

In [59], [60], [61], [62], and [63], heuristic algorithms such as PSO, GA, and ACO were proposed and their effectiveness in solving EV charging scheduling problems was demonstrated. These methods prove to be adept in finding near-optimal solutions, even in scenarios where the problem is too large or complex. Broadly, PSO exhibits lower computational complexity and faster convergence compared to ACO and GA. The computational complexity of GA and ACO tends to rise, particularly with larger problem sizes. However, it is essential to understand that heuristic algorithms require tuning of algorithm-specific parameters, which can be a complex process. The study in [59] focused on reducing charging costs and time consumption for EVs in microgrids, benefiting both grid operators and EV owners. A centralized charging scheme was employed for deciding charging schedules, determined by the microgrid's energy management team. Although that study did not discuss the computational complexity and time taken by each algorithm, we can infer general principles here. The PSO algorithm is relatively more complex compared to the ATP and SBP algorithms because it involves multiple particles searching through the solution space, which may take longer time due to its iterative nature and higher complexity.

### 3) OPTIMIZED EV CHARGING: CENTRALIZED AND DECENTRALIZED APPROACHES

The study in [60] focused on minimize charging costs for parking lots, from the perspective of a grid operator, indirectly benefiting the grid. Optimal charging schedules are determined for all EVs at a parking lot *in a centralized manner*. The study ascertains that the proposed method does not require sophisticated systems, implying manageable computation time. Moreover, the study in [61] concentrated on charging optimization for power grid operators, by employing a GA-based model to manage EV charging schedules in a centralized system. That study also reveals the effectiveness of GA in solving complex optimization problems, which can be computationally intensive.

Furthermore, the study in [62] put more effort on optimizing the performance metrics that are related to EV charging rather than minimizing computational complexity or costs. Therein charging schedules are managed *in a centralized system*, by taking the entire network of EVs and CSs into account. The authors found out that the GA converged to the solution before reaching the maximal iteration counts, and recommended keeping the population size and the number of iterations up to 200 for maintaining optimal results. This implies that increasing the number of iterations does not necessarily lead to better results but instead would extend computation processing and time. On the other hand, [63] focused on optimizing charging operational efficiency within CSs rather than taking care of individual EV user preferences, by utilizing *a centralized charging system*. That study indicates that ACO is efficient in solving problems within reasonable time frames and suggests using the same termination conditions and the same number of iterations (i.e., 200) for both ACO and GA methods. Both ACO and GA can be computationally demanding, and their performance and computational load may vary significantly depending on the specifications of the implementation and the problem at hand.

Reference [65] focused on predicting power demand of CSs, providing benefits for grid operators in regulated electricity markets. The approach can be applicable *in both centralized and decentralized charging systems*. Although DRL models, especially GRU, are known for their computational intensity and require many resources, they are highly effective for performing prediction tasks. A single hidden layer in the GRU model emerged as the best-performing model in [65], demonstrating the highest accuracy in predicting EV charging demands. It was suggested that using DL models such as LSTM and GRU could lead to cost savings and efficiency in managing energy demand and supply.

The authors of [66] studied total charging time and cost minimization from an EV user perspective. They proposed a DRL-based a centralized system, where the SDN controller collects real-time information and schedules charging schedules of EVs. They conclude that traditional game-theoretical methods (which perform exhaustive searches) are not applicable when dealing with large numbers of EVs due to their high computational complexity. In contrast, the proposed DRL-based solution appears to be more efficient even with incremental updates. Also, the computational time of DRL-based methods is less than that of game-theoretical methods.

In Table 3 above, we provide a comprehensive analysis that summarizes various algorithms for EV charging, and present their applications, advantages, limitations, as well as computational complexity.

### *B. LIMITATIONS AND GAPS*

In this subsection, we identify the limitations and gaps that exist in the state-of-the-art studies within this topic.

1) Scalability: Several studies, including [52], [53], and [56], were conducted in small-scale environments with specific scenarios. The applicability of these schemes may not be suitable for larger-scale areas or more complex grid systems. For instance, these schemes may face scalability problems in handling many EVs or complex charging scenarios, making them computationally intractable or less effective.
2) User-centric optimization: Most of these studies, e.g., [49], [52], [53], [56], [61], and [63], have focused on EV charging optimization from a grid perspective. However, individual EV user information, such as EV arrival times, charging mode preference, SOC, or EV location, in generally overlooked. Although incorporating users' information with respect to their needs and preferences would increase scheme complexity and requires sophisticated algorithms, more efficient charging schemes could be developed when this aspect is considered. As such, user-centric schemes that achieve close-to-optimal performance are expected.
3) Handling real-time data: Many approaches rely on predictive models or historical data, which may not fully account for dynamic real-time changes, resulting in suboptimal charging schedules. For example, uncertainty in various factors, such as PV power and predictions of load demand, number of EV trips, and energy consumption, was ignored in [57]. While some studies such as [52], [53], [56], [63], and [66] seem to be dynamic and suitable for real-time systems, other studies like [57], [59], [60], and [62] rely heavily on static data and do not address their adaptability to real-time grid variations. In general, adopting real-time data calls for more efficient and adaptive EV charging schemes.
4) Integration with other technologies: The integration of the grid system with the V2G technology, RES systems, or dynamic price strategies is only explored in a few studies like in [52], [53], [56], [63], and [66]. Other solutions like presented in [56], [61], and [65] suggest that they can be potentially integrated into a V2G system.

In Table 4, we summarize multiple popular charging optimization solutions highlighting their findings and contributions, address their integration feasibility, and point out their limitations and gaps.

### *C. OPEN RESEARCH AND FUTURE DIRECTIONS*

Based on the above observations, we share our thoughts on open research questions and shed light on potential directions for further development of optimal EV charging schemes.

#### 1) INCREASING THE AVAILABILITY OF PUBLIC CHARGING DATASETS

Developing ML models to optimize EV charging encounters a substantial obstacle due to the limited availability of public charging datasets. Effective ML techniques demand a vast amount of data for training and validation. The absence of open access, comprehensive datasets on charging behavior, infrastructure utilization, and related factors can impede the development of accurate and generalized models. Despite a few public available datasets, such as those from ElaadNL and MyElectric Avenue [75], [76], that offer valuable insights into residential and public charging facility usage, they are restricted to specific geographical locations and periods. This scarcity often results in over-reliance on proprietary or simulated data, which may not always accurately reflect real-world conditions. To address this challenge, enhanced collaborations among various players and stakeholders along the EV transport value chain, including industries, governmental organizations, researchers, engineers, and EV owners are highly recommended. Creating standardized, anonymous public datasets could enable more researchers to engage in developing robust models. Accordingly, developing novel business models to encourage sharing experimental datasets among stakeholders would also be interesting. Such efforts would improve the accuracy and reliability of optimized ML models, leading to cost-effective and stable grid operations.

#### 2) MAXIMIZING THE UTILIZATION OF RESS

Effectively integrating RESs into the charging scheduling process is a vital element in maximizing the utilization of green energy while minimizing environmental impact and cost [77]. For instance, contemplate a scenario where a community possesses an abundant source of wind energy, particularly during nighttime when wind speeds are at their peak. On the other hand, the demand for electricity in this community is low during this period of time. Therefore, this excess energy could be used to charge EVs. A smart charging

**TABLE 4. Examples of charging optimization solutions.**

| Ref. | Algo. | Key Findings/Contributions | Charging System | Integration With | Limitations and Gaps |
|---|---|---|---|---|---|
| [49] | LP | Developed an LP model to optimize power consumption at parking lots, demonstrating effective peak shaving and valley filling strategies (optimizing from a grid perspective) | Decentralized | None | • The study was conducted in a small-scale area (a university) with a limited number of EVs and parking spots.<br>• Lack of consideration of EV user preferences such as required SOC and charging mode, or a specific time for charging. |
| [52] | LP | Utilized LP to enhance self-consumption of PV in a microgrid, showing significant reduction in peak demand and increased efficiency (optimizing from a grid operator's perspective) | Decentralized | V2G and RES (PV) | • The study is limited to small-scale areas, so improvement is needed in order to apply it to large-scale areas.<br>• Uncertainty in various factors, such as PV power and load demand predictions, EV trip times, and energy use.<br>• Lack of consideration of the EV constraints (e.g., SOC, charging mode, EV location). |
| [53] | MLP | Demonstrated cost-effective EV charging management with PV and minimizing charging costs of EVs and power load on the grid to enhance the grid stability (optimizing both the grid and the user perspectives) | Decentralized | V2G, RES (PV), and TOU | • The study was limited to a small area and may face challenges in real-world implementation at a larger scale.<br>• The model relies on prediction data of solar generation and energy prices.<br>• Lack of consideration of the EV constraints (e.g., SOC, charging mode, battery capacity). |
| [54] | MILP and LP | Presented a novel approach for optimizing EV charging, significantly maximizing aggregator revenue and energy storage usage (optimizing from the grid operator's perspective) | Centralized | None | • The model was based on simulations and its effectiveness needs validation in real-world applications. |
| [56] | DP and MPC | Proposed effective algorithms for managing dynamic EV arrivals and charging, focused on minimizing EV charging cost, power load, and computation time (optimizing from the grid perspective), suitable for fluctuating EV numbers and demands | Centralized | None | • The study was based on simulations and may need further validation with real-world data. For instance, information such as arrival EVs is not known. This makes the potential to apply real-time scenarios integrated into a V2G system. |
| [57] | DP | Suggested a DP-based method for reducing battery replacement costs in EBFs, enhancing sustainability and economic efficiency (optimizing from a user perspective) | Centralized | None | • The study was conducted in a public transit system for five EBFs with five routes a day.<br>• The applicability to different or larger-scale transit systems (e.g., decentralized) was not discussed. |
| [59] | PSO | Developed a PSO-based method to minimize charging costs and time in parking-lots (optimizing both the grid and the user perspectives) | Centralized | RESs (wind turbine and five PV) | • The study considered a small number of EVs and did not account for varying user behavior and preferences in charging. |
| [60] | PSO | Implemented PSO for efficient EV charging management to minimize charging costs of parking lots (optimizing from a grid operator's perspective) | Centralized | V2G | • The study did not use the aggregation technique. |
| [61] | GA | Introduced a GA-based scheme for load profile optimization, by flattening the load prevent aging of power system elements (optimize from a grid operator's perspective) | Centralized | None | • Lack of consideration of the EV preferences or constraints (e.g., SOC, charging mode, battery capacity). |
| [62] | GA, NJF, and EDF | Proposed a GA-based scheme to minimize waiting time and distance for emergency EV charging during peak times (optimizing from a user perspective) | Centralized | None | • The study was conducted for urgent EV charging in high-density regions and did not consider the charging costs aspect. |
| [63] | ACO | Optimizing charging operation efficiency for a grid perspective by minimizing the total delay in EV charging at stations with high traffic | Centralized | None | • The study did not address the variability in individual EV charging needs or preferences. |

**TABLE 4.** ***(Continued.)*** **Examples of charging optimization solutions.**

| | | | | | |
|---|---|---|---|---|---|
| [65] | GRU | Developed DL models to accurately predict EV charging demand, particularly effective in the context of Morocco (optimizing from a grid operator's perspective) | Centralized or Decentralized | None | • The study was specific to Morocco's regulated electricity market, and the applicability of the findings to other regions or market structures may vary.<br>• The study did not consider the variability of EV user behavior and its impact on charging demand predictions. |
| [66] | DRL | Utilized DRL for efficient CS selection and route planning, reducing EV charging costs and time for EV (optimizing from a user perspective) | Centralized | SDN, VEC, and TOU | • Inflexible to select the charging mode of the EV user, its adaptability to different urban environments with varying traffic needs to be further explored. |

system could encourage EV owners to charge their vehicles during these periods of time of high wind energy generation. In this way, integrating RESs into EV charging schedules can maximize the utilization of clean energy, reduce carbon footprint, and potentially save costs.

However, the output of energy volume from solar and wind sources may vary over time, and their production may not always meet the demand in a real-time manner. To overcome this drawback, future research could investigate the effectiveness of integrating the EV technology into RESs. As mentioned earlier, EV batteries can act as a mobile CS, that stores the energy generated by renewable sources (e.g., wind or solar), and the saved energy can be used to power vehicles or feedback into the grid during peak demand hours. EVs have the potential to reshape the dynamics of the grid by acting as mobile energy storage units. As the number of EVs in parking lots increases, the aggregation of their battery energy may serve as a dynamic resource for stabilizing the grid. Therefore, how to integrate RESs with EV charging systems to improve energy efficiency and environmental sustainability requires more research efforts.

### 3) IMPROVING TIME EFFICIENCY AND DEMAND AWARENESS

Developing optimal charging schemes that can respond to changes in real-time, handle large-scale charging demands, and deliver effective charging services in a computationally manageable manner is another interesting topic deserving further investigation [78]. This topic addresses the need for time-efficient charging solutions by reducing waiting time and ensuring reliable access to charging infrastructure with enhanced user convenience.

For instance, consider a large city with a high concentration of EV penetration. An unexpectedly high demand for EV charging during specific periods of time (e.g., public events or even workday hours) may arise for such a scenario. Furthermore, the charging requirements of these vehicles may vary, depending on their battery capacity, SOC, preferred charging mode, and the accessibility of charging infrastructure (e.g., public or home). This situation may lead to increased waiting time for EV charging and an undue burden on the grid, leaving EV owners unsatisfied as normal charging schemes are unable to deal with unexpectedly high demand.

Therefore, data monitoring-based charging schemes, that can dynamically modify charging schedules and optimize charging criteria according to current circumstances and context, need to be developed. For example, if a particular part of a grid (e.g., stations) is under heavy load, the system could redirect charging demands to other less-loaded energy sources, to ensure stable operations and guarantee reliable operations. Furthermore, to effectively manage energy resources, it is recommended to consider various factors like current power demand, charging infrastructure availability, power grid capacity, and real-time traffic data when developing charging schemes.

### 4) INCREASING GRID STABILITY AND USER ACCESSIBILITY

Load balancing is an important aspect for charging scheme design, especially when grid capacity and demand fluctuation at CSs are taken into consideration. A challenging task for grid operators is how to manage overloaded CSs and accommodate high charging demands during peak hours. To address this issue, future research efforts towards more dynamic and adaptive approaches are required.

Within this topic, ML techniques can be applied as they exhibit promising potential for charging scheme optimization. ML-based solutions may implement adaptive algorithms that introduce constraints or measures on charging services when heavy load is observed in a grid, such as enforcing a maximum SOC threshold for EVs to be charged during peak hours. Through such a measure, a well-balanced and stable grid could be ensured while maintaining accessibility for all EV users.

### 5) MAINTAINING USER CONVENIENCE AND COST OPTIMIZATION

Despite the importance of satisfying dedicated requirements for battery charging, a carefully designed charging scheme can ensure a convenient, efficient, and cost-effective experience from the perspective of user convenience.

**TABLE 5.** List of abbreviations.

| Acronym | Full Name |
|---|---|
| AC | Alternative Current |
| ACO | Ant Colony Optimisation |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| ATP | Arrival Time-Based Priority |
| AVG | Heuristic Online Average |
| BEV | Battery Electric Vehicle |
| BSS | Battery Swap Stations |
| CC | Conductive Charging |
| CPP | Critical Peak Pricing |
| CS | Charging Station |
| DC | Direct Current |
| DL | Deep Learning |
| DNN | Deep Neural Network |
| DP | Dynamic Programming |
| DRL | Deep Reinforcement Learning |
| EBF | Electric Bus Fleet |
| EDF | Earliest Deadline First |
| EDT | Earliest Due Time |
| ELF | Expected Load Flattening |
| ELM | Extreme Learning Machine |
| EV | Electric Vehicle |
| EVSE | Electric Vehicle Supply Equipment |
| FCFS | First Come First Serve |
| FCEV | Fuel Cell Electric Vehicle |
| FCS | Fast charging Station |
| FFNN | Feed Forward Neural Network |
| GA | Genetic Algorithms |
| GECS | Genetic Algorithm-based Emergent Charging Scheduling |
| GRU | Gated Recurrent Unit |
| GWO | Grey Wolf Optimizer |
| HEV | Hybrid Electric Vehicle |
| ID | Identity |
| KNN | K-Nearest Neighbors |
| LSTM | Long-Short-Term Memory |
| LST | Latest Starting Time |
| LP | Linear Programming |
| MILP | Mixed-Integer Linear Programming |
| ML | Machine Learning |
| MPC | Model Predictive Control |
| NB | Naive Bayes |
| NJF | Nearest Job First |
| NN | Neural Network |
| PEV | Plug-In Electric Vehicle |
| PSO | Particle Swarm Optimization |
| PTR | Peak Time Rebates |
| PV | Photovoltaic |
| RES | Renewable Energy System |
| RF | Random Forests |
| RL | Reinforcement Learning |
| RNN | Recurrent Neural Network |
| RTP | Real-Time Pricing |
| SAA | Sample Average Approximation |
| SBP | State of Charge-Based Priority |
| SDN | Software-Defined Networking |
| SHAP | Shapley Additive Explanation |
| SL | Supervised Learning |
| SOC | State of Charge |
| SSL | Semi Supervised Learning |
| SVR | Support Vector Regression |
| SVM | Support Vector Machine |
| TOU | Time of Use |
| UL | Unsupervised Learning |
| VEC | Vehicular Edge Computing |
| V2G | Vehicle-to-Grid |
| WPT | Wireless Power Transfer |

Service providers should allow EV owners to specify their charging preferences, such as preferred charging infrastructure (e.g., home, public, or via a mobile station), charging modes, acceptable price rate, and intended charging hours. Customized preferences for an optimal charging scheme are an essential aspect that should be considered for EV charging scheme design when user convenient is considered.

For instance, some EV owners may prioritize fast charging (e.g., mode 3 or mode 4) over slow charging (e.g., mode 1 and mode 2), especially during peak hours. A drawback with fast charging lies in its high requirement for power supply rate, which faces a risk of straining the grid and, and in extreme cases, leads to power outages if the overall demand exceeds the grid's capacity. To diminish this risk, how to optimize charging schedules based on user demands and grid capacity, e.g., potentially by adopting a TOU pricing strategy to manage the charging demand during peak hours, needs to be explored.

Finally, how to balance user convenience with cost-effective grid management in terms of cost optimization needs to be further studied. For instance, a charging scheme could schedule EV users for fast charging only for those who have long-drive route or urgent demand, particularly during peak hours by increasing charging prices. In contrast, those EV users who are not urgent would be advised to select slow charging to enjoy the benefit of lower pricing rates for electricity. Such a strategy can not only flatten the power demand curve and increase the revenues of grid operators but also meet the requirements of EV users.

## IX. CONCLUSION

This article addresses several facets of EV charging including the adoption of EVs, their impact on power grid, and the necessity for charging scheme optimization. Two major classes of charging systems, namely, uncoordinated and coordinated (where the latter one includes both centralized and decentralized), are presented with their advantages and disadvantages elaborated. Both classical and machine learning based techniques for optimization are analyzed. In addition, we present and analyze recent research efforts that have utilized these techniques in order to achieve charging scheme optimization. The computation time and complexity of various algorithms are also summarized. Furthermore, the limitations and gaps existing in the state-of-the-art solutions are identified. Finally, a few potential research directions related to the theme of EV charging optimization, such as adaptation to dynamic charging demands, load prediction and balancing, time efficiency improvement, and the integration of RESs and V2G with EV charging, are pointed out.

## APPENDIX A
## LIST OF ABBREVIATIONS

A list of the abbreviations introduced in this article is tabulated in Table 5.

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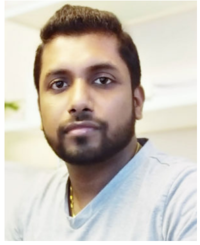

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