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TOPICAL REVIEW

Charge Scheduling Optimization of Electric Vehicles: A Comprehensive Review of Essentiality, Perspectives, Techniques, and Security

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ABSTRACT The transportation sector is one among the key sources of greenhouse gas emissions (GHGs) leading to climate change and global warming. Energy transition through electrified transportation is one of the solutions to tackle the issues. Electric vehicles (EVs) offer significant environmental and economic advantages against the conventional Internal Combustion Engine (ICE) vehicles. EVs are called mobility loads and their connectivity to the utility grid for charging is unpredictable. The large penetration of such unpredictable loads into the utility grid will lead to undesirable impacts on the utility service. This paper highlights the importance of managing and optimizing the charging schedules. The optimization of EV charging has diverse aspects, and the perspectives of EV charging differ among consumers, aggregators, and utility services. Proper planning and management of EV charging is essential to achieve harmony amongst these stakeholders. A comprehensive review on the objectives of electric vehicle charging optimization from various perspectives is presented and discussed in this paper. EV charging optimization techniques including mathematical programming, meta heuristics algorithms and machine learning techniques are explored. The main objectives, constraints, strength, and limitations of different charging optimization techniques are analyzed in detail. A brief discussion on the communication strategies for data exchange in EV charging framework is presented and the need for a communication security constrained EV charging scheduling is also emphasized.

INDEX TERMS Electric vehicles (EVs), charging scheduling, optimization, machine learning, metaheuristics, renewable energy.

I. INTRODUCTION

Fossil fuels have been acting as the principal energy sources since the industrial revolution. They have also played a major role in improving the world economy. However, their contribution to the undesirable climate changes in the world and the anxiety towards their long-term availability have created a need to focus on sustainable energy transition. To ensure leaving a healthy planet for the future generations to live on, immediate actions should be taken to reduce carbon emissions. The statistics for global CO2 emissions by various sectors obtained from [1] shows that the transport sector acts as the second largest contributor to the global carbon emissions. Fig. 1 shows the comparison of global emission in Mt CO2 by various sectors in the year 2021 and 2022 [1]. The environmental degradation and climate changes due to these emissions could be tackled by the move towards electrified transportation [2]. International Energy Agency (IEA) has

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reported in its 2023 CO2 emissions report that the adoption of EVs together with energy transition has prevented a threefold increase in emissions growth since 2019 [3]. In recent years, the popularity of Plug-in Electric Vehicles (PEVs) is steadily rising and the usage of PEV is on a definite upswing. The transportation landscape is rapidly transforming with the rise of EVs, thus promising a cleaner, quieter, and more sustainable future. Based on the sales of EV in the first quarter of 2023, a projection was made indicating a 35% increase in global EV sales in 2023 compared to 2022, with an expected sale of 14 million EVs [4]. The actual EV sales in 2023 nearly aligned with this prediction, reaching 13.6 million, leading to 31% increase in sales of EV [5]. China leads the global electric car market, with over half of all electric vehicles on the roads worldwide now found in the country. In 2022, China marked its total EV sales as around 5.9 million which is double the number of global EV sales a couple of years before in 2020 [4]. The steady increase in EV sales numbers in recent years confirms their wide acceptance as the future of transportation.

As EV usage is increasing rapidly, a thorough examination of its impact on the grid becomes essential. Though there are a lot of potential advantages of EV in terms of environmental sustainability and energy efficiency, the integration of EVs in large-scale brings various challenges, including grid strain, limited charging structures, and managing energy demands. As the EV sales increase, the energy demand for charging also increases. This also could result in uncontrolled charging and put a strain on the grid systems. These negative impact may act as a barrier for future EV adoption. Grid integration of EVs in large numbers requires costly upgrades to smart technologies. When many EVs charge at the same time without planning which in other terms referred as an uncoordinated EV charging creates unpredictable demand spikes, pushing power grids beyond capacity. Uncoordinated EV charging is dictated solely by customer preferences, so it creates difficulties for grid operators and utilities in ensuring grid stability and electricity distribution. This leads to infrastructure overload, voltage instability, and energy losses [6]. Certain concerns also arise from the user's standpoint which includes range anxiety due to limited charging stations (CSs), longer charging durations, and the lack of fast charging system to match the recent advancement in EV technologies. These issues highlight the need for smarter charging management solutions.

Coordinated electric vehicle charging system with efficient scheduling algorithms ensures optimum charging/discharging and presents a potential avenue for the enhancement of grid utilization and the mitigation of network expansion requirements [7]. Some of the important constraints to be considered to develop an efficient scheduling algorithm are vehicle configuration (such as vehicle type, model, battery capacity etc.), vehicle profile (including arrival and departure times, current state of charge (SOC) of the battery, required charging energy etc.), grid and aggregator parameters [8]. Optimization of the charging schedules

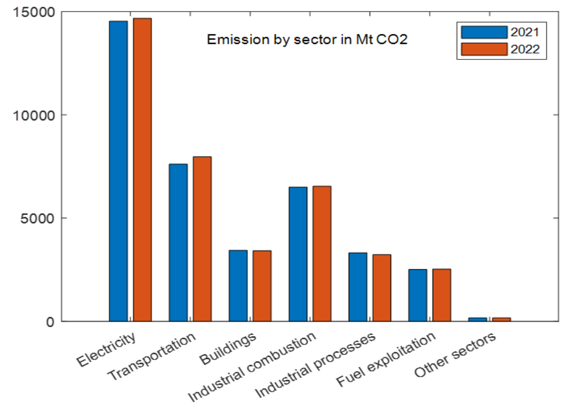


FIGURE 1. Comparison of global CO2 emission by various sectors in the year 2021 and 2022.

is essential to effectively manage EV charging, considering different objectives from the perspective of different stakeholders. These diverse goals of optimization problems have been solved in numerous research by employing different optimization techniques.

This review paper analyzes various objectives of optimization and the optimization techniques ranging from the conventional mathematical optimization techniques, followed by metaheuristic algorithms to the recently emerged machine learning techniques. The major contributions of this review paper are:

- Emphasizing the role of EVs in sustainable transportation, while highlighting their advantages over conventional internal combustion engine vehicles by comparing their well to wheel emissions and efficiency.
- Study of electric vehicles charging system and their core elements, as well as the various charging levels available along with their technical specifications.
- Reviewing the need for coordinated charging scheduling of EV and a look into different coordinated charging scheduling approaches, including centralized, decentralized, and the emerging field of hierarchical scheduling.
- Exploring the necessity of EV charging scheduling optimization from the viewpoint of different entities participating in the EV charging structure.
- Surveying various optimization techniques employed to solve different optimization problems with varying constraints.
- Analyzing the strategies for data exchange between various stakeholders in a smart charging network, assessing their vulnerability to cyber-attacks and exploring methods for achieving secured communication within the network.

II. EVS VS. ICE: WELL-TO-WHEEL ADVANTAGE

Battery Electric Vehicles (BEVs) or Plug-In Electric Vehicles (PEVs) are considered zero emission vehicles. The fact is that PEVs have no direct emissions i.e., PEVs produce zero tailpipe emissions [9]. However, the tailpipe emission is just one aspect, which means that EVs possess indirect carbon

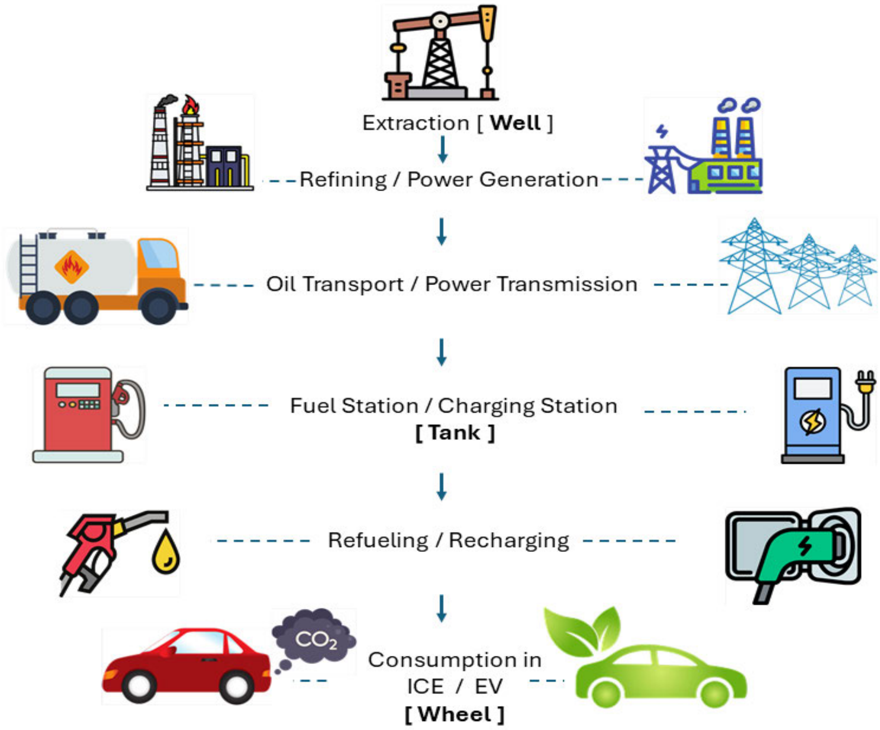


FIGURE 2. Fuel pathway from Well to Wheel.

emission. For example, EVs are mainly charged from utility grids in which the source for production of electricity is fossil fuel [10]. The fuel pathway for electricity generation has life cycle emission at various stages through fuel extraction, refining, production, and transportation. But PEVs, and Plug-In Hybrid Electric Vehicles (PHEVs) still exhibit reduced life cycle emissions compared to the ICE vehicles.

The carbon emission of PEVs and ICEVs can be assessed through a Well-to-Wheel (WTW) and Tank-to-Wheel (TTW) analysis. The fuel pathway from Well-to-Wheel for ICEV and PEV is shown in Fig. 2. WTW analysis is divided further into Well-to-Tank (WTT), and Tank-to-Wheels (TTW) analysis [11]. In WTW assessment, the energy efficiency, and GHG emissions at various stages during the entire fuel life cycle are examined.

For ICEVs the WTW fuel pathway includes fuel extraction, oil refining, transportation to fuel station, refueling and consumption. In the case of PEVs, fuel extraction, electricity generation and transmission are considered as WTT pathway and the TTW pathway stages are the electrical power transmission stages at charging stations, vehicle charging, and energy consumption.

A lifecycle emission assessment of ICEV and PEV is carried out in [12]. The study considered the life cycle emission of a vehicle in terms of emissions due to vehicle manufacturing, battery manufacturing, and emissions associated with production of electricity and/or fuel, consumption, and maintenance of the vehicles. From the study it is observed that the emission of medium sized PEVs in Europe are 66%-69% less than the comparable ICEVs. Likewise, the emission is 60%-68% lower than the ICEVs in the United States. In India and China, the emission reduction is 37%–45%, and 19%–34% respectively.

The WTT and TTW efficiency of ICEVs based on fuel pathway are depicted in Fig. 3(a) and Fig. 3(b) respectively. The efficiency of crude oil extraction is about 95% [13]. The processing and transmission efficiency of fuel is 88% and 99% respectively. Thus, the overall WTT efficiency is around 82%. The TTW efficiency of ICEVs accounts for various losses associated with vehicle operation. It mainly includes engine losses of around 68-72%, and drivetrain losses of 3-5%. The parasitic losses of ICEVs are between 4-6%, and the losses due to auxiliary electricity services accounts to 0-2% [14]. Therefore, the TTW efficiency of gasoline powered ICEVs are from 16% to 25%. Thus, the Well-to-Wheel efficiency of gasoline ICEV is calculated as only 13-20%.

The power generation, transmission and the charging efficiency determine the WTT efficiency of PEVs. The power generation efficiency using fossil fuels is around 50% and the transmission efficiency is 92% [13]. While accounting for the fuel extraction efficiency of 95%, the WTT efficiency of EV is approximately 44%. For TTW efficiency assessment of EVs, the losses occur between charging to wheel are considered. The charging losses are assumed to be nearly 10%. The drivetrain losses are 18%, power train cooling and steering loss of 3%. The auxiliary electricity use losses ranges from 0-4%. Thus, the TTW power conversion efficiency of EVs lies in the range of 65–69%. Another important feature of EVs is regenerative braking where the power is generated and fed back to the tank during braking. While taking the regenerative

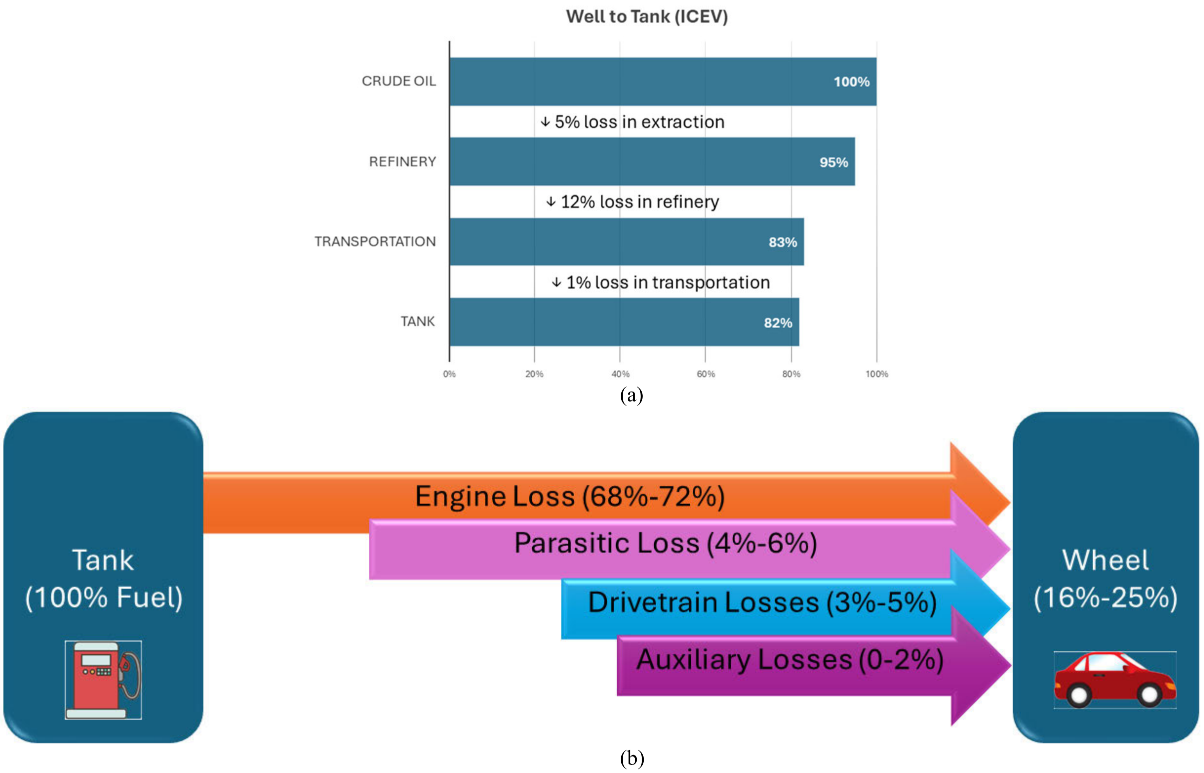


FIGURE 3. (a). WTT efficiency of ICEV. (b). TTW efficiency of ICEV.

braking efficiency of 22% into account, power conversion from tank(battery)-to-wheels in an EV throughout a drive cycle can vary between approximately 87% and 91% [14]. Thus, the overall WTW efficiency of EV falls between 30% and 40%. The WTT and TTW efficiency of EVs based on the fuel pathway is shown in Fig. 4(a) and 4(b) respectively. In Fig. 4(b), the higher range in the calculated efficiencies with and without regenerative breaking respectively are shown as the range of TTW efficiency. The losses shown in Fig. 3(a) and Fig. 4(a) are derived from the efficiency at each stages in [13] which comprehensively analyses the WTW, TTW efficiency at various stages. The methodology and assumptions made for the calculation of WTW, and TTW efficiency are described in [13].

From the above discussions, it is evident that EVs are more energy efficient than ICEVs. The overall WTW efficiency of EVs is at least 17% higher than the comparable ICEVs even with fossil fuel as a source of electricity. Charging EVs from the stations integrated with renewable energy system (RES) could further increase the overall WTW efficiency [15].

III. ELECTRIC VEHICLE CHARGING

The impact of PEV charging on distribution grids under various conditions has been investigated in several studies, including diverse charging strategies and operational settings. The following subsections briefly discuss the EV charging system and different EV charging levels.

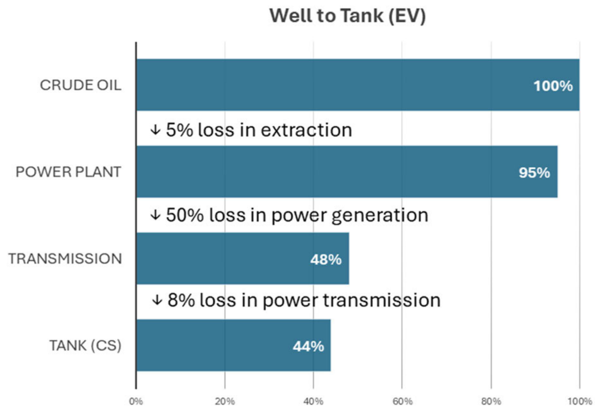
A. ELECTRIC VEHICLE CHARGING SYSTEM

An EV charging system is a network of components that collaborate to recharge an EV's battery. The core elements of an EV charging system include:

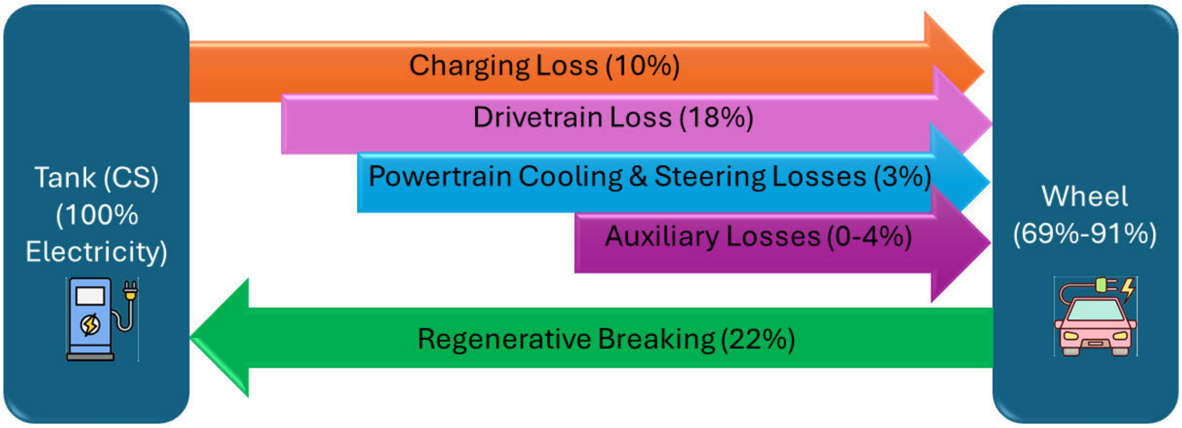
i. Power source: This supplies the energy required for charging the EV. The source can either be the grid, RES, or a combination of both.
ii. Electric vehicle supply equipment (EVSE) or charging station: This is the physical unit where the EV connects for charging.
iii. Aggregator or energy management system (EMS): This crucial component manages a substantial fleet of EVs, controlling their charging and discharging to maintain desired grid frequency [16].
iv. Communication protocols and user interface: These elements enable communication between the EVSE and EV, electric vehicle charging system and users [17], [18].

B. EV CHARGING LEVELS

EV charging includes different levels, each offering distinct charging speed and power outputs [19]. These levels differ in voltage, application, and cost. Table 1 represents the EV Charging level [20]. Level 1 (L1) and level 2 (L2) are Alternating Current (AC) charging, typically used for home and/or commercial charging stations. Level 1 utilizes readily available standard 120 V_{AC} or 240 V_{AC} household outlets, but delivers limited power, adding only 15-20 kms of range for one hour of charging. L1 charging is the slowest among



(a)



(b)

FIGURE 4. (a). WTT efficiency of EV. (b). TTW efficiency of EV.

all EV charging levels. Level 2 charging utilizes a 3 phase, 415 V supply system, and it necessitates an EVSE or a designated charging station and is frequently encountered in residential areas, workplaces, and public charging stations. It provides a range of 20 to 130 kms per hour of charging [21]. Utilizing DC fast charging, Level 3 (L3) offers the most rapid charging solution for electric vehicles. It is primarily found at public charging stations situated along highways and main travel corridors and is generally the most expensive but fastest charging option. Electric vehicles (EVs) have built-in chargers with AC-DC converters that convert grid power to DC for the battery. These are called onboard chargers. Level 1 and Level 2 chargers with AC power, charge the EV battery via onboard charger. In contrast, Level 3 chargers, which are also called off-board chargers, have the AC-DC converter located off-board, e.g. inside the charging station itself. So, they bypass the onboard charger and deliver high-voltage DC directly to the battery via the EV's Battery Management System (BMS) [22]. This enables significantly higher charge rates, with charger output power ranging up to 400 kW and with voltages ranging from 200-1000 V. The charging voltage may vary depending upon the type of charger used. Newer EVs with high-voltage batteries are particularly well-suited for this efficient charging method. It offers a recharge rate of 5 to 32 kilometers of range per minute [21], significantly reducing charging times.

TABLE 1. Charging levels of electric vehicles.

Charging Level	Charger Types	Power Rating (kW)	Connector Type
L1	AC	<=3.5 kW	Type 1
L2	AC	<=22 kW	Type 1, Type 2, GB/T
L3	DC	Up to 400 kW	CHAdeMO, CCS1, CCS2

It is important to note that setting up an Electric Vehicle Charging Station (EVCS) involves various stakeholders including investors, operators, developers, utility systems, and several other government agencies. From initial planning to the operation, a rigorous process is involved. The grid feasibility in the location, maximum possible loading capacity are the key factors in identifying a suitable location for the EVCS. The total electricity demand of the charging station is a most crucial and challenging factor in the process. Likewise, scaling up a CS is also challenging since it must go through most of the processes involved at the initial set up. Other than

TABLE 2. Specifications of few selected EVs in current market.

Model	Charge Port	Charge Power	Battery Capacity (kWh)	Range (km)	Energy Consumption (Wh/km)
BMW IX XDRIVE40	Type 2/ CCS	11 kW AC/ 148 kW DC	76.6	360	197
HYUNDAI KONA EV	Type 2/ CCS	11 kW AC/ 77 kW DC	67.5	390	147
KIA NIRO EV	Type 2/ CCS	11 kW AC/ 80 kW DC	68	385	168
MG ZS EZS DEL	Type 2/ CCS	7.4 kW AC/ 94 kW DC	72.6	370	185
NETA V DELUXE	Type 2/ CSS2	6.6 kW AC/ 100 kW DC	38.54	380	112
NISSAN LEAF	Type 2/ CHAdeMO	3.6 kW AC/ 46 kW DC	40	235	166
PORSCHE TAYCAN	Type 2/ CCS	11 kW AC/ 223 kW DC	79.2	410	173

the financial constraints the grid constraints play a crucial role in the scaling up process. Moreover, the regulations and policies for setting up and scaling up the charging stations are not in place in many countries which is another major challenge for charge point operators.

Table 2 provides the specifications of some of the EVs in the current market [23]. The details in Table 1 and 2 provide insights about the power rating of different levels of EV chargers as well as the energy consumption of different EVs. From Table 2 it can be realized that most of the EVs charge at the power rating of 11 kW (Level 2). Every EV can be treated as equivalent to a residential load on the grid when it is connected for charging at Level 2 AC charging. When many EVs simultaneously connect to the grid for charging particularly during the peak demand hours, the unforeseen surge in demand could strain the grid and lead to issues such as voltage drops or overloaded transformers. EVs are mobility loads and their penetration to the grid is unpredictable. The intermittent nature of EV charging could create significant changes on the grid, if not managed effectively. This necessitates the need for EV charging scheduling which becomes the core theme of this review.

IV. EV CHARGE SCHEDULING

The huge adoption of electric vehicles could pose a challenge to existing grid infrastructure if their charging is uncontrolled. This unforeseen peak demand could lead to unpredictable and significant strain on the network. Fig. 5 depicts some of the various negative impacts caused by EV charging on the existing grid structures. To address these challenges and effectively reduce negative impacts on the distribution grid, charging control management systems are crucial. These systems schedule EV charging based on various factors and thus optimize the charging process [24]. Based on the presence of management strategies, charging methods fall into two categories namely the uncoordinated and coordinated methods. Within coordinated EV scheduling, based on the decision-making process, it is further classified as centralized, decentralized (or distributed), and hierarchical charging techniques [25].

A. CENTRALIZED EV CHARGING

In centralized decision-making for EV charging, a sole entity, such as an operator or aggregator, takes charge of control and management. This entity collects data from both EVs and the grid. Using this data, the aggregator solves an optimization problem which is mostly a complex mathematical problem, the ideal charging rate and optimal time for charging each EV is determined [26]. The optimization process factors in multiple parameters, including grid capacity constraints, real-time electricity costs, and the specific charging needs of each connected vehicle. The ultimate objective is to ensure optimal power utilization while fulfilling the individual charging requirements of all EVs. Once the optimal charging schedule is established, the aggregator transmits it to the charging station. The charging station would then direct each EV connected to it, dictating the precise charging rate for their vehicle and/or the time of charging according to the charging schedule it received from the aggregator.

Centralized EV charging systems use various optimization algorithms to achieve a diverse set of objectives. The role of these optimization algorithms is crucial in maximizing the profitability of aggregators while also ensuring efficient utilization of the available network capacity. Centralized control allows EVs to participate in the ancillary service markets, offering services like voltage regulation, and frequency control to the grid. Scalability poses a significant obstacle for centralized approaches, particularly as the optimization problem grows over longer planning timeframes and with an increasing number of connected EVs. Consequently, implementing centralized approaches may become computationally infeasible due to the growing complexity and time required for execution. A smart centralized scheduling method is proposed in [27] which tackles a two-fold optimization challenge namely minimizing charging costs and maximizing user priorities for charging. The research in [41], [63], [82], [92], and [109] which are later reviewed in this paper make use of centralized charging approaches.

B. DECENTRALIZED EV CHARGING

In a decentralized or distributed charging system, each EV operates independently and takes charge of calculating their own charging schedules [28]. This requires EVs to gather information from the aggregator through their connected charging stations. Additionally, decentralized architecture often involves an iterative scheduling process. EVs are required to share their calculated charging profiles with the aggregator to update overall system information.

FIGURE 5. Various impacts of EV charging on Grid.

Decentralized EV charging prioritizes flexibility and scalability. Unlike centralized systems with a single decision-maker, each EV operates independently. This distributed approach allows the system to seamlessly adapt to a growing number of EVs without burdening the charging network with excessive processing demands. However, this decentralized approach comes with limitations. Customers take ownership of their charging decisions, determining the rate and duration based on their individual needs. These individual decisions, while solving a localized problem, may not always lead to the most optimal charging strategy for the entire grid. This is especially true when EVs lack complete information about the broader grid conditions. Participation in ancillary services, which offer grid stability functions like frequency regulation, is limited in this approach. While some services may be available, their scope is often restricted. Additionally, as many EVs attempt to charge concurrently during lower electricity rates, decentralized system performance is minimized. A decentralized method to optimize the EV charging costs based on prices, while considering grid and battery health is proposed in [29]. The decentralized control method in [30] schedules EV charging to fill the low demand, off-peak hours while meeting customer needs. Decentralized charging approaches are also employed in [43] and [62], which are later reviewed in this paper.

C. HIERARCHICAL CHARGING

Hierarchical Charging has recently gained attraction in EV charging management scenario. It is a multi-layered EV charging framework that includes multiple aggregators at each level [25]. The aggregators located at each charging station may be referred to as a Sub-Aggregator (SA). Each sub-aggregator controls the group of EVs connected to it and thus all the group of EVs connected to its SA makes the lowest level of the framework. The sub-aggregators are controlled by a central aggregator (CA). The central aggregator may be controlled by the Distribution Network Operator (DNO), which would then occupy the highest layer of the hierarchy. In some cases, the SAs may be directly under the control of the DNO. The sub-aggregators are responsible for collecting data from the EVs such as their charging requirements and vehicle profile and they transfer it to their CA. Considering the customer charging needs as well as local transformer capacity limitations, once CAs determine their allowable charging load limits, an optimization model is executed either at the DNO level or in the CA level itself. This model generates an ideal charging curve for each aggregator, outlining the optimal power distribution throughout the charging period. The sub-aggregator is responsible for managing the operation of chargers, and the charging power of individual charging points in the charging station. Additionally, SAs are obligated to adhere to the charging regulation directives set forth by the central aggregator. A type of hierarchical EV charging architecture is shown in Fig. 6. However, there are several other variations in the hierarchy depending on the number of levels and type of control. To address the optimal charging coordination problem, hierarchical distributed approach which utilizes the exchange problem, is presented in [31]. Alternating Direction Method of Multipliers (ADMM) technique is adopted to solve the problem. This approach schedules the charging of electric vehicles in a privacy preserved way that reduces the cost and doesn't overload the power grid. ADMM was chosen because it can handle the challenges of charging multiple EVs at the same time. The outcomes demonstrated that the suggested approach led to a considerable reduction in the number of iterations when compared to traditional charging methods. A study in [32] proposes a mathematical model for a three-level system that coordinates EV charging for the vertically regulated electricity market in China. This hierarchical approach schedules EV charging at stations using a combination of pre-planned and real-time adjustments. The model incorporates a real-time, low-complexity heuristic algorithm to manage uncertainties related to EV mobility patterns. This combined approach optimizes both the overall electricity system load profile and charging costs, while still meeting customer needs for charging.

V. OPTIMIZATION OF EV CHARGE SCHEDULING

EV charge scheduling optimization is the method to find the most efficient way to schedule EV charging, given a set of limitations. Optimization algorithms are implemented to achieve one or more well-defined objectives during the electric vehicle charging process. Effective optimization for EV charging scheduling hinges on understanding the problem from different perspectives. Here, we categorize these problems into three classes based on the objectives of the stakeholders involved namely, power grid operators, aggregators, and EV owners. This classification is crucial because it considers the unique goals of each stakeholder. In the electricity sector, participants often have distinct legal and functional roles, leading to diverse objectives within the larger system. The classification of the objectives of EV charge scheduling from different perspectives is presented in Table 3.

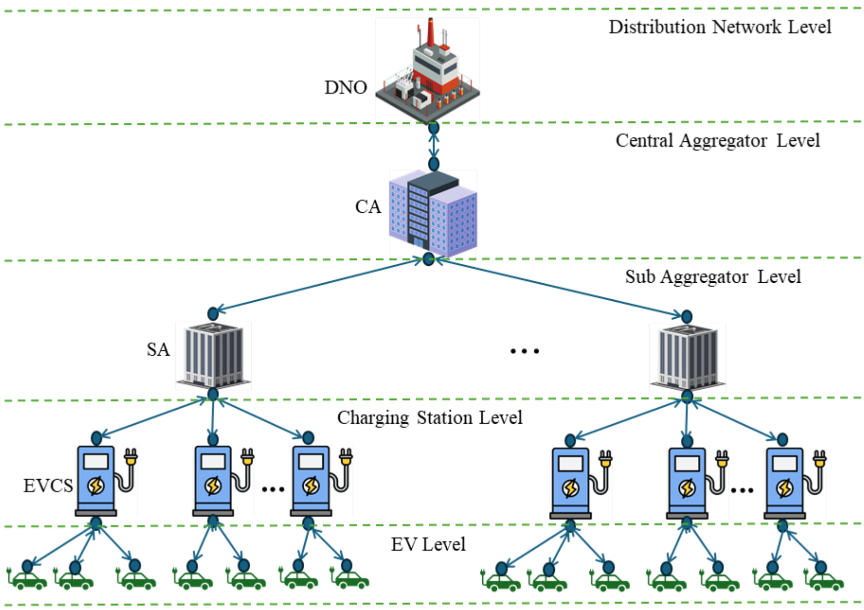


FIGURE 6. Hierarchical EV charging control architecture.

A. POWER GRID ORIENTED OBJECTIVES

EV charging introduces new challenges for the power grid like managing active power losses, minimizing voltage deviation and load variance. They also deal with economic constraints like reducing the operating cost and increasing grid operator's revenue for those distribution grids managed by DNOs [33]. Multiple EVs charging at a time can trigger surges in demand, causing voltage dips and increased resistive losses in power lines. These losses rise with the square of the current, so even small voltage fluctuations during peak charging can be significant. Additionally, EV chargers without proper power factor correction can inject reactive power, further reducing grid efficiency. The combined effects of rising power demand, voltage instability, overloaded transformers, and power factor issues all contribute to substantial active power losses during EV charging. To mitigate these challenges and ensure grid stability, numerous optimization strategies have been proposed. A coordinated charging strategy to optimize the power usage for PHEVs is proposed in [34]. This method aims to minimize both power losses in the grid and maximize its overall load factor. Since accurately predicting household electricity loads is challenging, the approach employs stochastic programming, a technique suitable for handling uncertainty and optimal charging profiles are achieved with two mathematical modelling techniques namely, quadratic programming and dynamic programming. A study in [35] identified a critical voltage drop at feeder ends when the EV penetration rate surpassed 50%. The findings suggest that exceeding this threshold would cause voltage levels to breach the standard tolerance of 7%. However, the study also demonstrates that implementing a smart charging strategy effectively mitigates this issue, ensuring all voltages remain within acceptable limits.

The study in [36] proposes a coordinated charging scheduling strategy which tackles two key challenges: the peak-to-valley load adjustment and charging cost minimization. This method achieves these goals by shifting charging patterns. The coordinated scheduling model strategically transfers this charging load to periods with lower electricity prices and lower base load, effectively reducing both total charging costs and the peak-valley difference. Building on economic and environmental considerations, the work in [37] explored charging and discharging schedules of EVs within existing distribution networks. It proposes a complementary multi-objective management model for scheduling the PEVs in a smart distribution network. This model prioritizes minimization of operating costs and greenhouse gas emissions. Both [38] and [39] discussed the integration of RES into the power grid, thus minimizing the reliance on grid electricity during peak hours for EV charging and consequently reducing overall charging costs.

B. AGGREGATOR ORIENTED OBJECTIVES

Aggregators are entities that manage one or more charging stations at various sites. They procure electricity from the grid or an energy provider to fulfill their customers' charging needs. Research on EV charging scheduling issues from the aggregator's standpoint emphasizes minimizing electricity costs, maximizing profits, optimizing capacity, and enhancing service quality while adhering to grid constraints. An auction-based coordinated charging heuristic for EV scheduling at the aggregator level is explained in [40]. This method empowers aggregators to perform direct energy trading between each other, reducing their reliance on the grid for energy procurement. This approach helps mitigate the impact of forecasting errors, demonstrably lowering energy costs for aggregators and consequently maximizing their profits.

An optimal discharging schedules for electric vehicles parked privately, considering both their movement patterns and parking behavior is explored in [41]. The authors propose an effective recharge scheduling scheme for parking areas by categorizing EVs into regular and irregular groups. This scheme factors in EVs' entry and exit times, state of charge (SoC), and travel range to determine the ideal charging spot, time, and amount of energy delivered. The model aims to achieve a dual optimization of maximizing the total revenue for the aggregator while also maximizing the number of EVs served by the aggregator. Building on cost minimization from aggregator perspective, [42] proposed an optimal online scheduling method for price-responsive, early charging adaptive control. Analyzing historical EV mobility data, a control factor for the early charging adaptive control was derived offline, which was then utilized to optimize early charging decisions and enhance the online scheduling performance. This approach involves a two-tiered control structure with a base-level and upper-level controller utilized by the parking operators and the aggregators respectively to schedule EV charging. The study highlights the method's advantages in achieving optimal cost reduction, maximizing power capacity utilization and task completion efficiency, and improving profitability of the aggregator.

C. EV USER ORIENTED OBJECTIVES

Customer satisfaction is a crucial factor for charging service management systems. EV users who experience inconvenience during charging are unlikely to return. Recognizing this, research is increasingly focused on EV charging scheduling that prioritizes user needs. Several papers proposed user-centric optimization objectives, including minimizing charging losses, ensuring desired SoC, reducing charging costs, and mitigating battery degradation. Using a multi-agent system framework, [43] proposed a decentralized approach for power losses minimization due to EV charging while adhering to system constraints. The primary focus lies in addressing charging power loss relative to battery's internal resistance, which holds significant potential for stimulating user participation in the charging process. In [44], a smart charging algorithm based on an integrated data-driven regression model is proposed. This approach not only optimizes charging efficiency but also enhances EV user satisfaction. The algorithm maximizes the average SoC for multiple EVs charging concurrently at a location. This is achieved by employing a methodology for data pre-processing and training a regression model to predict battery charge profiles which succeeds in achieving a higher average final SoC for the entire EV fleet. Considering diverse user preferences, [45] explored coordinated EV charging at stations by proposing a hybrid strategy, combining centralized and decentralized control. The centralized layer utilizes an offline scheduling approach to minimize energy costs while fulfilling EV charging needs. The decentralized part of the proposed algorithm is used to model the communication between the EVs and system controller in a game-based approach so that the EVs are enabled to attain greater benefits. The authors in [46] proposed an intelligent heuristic algorithm for optimizing the charging schedules of PEVs encompassing home and public charging infrastructure. The algorithm prioritizes charging cost minimization of PEVs by introducing an interrupted charging strategy. A practical charging scheme that considers battery degradation during EV charging is explained in [47]. A cost model to capture battery degradation is proposed, which is integrated into an optimal scheduling scheme that makes of a Vacant Resource Allocation algorithm, to minimize total battery degradation cost.

VI. OPTIMIZATION TECHNIQUES FOR EV CHARGE SCHEDULING

EV charging optimization involves multiple steps, starting with formulating mathematical models for the various

TABLE 3. Classification of the objectives of EV charging scheduling.

Grid Operator's Perspective		Aggregator's Perspective		EV User's Perspective	
Efficiency	Economic & Environmental	Efficiency	Economic & Environmental	Efficiency	Economic & Environmental
Power loss Minimization [34], [56], [90], [103], [106], [107], [110], [133]	Operational Cost Minimization [37], [55], [86], [91], [100]	Customer Satisfaction [72], [130]	Energy Cost Minimization [29], [73], [42]	Minimizing Charging Power Loss [43]	Charging Cost Minimization [27], [31], [36], [46], [82], [83]
Voltage Variance Reduction [108]	Grid Operator Profit Maximization [33]	Managing Ancillary services [102]		SOC Fulfillment [44], [45]	
Load Variance Minimization [36], [49], [87] [109], [117]	Support for RES [38], [39], [110]	Capacity Improvement [42], [90]	Aggregator Profit Maximization [40], [41], [42], [51], [138]	Battery Degradation Minimization [47], [53], [57], [137]	EV as energy storage [99]
Peak Demand Reduction [52], [89], [102]	Emission Reduction [37],[99], [101] [116]	EV Congestion Management [24], [40]		User Convenience [27], [130]	

constraints to be optimized. In the domain of optimization, a wide range of techniques are available for developing, optimizing, and validating the EV charging models. While a diverse array of optimization techniques exists, each possesses unique strengths and weaknesses, thus making them suitable depending on the specific challenge at hand. The selection of the most appropriate technique is very important to achieve successful problem resolution. Various techniques used for solving optimization problems under the realm of EV charging scheduling are broadly classified as (i) Mathematical Optimization techniques, (ii) Metaheuristic Algorithm based techniques, (iii) Machine Learning techniques.

A. MATHEMATICAL OPTIMIZATION TECHNIQUES

Many studies address the electric vehicle charging scheduling challenge by formulating it as a mathematical programming problem. These studies often utilize conventional mathematical optimization techniques due to their ease of implementation and minimal computational burden. However, these techniques may struggle with complex, multi-objective scenarios involving numerous decision variables and intricate non-linear constraints. Common examples of conventional mathematical optimization methods applied to scheduling problems of EV integrated to grid include Linear Programming (LP) [48], [49], [50], [51], [52], [53], Non-Linear Programming (NLP) [54], [55], [56], [57], [58], Quadratic Programming (QP) [59], [60], [61], [62], Mixed-Integer Programming (MIP) [63], [64], [65], [66], [67], [68], [69], [70], [71], and Dynamic Programming (DP) [72], [73], [74], [75], [76].

1) LINEAR PROGRAMMING (LP)

Linear programming (LP) represents a well-established optimization methodology, employing the solution of a defined mathematical function to identify the optimal outcome within a framework of defined constraints. This approach is particularly suited to problems involving linear relationships and resource limitations. However, with increasing problem dimensionality, linear programming algorithms experience computational limitations, rendering them unsuitable for timely solution. Different optimization methods utilize linear programming to aim for the establishment of a highly effective system. Using linear programming, [48] proposed optimal charging strategies for mitigating grid congestion and minimizing costs under dynamic tariffs, employing real-time control. The study focuses on two charging scenarios validated through experiments with an actual electric vehicle, comparing results to the default charging method. However, this study does not encompass fast and public charging. In study [49], a dynamic and clustered linear programming method was applied to a fleet of electric vehicles to promote a coordinated charging pattern for EVs and to achieve a load scheduling pattern that minimizes the cost of charging. To optimize energy usage of electric vehicles connected in Smart Buildings incorporated with PV arrays, [50] introduced a Linear programming model with Artificial Neural Network (ANN) based predictions to obtain the optimum charging/discharging schedule for EVs. However, the model assumed a fixed driving pattern, neglecting its uncertainty, and concluded limited cost savings under time of use pricing schemes. EV charging schedules from the customer's perspective, considering both planned and unplanned charging needs is investigated in [51]. It proposes an LP approach to minimize charging costs under real-time pricing, balancing customer savings with the aggregator's revenue. Two dynamic LP solutions are offered, one for new arrivals and one for rescheduling all connected EVs. To optimize energy costs and reduce peak demand, researchers in [52] applied LP to create a hierarchical coordinated system involving the electricity provider and EV aggregators. This approach promotes a stable and secure power distribution network. Reference [53] utilized LP to minimize EV energy costs, considering factors like day-ahead electricity prices, battery degradation costs, SoC limits, maximum power, and distribution feeder capacity. The work incorporates uncertainty through Monte Carlo simulations to account for variability in these factors.

2) NON-LINEAR PROGRAMMING (NLP)

Nonlinear programming (NLP) is well-suited for addressing optimization problems where the objective function or constraints exhibit non-linear characteristics [54]. An illustrative example is the minimization of load deviation formulated quadratically for optimizing electric vehicle charging schedules. NLP methods excel at efficiently solving large-scale problems with relatively few local minima. However, they tend to find a good solution quickly and may not explore the entire solution space, potentially missing the absolute best outcome. Nonlinear programming is used to create the upper-level model of the two-stage hierarchical decomposition approach proposed in [55] that designs the charging strategies, which is followed by the lower level formulated by a branch and bound algorithm. The lower-level is focused on implementing dispatching instructions provided by the upper-level decision-maker and the aim is to minimize the total cost of system operation. A non-linear optimization technique is utilized in the study presented in [56] to establish an optimal power flow model for coordinated control of Plug-in Hybrid EVs and On-Load Tap Changer (OLTC) Optimizing the operation of the distribution network by minimizing power losses in the main objective of this study. In the study, [57] proposed a way to optimize charging schedules for overnight EV bus fleets using NLP. The primary goal is the reduction of expenses linked to battery degradation, but it doesn't factor in peak and valley electricity prices. Reference [58] introduced a smart system for managing electric vehicles in a parking lot. This innovative system lets EVs charge and sell energy back to the grid. It uses a nonlinear programming solver and considers factors like owners' desired prices, battery levels, charging time, and battery age to optimize the scheduling.

3) QUADRATIC PROGRAMMING (QP)

Quadratic Programming falls under the umbrella of nonlinear programming, distinguished by its quadratic objective function and linear constraints [54]. Quadratic problems can either be solved directly or can be broken down into smaller problems (sub-problems) for a more efficient solution. For a residential area with 63 households, quadratic programming is employed in [59] for EV charging scheduling in a residential parking EV charging station. Three QP-based algorithms are explored, namely the local, iterative global, and global algorithms, each assuming varying degrees of knowledge about components within the grid. By implementing a controlled charging, the proposed approach effectively reduces the demand variability, peak load, and voltage deviations of the grid. Reference [60] proposed an optimized method based on quadratic rotated conic programming for balancing power in distribution systems that include both EV charging, and distributed generation (DG). The goal is to minimize the operating costs while considering the uncertainties in the output power of distribution systems and the EVs' charging behavior. To optimize charging and discharging of PHEVs within a vehicle-to-grid (V2G) system, a quadratic programming model is used in [61] The objective of proposed algorithm is to manage peak loads in the power grid and stabilize the system. The article [62] presented a distributed algorithm for optimizing charging and discharging schedules of V2G-equipped EVs, considering both battery efficiency and varying energy prices using a mixed-integer quadratic programming (MIQP) model for efficient resource utilization.

4) MIXED INTEGER PROGRAMMING (MIP)

Mixed-integer programming (MIP) is a widely used technique to tackle problems where some variables take whole number (integer) values. Notably, MIP can handle problems where the objective function or constraints involve piecewise linear functions, meaning they consist of multiple linear segments. The specific segment used in the calculation is determined by the chosen integer values. The research in [63] introduced a novel energy scheduling system that allows bidirectional energy flow between the EVs and the power grid (V2G), as well as energy sharing between EVs (V2V). The authors formulated the energy transfer optimization problem using mixed-integer programming and solved it offline to maximize customer satisfaction and energy utilization. A comparison of offline and online algorithms for EV charging at a single station is presented in [64], formulating the cost-minimization problem as a mixed integer program. In [65], researchers classify EV drivers as premium, conservative, and green based on their charging habits using MIP and allocate separate charging schemes for each type to optimize the system. The proposed method aims to reduce energy costs for charging stations with solar photovoltaic (PV) power integration and compensate the impact of intermittent nature of PV generation. The model proposed in [66] helps customers make informed decisions about solar panels, battery storage, and modes of EV charging. The model used mixed integer programming for optimization which considers net metering policies, time-of-use pricing, and smart meter data. A case study in [67] demonstrated solving an electric vehicle routing and charging optimization problem by breaking down the original mixed-integer program into two simpler linear programming problems. The work presented in [68] analyzes the impact of different EV charging strategies on a power system under various scenarios. A Mixed Integer Linear Programming (MILP) framework is adopted in the study. To optimize the EV integration into the Distribution Systems (DSs), [69] introduced a novel MILP model that facilitates the joint expansion planning of both the DS and EVCSs, accounting for uncertainties in both the existing grid and future EV demand. A mixed-integer non-linear programming (MINLP) approach is used in [70] to identify ideal locations and optimal charging capabilities for fast charging stations and to minimize the cost of EV charging. A long-term, MINLP model for optimizing the sizing and allocation of wireless charging infrastructure for EVs, considering power systems, losses, routing, and traffic is presented in [71].

5) DYNAMIC PROGRAMMING (DP)

Dynamic Programming (DP) is a powerful technique for solving time-varying optimization problems. It achieves this by working backward from the end, effectively breaking them down into smaller, more manageable subproblems, making it ideal for scenarios where conditions change over time [54]. This ability has been leveraged to optimize charging schedules for PEVs, where multiple factors like grid constraints, device characteristics (PEV battery), and user preferences need to be considered. Reference [72] employed stochastic dynamic programming (SDP) for a dynamic pricing approach, helping charging providers to balance competing objectives, such as enhancing profitability, customer satisfaction, and minimizing grid impact, amidst inherent uncertainties. Reference [73] proposed the utilization of a stochastic dynamic programming approach to minimize the operational expenses of CSs, mitigate the influence of CSs on the grid, and optimize the schedule for power dispatch. Like this, [74] also developed a dynamic linear program-based approach for automatic demand response in charging stations with integrated PV systems to achieve optimized charging decisions based on real-time electricity prices. In [75], dynamic programming is utilized to optimize large-scale EV charging in a power grid, with the integration of RES and considering electricity tariff. The formulated program is then characterized as a Nodal Multi Target and Soft Actor Critic framework to reduce problem complexity by addressing state variable dimensionality. While dynamic programming offers flexibility in power system scheduling due to its ability to handle time-varying parameters and strategy periods, it suffers from the 'curse of dimensionality' [76]. This refers to the increase in computational and storage costs as the number of variables (dimensions) increases. This limitation makes DP more suitable for low-dimensional problems with time-varying variables, such as scheduling PEV charging in smaller systems.

B. METAHEURISTIC ALGORITHM (MA) BASED TECHNIQUES

Metaheuristic algorithms (MAs) are a category of optimization algorithms inspired by various natural phenomena, such as the evolutionary process found in biology, the collective behavior observed in swarms, and the underlying principles of physics. MAs work by maintaining a population of randomly generated solutions and iteratively improving them using heuristic techniques. Though they are not guaranteed to find an absolute optimal solution, their approach makes them well-suited for tackling non-linear, non-convex, and high-dimensional problems [77]. So, metaheuristics excel at optimizing complex EV charging problems, which involve extensive computations, require precise solutions within high-dimensional spaces, and are subject to numerous constraints. Candidate solutions in these algorithms represent the individual elements within the search space that represent potential solutions to the optimization problem being addressed. MAs can be classified as, Single Solution Based Metaheuristic Algorithms (SSBMA) and Population Based Metaheuristic Algorithms (PBMA) [78].

1) SINGLE SOLUTION-BASED METAHEURISTIC ALGORITHMS (SSBMA)

These algorithms employ a single candidate solution, iteratively improving it using local search techniques in its neighborhood. Though they have an advantage of increased efficiency and speed, this approach has a risk of missing the global optimum by getting trapped in local optima [79]. The risk of local optima can be mitigated by parameter tuning, by increasing randomness in exploration of the search space and by introducing diversity in exploring different regions of the search space. Simulated Annealing Algorithm (SAA) [80], [81], [82], [83], Hill Climbing (HC) [84], and Tabu Search (TS) [85] are some of the most common SSBM algorithms.

2) POPULATION BASED METAHEURISTIC ALGORITHMS (PBMA)

Population-based algorithms work with a set of diverse candidate solutions and each solution represents a single point in the search space. This helps them avoid getting trapped in local optima. The multiple set of solutions allow them to explore multiple regions of the search space simultaneously and each solution investigates a different solution to the optimization problem [78]. Such algorithms move towards more suitable areas of the search space in every iteration with the help of competition and collaboration among the set of solutions. This collaborative exploration helps them to overcome the disadvantages of single-solution approaches.

Some of the popular PBMA algorithms are Genetic Algorithm (GA) [86], [87], [88], [89], [90], [91], Differential Evolutionary Algorithm (DE) [92], Harmony search [93], [94], Ant Colony Optimization (ACO) [95], [96], Artificial Bee Colony Algorithm (ABC) [97], Particle Swarm Optimization (PSO) [98], [99], [100], [101], [102], Grey Wolf Optimizer (GWO) [103], [104], Firefly Algorithm [105], Cuckoo Optimization Algorithm (COA) [106], Gravitational Search Algorithm (GSA) [107], Artificial Hummingbird Algorithm (AHA) [108],, Whale Optimization Algorithm (WOA) [109], Grasshopper Optimization Algorithm (GOA) [110], Artificial Fish Swarm Algorithm (AFS) [111], Chicken Swarm Optimization (CSO) [112], Teaching Learning-Based Optimization Algorithm (TLBO) [113], Bald Eagle Search Algorithm (BESA) [114], Bat Algorithm (BA) [115], Virus Colony Search (VCS) Algorithm [116], Fruit fly Optimization Algorithm (FOA) [117], flower pollination algorithm (FPA) [118], and Binary Lightning Search Algorithm (BLSA) [119]. Among all different metaheuristic algorithms, GA and PSO are most used techniques for solving problems related to EV charging infrastructure.

Table 4 provides a list of several Metaheuristic Algorithms which are successfully applied to solve EV charge scheduling problems along with their optimization objectives. The hierarchal classification of the metaheuristic algorithms applied for EV charge scheduling are presented in Fig. 7.

a: GENETIC ALGORITHM (GA)

Genetic Algorithm represents a population-based optimization methodology, employing the principles of natural selection to identify the optimal solution within a set of potential candidates. Each solution, acting like a chromosome, is evaluated based on a specific goal (objective function). Through processes that mimic the selection, crossover, and mutation, GA iteratively improves the solutions, leading towards increasingly optimal outcomes. GA based algorithms are powerful tools for scheduling problems. They can handle enormous search spaces and incorporate expert knowledge from the specific scheduling domain. This makes them highly competitive with even the most efficient scheduling methods. A real coded genetic algorithm-based optimization model is proposed in [86]. The focus of algorithm is to manage energy use and scheduling of EV for charging in a smart home with a hybrid energy system. Building on the concept of integrating vehicular networks with the smart grid, [87] introduces an EV charging scheduler which is a hybrid approach, combining the speed of a time-efficient heuristic methods with the optimization capabilities of genetic algorithm (GA). The core functionality of the scheduler involves two steps. First is initial population selection which is done by a fast heuristic method which generates a starting set of potential charging schedules, and the next step is to apply genetic algorithm to further refine the initial schedule and identify the most optimal solution for minimizing load. This approach allows the scheduler to be both efficient in processing requests and effective in optimizing EV charging station management. In [88], the charging station location optimization is done using GA. The objective function and the constraints are determined using a MILP model which is followed by the application of an improved GA for optimal location selection for EVCS. Research in [89] proposes a GA-based strategy to optimize EV charging schedules. The main focus of this research is to flatten the power consumption profile in a residential distribution system by introducing valley filling and peak shaving with G2V/V2G technologies. It considers constraints like voltage limits, transformer load, availability of parking, and arrival/departure patterns. Their successful test on a low-voltage Spanish distribution system with 100 customers demonstrates the effectiveness of GAs for managing EV charging and grid constraints. The study presented in [90] shows that GA offers a good convergence when solving the multi-objective optimization model of EV charging network. A planning model for EV charging network that considers both the optimization of service capacity and the network losses is proposed and discussed. The fuzzification of the optimization objectives is done before applying genetic algorithm. The research in [91] utilizes a two-level programming model combined with a genetic algorithm to address a scenario where a workplace has a limited number of chargers and an uncontrolled EV charging, aiming to minimize operational costs.

b: PARTICLE SWARM OPTIMIZATION (PSO)

The PSO algorithm is inspired by the flocking behavior of birds and tackles problems like a collaborative search. Each bird, representing a potential solution, explores a vast search space and learns from its neighbors' successes. Particles move based on their own best discoveries or the personal best and the best findings of the entire group or the global best solution. This social learning helps them gradually converge on the optimal solution. The algorithm continuously updates each particle's position using dynamic velocity adjustments, influenced by information from both global and local best solutions. PSO has emerged as a prominent technique for developing electric vehicle charging schedules. Compared to established approaches like GA and other metaheuristic methods, PSO frequently achieves satisfactory solutions with lower computational demands. Consequently, PSO offers an efficient path to attaining computationally tractable solutions, outperforming methods that may incur unpredictable computation times or struggle with a high number of variables. Different methods for optimizing DER scheduling, considering both network limitations and cost efficiency were analyzed in [98] by comparing three variations of PSO algorithm namely standard PSO, Evolutionary PSO (EPSO) and New PSO (NPSO). This research focused on a large-scale case study for day-ahead scheduling. The analysis revealed that EPSO achieved superior solution quality while still maintaining reasonable execution time. This suggests that EPSO could be a valuable tool for optimizing DER scheduling in practical applications. PSO is employed in [99] to identify the most economical dispatch solution while simultaneously integrating data from RESs such as wind speed, solar irradiation, and power generated by RES. It proposed an approach that exploits electric vehicles to act as distributed energy storage devices within the smart grid. An energy storage model that incorporates network-connected vehicles for economic load dispatch within the smart grid and it optimizes a multi-objective function, considering both cost and emission reduction is introduced. Research in [100] proposed an improved PSO algorithm called IPSO. This enhanced PSO leverages principles from GA and SAA to optimize the EV charge scheduling. Simulation results demonstrate that the proposed IPSO strategy effectively reduces operational costs for the power grid while ensuring that EV owners can meet their driving needs. Additionally, the study verifies that IPSO offers improved performance in terms of finding optimal solutions and its ability to explore a broader range of possibilities. The optimization problem of V2G in a complex unit commitment setting has been effectively addressed in [101] through a well-balanced hybrid PSO technique, capable of managing variables represented in both binary and integer formats. This study includes V2G technology, where EVs essentially act as small, mobile power plants. Binary PSO allows for smart control of power generation from RESs to find a balance between reducing emissions and keeping costs low. A two-layer optimization approach for the EV's load demand using a combination of Evolution Strategy and Particle Swarm Optimization (ESPSO) algorithms is proposed in [102]. This approach helps to manage the residential distribution grids by providing ancillary services, and ultimately reducing peak electricity demand. Additionally, the study utilizes a data-driven fuzzy logic model to account for the unpredictable nature of EV charging behavior, which includes factors like entry and exit time, and daily mileage.

C. MACHINE LEARNING TECHNIQUES

Machine learning (ML) is a subdivision in the domain of artificial intelligence (AI). It aims to develop analytical models by employing data-driven learning methods. Machine learning trains algorithms to recognize patterns and relationships between the data. The patterns thus identified can then be used for predictions or making decisions on new data, aiming to achieve the best results within a specific context. Machine learning algorithms usually exhibit a rapid improvement in accuracy and efficiency at first when applied to real-world problems that involve diverse datasets. Then as more data is fed into the system, the accuracy of prediction and decision making gets gradually enhanced. Machine learning encompasses three main categories namely supervised learning, unsupervised learning, and reinforcement learning methods, each of which is appropriate for specific investigation purposes [120]. Machine learning has emerged as a prominent force in tackling various aspects of infrastructure planning EV charging stations, from place-

TABLE 4. Metaheuristic algorithms applied in EV scheduling.

Classification	Metaheuristic Algorithm	Optimization Objective	Reference No.
Single Solution Based	▪Simulated Annealing Algorithm (SAA)	System cost minimization Energy Resource Management EV operating cost minimization Charging cost minimization	[80], [81], [82], [83] [81] [82] [83]
	▪ Hill Climbing (HC)	Cost minimization	[84]
	▪ Tabu Search (TS)	EV routing problem	[85]
Population Based	→Evolutionary Based		
	▪Genetic Algorithm (GA)	Operational cost minimization Peak load reduction EV charging station placement Reducing peak demand, Flattening load profile Charging capacity maximization, Power loss reduction	[86], [91] [87] [88] [89] [90]
	▪Differential Evolution (DE)	EV battery swapping station placement	[92]
	→Nature Inspired		
	▪Artificial Bee Colony (ABC)	Optimal power utilization	[97]
	▪Ant Colony Optimization (ACO)	EV route optimization	[95], [96]
	▪Artificial Fish Swarm (AFS)	Network loss minimization	[111]
	▪Artificial Hummingbird Algorithm (AHA)	Dynamic Volt-VAR control	[108]
	▪Bat Algorithm (BA)	System cost minimization	[115]
	▪Bald Eagle Search Algorithm (BESA)	EV charging station placement	[114]
	▪Binary Lightning Search algorithm (BLSA)	Fast EVCS sizing and placement	[119]
	▪Cuckoo Optimization Algorithm (COA)	Cost and power loss minimization	[106]
	▪Chicken Swarm Optimization (CSO)	EV charging station placement	[112]
	▪Firefly Algorithm	EV load prediction	[105]
	▪Fruit Fly Optimization Algorithm (FOA)	Load variance minimization	[117]
	▪Flower Pollination Algorithm (FPA)	Load frequency control	[118]
	▪Grasshopper Optimization Algorithm (GOA)	Operational cost minimization	[110]
	▪Gravitational Search Algorithm (GSA)	Power loss minimization	[107]
	▪Grey Wolf Optimizer (GWO)	Operational cost minimization EV charging station placement	[103] [104]
	▪Harmony Search (HS)	Unit Commitment EV charging station planning	[93] [94]
	▪Particle Swarm Optimization (PSO)	Energy management in smart grids Loss avoidance in V2G discharging Operational cost minimization Unit Commitment with V2G Peak load shaving	[98] [99] [100] [101] [102]
	▪Teaching-Learning Based Optimization (TLBO)	EV charging station placement	[113]
	▪Virus Colony Search (VCS)	Dynamic economic emission dispatch	[116]
	▪Whale Optimization Algorithm (WOA)	Charging cost, power loss and load variance minimization	[109]

ment of charging station and prediction of demand to charge scheduling. Its applications extend to service operations planning and optimization, further enhancing efficiency in this domain. To address challenges in EV charging, machine learning models are trained using extensive real-world data, including vehicle load [121], [122], price of electricity [123], charging duration [124], battery SoC [125], infrastructure availability [126], weather information [127] and other relevant factors. These models then generate forecasts that are used as inputs for optimization models, ultimately improving the efficiency and effectiveness of charge scheduling. Classification of the Machine learning algorithms used for EV charge scheduling problems is shown in Fig. 8.

1) SUPERVISED LEARNING METHODS

In supervised learning approach, models are trained on datasets where each data point has a corresponding label, acting as a guide for the model's predictions. These labels

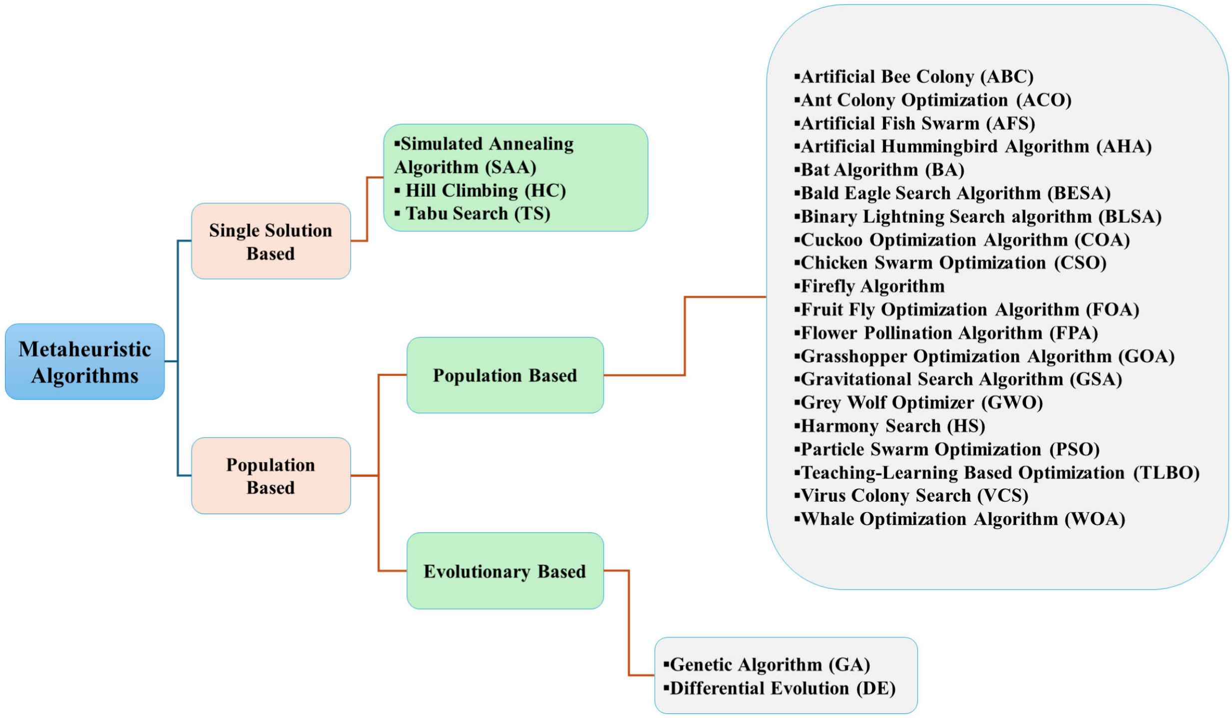


FIGURE 7. Classification of metaheuristics algorithms applied for EV charge scheduling.

can be categories or numerical values. The relationship between the input (features) and the desired output (targets) is learned by the model during the training phase. Supervised learning tackles two main problem types: classification and regression [128]. Classification algorithms utilize input data to categorize new data points into predefined classes. Support Vector machine (SVM), Naïve Bayes and K-Nearest Neighbors (KNN) algorithm are some of the algorithms used for classification purposes. Regression analysis aims to predict the continuous value of a target variable based on the observed values of one or more independent variables. This involves finding a mathematical function that maps the relationship between the input variables and the continuous output variable. Linear Regression (LR) and Support Vector Regression (SVR) can be used for regression analysis. Artificial Neural Networks (ANNs), Ensemble Boosting / Bagging and Random Forest (RF) Algorithms are capable of solving both regression and classification problems. The authors of [121], introduced short-term load forecast model using SVM influenced by travel patterns, power consumption, distance travelled per day and connection time and proved to outperform Monte Carlo forecasting technique applied for the same problem. SVM is used together with GA in [122] for long-term forecasting of daily peak load demand using a model with seven support vector machines. Each support vector machine corresponds to a specific day of the week trained on historical data, and applied iteratively to forecast loads for the forthcoming month. In [123], a prediction-based charging mechanism is proposed which uses KNN to predict future electricity costs based on dynamic pricing obtained from the microgrid through wireless communication aiming to reduce EV's charging costs and carbon footprint. The effectiveness of K-Nearest Neighbors (k-NN) was investigated in [124] for predicting energy consumption at charging outlets within the university campus. The problem is framed as a time-series forecasting task, aiming for a day-ahead (24 hours) prediction of energy consumption at each outlet. This approach aimed to improve the accuracy of forecasts while also reducing the processing time needed for predictions. In [125], Naive Bayes algorithm is used to forecast the charging as well as discharging status of EV batteries to predict whether an EV battery will be in a charging or discharging state for day-ahead scheduling purposes considering participation from V2G systems. In this context, Naive Bayes classifier along with Gaussian fitting option achieved a prediction accuracy of 80%. Three supervised machine learning regression techniques namely Gradient Boosting, Random Forests, and XGBoost were employed in [126] to estimate the idle time of EVs at public stations that can negatively impact charging infrastructure by affecting its availability, sizing requirements, and overall cost. The results showed that XGBoost achieved the highest accuracy in predicting idle time for this specific dataset. Reference [127] used SVR to predict EV charging demand, considering factors like historical data, number of EVs, weather, and holidays. An approach to find the optimization EV charging and discharging schedule of an EV connected to a smart building integrated with a solar PV system is discussed in [50]. ANN is applied for power demand forecasting of the building and for solar PV power generation forecasting, linear programming

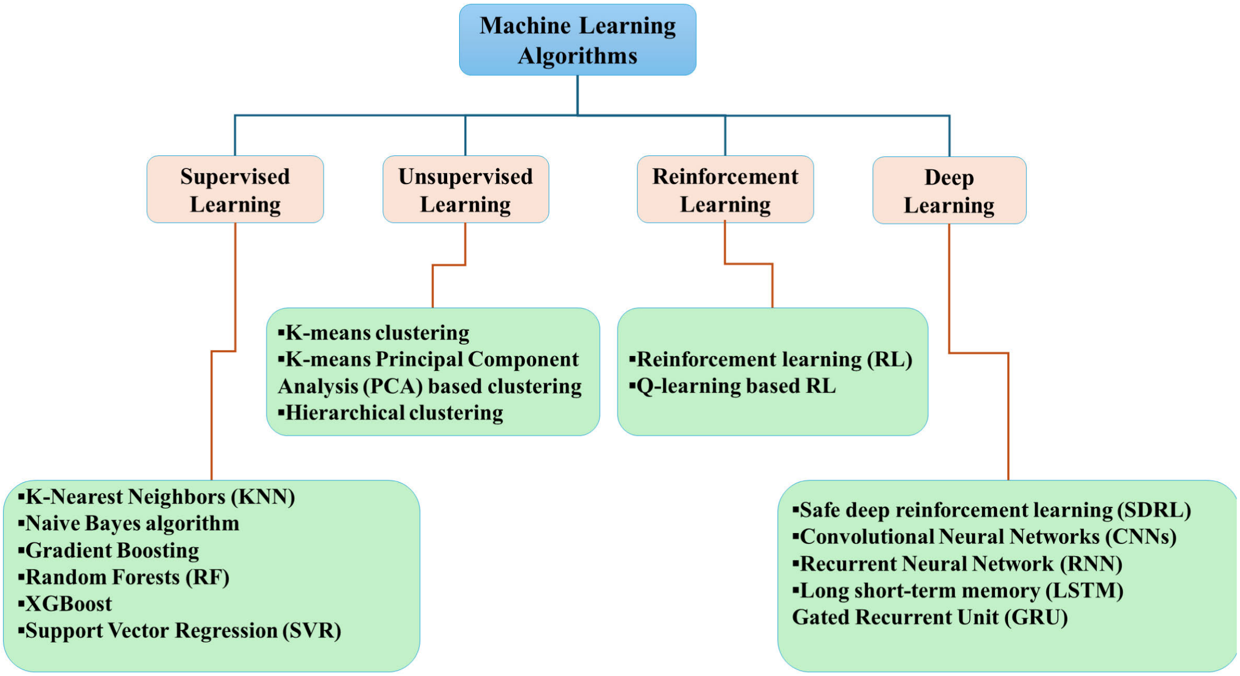


FIGURE 8. **Classification of machine learning algorithms applied for EV charge scheduling.**

is then used for charging and discharging schedule optimization.

2) UNSUPERVISED LEARNING METHODS

In unsupervised machine learning method, the algorithm learns from unlabeled data. It works with datasets that lack labels, which means that they only have input features without labels indicating the desired output or category. The algorithm explores the structure of the data to uncover hidden patterns and structures within it. K-means clustering, and Principal Component Analysis (PCA) are used for solving the clustering and dimensionality reduction problems respectively. It is crucial to identify the optimal location, number of EV parking lots and the capacity for efficient infrastructure development. The paper [129], used K-means clustering, to classify the distribution system into different sets of geographic area so that it can be given boundaries to distinguish as different zones. The model also estimates the expected number of EVs for each parking location which allows precise revenue predictions for newly established parking lots. K-means clustering is utilized in [130] to group areas with similar charging demands and to analyze the relationship between the user satisfaction and charging distance. After understanding the relationship, the model is further simulated using GA-PSO to optimize the EVCS placement while also considering the constraints of the power grid. To predict day-ahead EV parking needs and electricity load, [131] applies unsupervised k-means clustering and neural network on historical EV charging data. Among unsupervised ML algorithms, Principal Component Analysis (PCA) is one such powerful tool, which helps to understand complex datasets by reducing their dimensionality, which means it condenses the data into a smaller set of key features. Thus, the hidden patterns and relationships within the data can be found. In [132], PCA is applied to examine the impact of urban sprawl on the distribution of public smart charging stations for EVs. Utilizing K-means PCA-based clustering, researchers gained insights into the correlation between urban sprawl and energy demand in the city. This analysis facilitated the identification of potential energy clusters, enabling the optimal site selection for smart charging station deployment that would increase the charging infrastructure, and at the same time reduce the cost of energy consumption. Hierarchical clustering is another method of cluster analysis technique in unsupervised learning, which aims to construct a cluster hierarchy within a dataset. This method generates clusters where each level of the hierarchy is formed by merging clusters from the preceding level. Hierarchical clustering technique is utilized in [133] to identify the optimal location for semi-fast charging station incorporating technical considerations like minimizing power losses, user mobility aspects and the uncertainty associated with future EV demand.

3) REINFORCEMENT LEARNING (RL) METHODS

Reinforcement learning (RL) problems revolve around discovering optimal actions to take in various situations to maximize a numerical reward signal. These are closed-loop tasks, as the actions taken by the learning system affect subsequent inputs. Unlike other types of machine learning where actions are prescribed, in reinforcement learning, the learner must explore and experiment to determine which actions lead to the highest rewards [134]. Reinforcement learning can be further categorized as model based and model free learning. Q-learning (QL) is a powerful tool that helps agents learn the value of different actions in different situations, without needing a complete model of the environment. The ability of reinforcement learning to learn from past interactions makes it a promising approach for management and optimization of energy systems that experience dynamic changes. RL algorithms handle complex and changing environments by continuously learning from data. This allows us to develop efficient and effective EV charging strategies in real-world conditions. A reinforcement learning framework is proposed in [135] with centralized allocation of chargers, which is followed by decentralized execution in which the chargers make their own decision to charge or discharge to maximize the profit of EVCS. In [136], RL method is effectively used along with a heuristic benchmark policy to optimize the functions of EV battery swapping stations which is modelled as a Markov Decision Process (MDP). In [137], RL is successfully applied to enhance the battery degradation cost model. The primary goal is to reduce the EV charging expenses and the expenses associated with the wear on charging station batteries, while considering the constraints of V2G services and user dissatisfaction due to extended waiting times. Reinforcement learning based online dynamic pricing algorithms are implemented in several other articles aiming to maximize the profit of charging stations [138], load shifting [139] and system cost minimization [140]. A single-agent RL technique based on Q-learning is implemented in [141], charging cost minimization. This approach considers fluctuating electricity prices and the V2G capabilities to maximize efficiency. To tackle congestion at charging stations, the authors of [142] consider both waiting time in CS and travel time as part of the total charging time. A congestion game model that reflects the interaction between vehicles and charging resources for optimal charging allocation is proposed. This approach utilizes Q-learning in combination with communication technology to manage and avoid congestion in charging station allocation. The challenge of real-time electricity price uncertainty for EVs is modelled in [143] using MDP and then a Q-Learning algorithm that considers V2G control services to allow the system to make real-time choices about whether an EV should charge, discharge, or provide frequency regulation, ultimately maximizing its profitability.

4) DEEP LEARNING (DL) METHODS

Deep learning is a subclass of machine learning, inspired by the function and structure of the human brain. It employs artificial neural networks consisting of multiple layers, known as Deep Neural Networks (DNNs). In contrast to simple neural networks, DNNs usually comprise three or more layers, and often many more layers in practice. These deep networks undergo training on extensive datasets, enabling them to recognize patterns, categorize data, and even make predictions. Some of the popular DL techniques are Convolutional Neural Networks (CNNs), Recurrent Neural Network (RNN), Multi-Layer Perceptron (MLP), Deep Reinforcement Learning (DRL). There are few variants of the recurrent neutral network like Long short-term memory (LSTM), Bidirectional Long short-term memory (Bi-LSTM) and Gated Recurrent Unit (GRU) [144]. Studies have shown that various neural network models, like RNNs, LSTMs, Bi-LSTMs, and CNNs, are capable of predicting EV charging demands more efficiently. Safe deep reinforcement learning (SDRL) algorithm is used in [145] to find the best charging strategy for a single vehicle, in which the approach treats the charging/discharging process as a problem with certain limitations called a Constrained Markov Decision Process (CMDP). The above method makes use of a Multi-Layer Perceptron (MLP) to approximate the moments of the probability distribution function. CNNs are becoming increasingly popular for time series forecasting tasks. A hybrid approach was introduced in [146], combining a CNN with a fuzzy time series (FTS), utilizing fuzzy time series and CNNs to link load data and temperature data for the purpose of generating short term load forecasts. A study in [147] compared the performance of four popular DL techniques ANN, RNN, LSTM, and GRU for predicting EV charging demand at an EV charging station in Morocco. Their simulations revealed that GRUs achieved the most accurate predictions, followed by RNNs, LSTMs, and lastly, ANNs. Many studies explore combining LSTM networks with other machine learning models or even simpler techniques like heuristic algorithms to create hybrid deep learning approaches. These approaches have proven effective in solving forecasting and optimization problems related to EV charging.

Table 5 provides a list of several Machine Learning Algorithms which are successfully applied to solve EV charge scheduling problems along with their optimization objectives.

VII. EV COMMUNICATIONS AND SECURITY

Electric vehicles primarily search out for charging stations while in motion, where they subsequently connect and exchange information. Consequently, charging stations necessitate receiving latest and prompt updates regarding the battery status of approaching EVs, estimated remaining range, and information regarding the traffic conditions they encounter along their routes. These real time information is essential for optimizing the charging schedule and enhancing the charging experience for EV owners. Also, in centralized charging, the aggregator needs information exchange from the charging stations under its control as well as with the distribution network operators. To develop a smart charging infrastructure, an efficient communication strategy is a crucial component which allows data exchange among various stakeholders in the EV charging ecosystem. The communication protocols that exist in the EV charging infrastructure are divided in [148] as front-end and back-end protocols. Front end protocols like CHAdeMO and ISO15118-20 define the communication interface between EV and the charging points while the back end protocols like Open Charge point Protocol (OCPP), Open Automated Demand Response (OpenADR),

TABLE 5. Machine learning algorithms applied in EV scheduling.

	Machine Learning Algorithm	Objective	Reference No.
Supervised Learning	▪K-Nearest Neighbors (KNN)	Charging cost minimization, carbon footprint reduction	[124]
	▪Naive Bayes algorithm	Prediction of charging and discharging status	[125]
	▪Gradient Boosting ▪Random Forests (RF) ▪XGBoost	Prediction of Idle time of EVs in EVCS	[126]
	▪Support Vector Regression (SVR)	EV charging demand prediction	[127]
Unsupervised Learning	▪K-means clustering	Estimation of EVs User satisfaction Prediction of EV parking needs and electricity load	[129] [130] [131]
	▪K-means Principal Component Analysis (PCA) based clustering	optimal site selection for smart charging station	[132]
	▪Hierarchical clustering	Location optimization for semi-fast charging station minimizing power losses	[133]
Reinforcement Learning	▪Reinforcement learning (RL)	Maximization of EVCS profit Optimization of battery swapping Reduction of EV charging cost Optimization of load shifting Minimization of system cost	[135],[138] [136] [137] [139] [140]
	▪Q-learning based RL	Charging cost minimization Congestion reduction of CS Profit maximization	[141] [142] [143]
Deep Learning	▪Safe deep reinforcement learning (SDRL)	Charging optimization	[145]
	▪Convolutional Neural Networks (CNNs)	Prediction of EV demand	[146]
	▪Recurrent Neural Network (RNN) ▪Long short-term memory (LSTM) ▪Gated Recurrent Unit (GRU)	Prediction of EV demand	[147]

IEC63110, IEEE2030.5 and EEBus define the communication interface between charging points and the service providers [149].The authors of [150] integrated Vehicular Ad hoc Network (VANET) into a smart grid to facilitate communication among EVs within the smart grid and with roadside units, which collect information in real time such as battery SoC and EV mobility. Subsequently, a traffic server in the microgrid was utilized to process this information and generate a coordinated charging schedule, resulting in reduced travel costs for EVs and improved power utilization. A communication protocol that is based on VANET for EV charging/discharging in an intelligent grid infrastructure was introduced in [151]. The paper claims that its communication protocol outperforms the existing MAC protocols like IEEE 802.11p and VeMAC, used for VANETs. Recently, the integration of cloud based, Internet of Things (IoT) plays an essential role in effectively managing EVs within the charging infrastructure, a concept often termed as the Internet of Electric Vehicles (IoEV) [152]. IoEV involves EVs with embedded sensors and enables them to communicate with the onboard sensors as well as with other entities in the network which is collectively called V2X communications. This enables EVs to participate in V2G energy transfer, and thus contributes to building an Intelligent Transport System (ITS). The integration of IoT and V2G energy transfer technology has empowered EV to function as an individual and mobile energy storage device thus supporting grid stability by reducing demand fluctuations. Over-the-Air (OTA) cloud service is the latest attractive technology that offers solutions to manage the software components in vehicles and charging stations by automatically updating with the latest software versions and optimal settings, thus ensuring smooth and cost-effective operations [153]. But these communication strategies are at high risk of cyber-attacks by hackers. Few cyber-attacks in EV charging network like, malware injection in the supply equipment, man in the middle attack, false data injection attack, denial of service attack, eavesdropping, Address Resolution Protocol (ARP) spoofing, packet replay attack and physical attack are discussed in [154] and [155]. These attacks may have serious impacts like grid blackout and transmission line failures [156], damage to the EV battery [157], EV charging station out of service or malfunction [158], and loss of personal and financial information of EV users [154]. Any compromise in the security of OTA service can lead to fatal consequences that could even endanger human lives. So, secure data handling becomes a major issue for communication in EV charging network.

A. COMMUNICATION SECURITY CONSTRAINED CHARGING SCHEDULING

Several research projects are exploring the use of blockchain technology's encryption capabilities to address security and privacy concerns during data communication between EVs and charging stations that rely on cloud servers. This ensures secure data exchange within the EV charging infrastructure. In [159], a secure charging scheduling algorithm for EVs is introduced, incorporating blockchain technology for EV registration and secure data transfer. The implementation of this scheduling algorithm led to substantial cost reductions. In [160], the study outlines methods for storing and verifying EV charging data within a blockchain framework, as well as procedures for conducting secure payments for EV charging enabled by a blockchain system. A charging scheduling algorithm for EV based on a consortium blockchain model, ensuring both safety and confidentiality in electricity trading is introduced in [161]. The feasibility of a hybrid mobile charging vehicle to vehicle (MCV2V) charging scenario is evaluated and the aims to enhance customer satisfaction and to minimize user's expenses. Likewise, the concept of charging EVs from mobile vehicles is employed also in [162], where energy and data exchange occur in a Peer-to-Peer (P2P) manner. This method employs blockchain technology to ensure data security, while an Inter-Planetary File System (IPFS) is used for secured data storage alongside a scheduling algorithm for cost minimization.

VIII. DISCUSSION

A variety of optimization techniques, including mathematical methods, metaheuristic algorithms, and machine learning approaches were analyzed in this paper. Each technique was found to exhibit unique advantages for addressing different optimization objectives and constraints. For those problems that have a clear objective function and well-established constraints, mathematical methods can effectively find the absolute optimal solution. These methods have an ease of implementation and less computational burden and can efficiently solve such well-defined problems. But they struggle to solve complex problems like the evolving dynamic EV charging scenarios that may be multi-objective, having numerous decision variables and intricate non-linear constraints. Mathematical optimization techniques could still be employed for solving specific sub-problems within the wide area of EV charging optimization framework. Due to the limitations of mathematical methods, exploring alternative approaches like metaheuristic algorithms and machine learning techniques becomes essential.

Metaheuristic algorithms have good flexibility and ability to handle non-linear problems, and this makes them more suitable for handling EV charging optimization problems. Though metaheuristic algorithms provide many effective tools for complex EV charging optimization problems, they also exhibit certain limitations which should be carefully considered in the context of EV charging optimization. Generally, convergence to the global optimum is not always guaranteed by metaheuristic algorithms, leading to potential suboptimal solutions. Their performance can be influenced by the initial solution or population, leading to variability in results. These limitations must be carefully considered when employing metaheuristic algorithms to solve EV charging optimization problems. While the conventional methods rely on pre-defined models, machine learning approaches provide a promising problem-solving nature due to its ability to learn and adapt to changing patterns. They have proved their excellence in handling complex data and providing improved forecasts.

In the papers analyzed for the review, supervised machine learning techniques are mostly applied for load forecasting, future energy cost prediction in the case of dynamic pricing scenarios, predicting future power demand in charging stations and forecasting power generation in RES integrated charging framework. The unsupervised techniques are employed effectively in several research for grouping the areas with similar charging demands or EVs within same geographical zone, to find the optimal location for charging station placement.

Machine learning techniques are heavily dependent on the quality and quantity of the data provided for training. Data scarcity can lead to biased models, resulting in suboptimal charging schedules subsequently minimizing the effectiveness of the optimization process. Moreover, overfitting is a common problem that occurs with machine learning models when they become overly fixated on the training data which would lead to inaccurate predictions when applied to real world conditions that are highly variable in the case of EV charging. Also, the datasets collected in a location such as charging behavior or driving patterns can be used to develop machine learning models only for that location and cannot be used elsewhere as these characteristics need not be same for different geographic locations.

However, reinforcement learning methods can overcome these issues as they continuously interact with the charging environment and allow the system to learn from a trial-and-error approach. This makes them mostly beneficial for dynamic EV charging scenarios as they adapt to changing conditions and optimize charging strategies in real-time. Also, deep learning methods which possess enhanced feature extraction characteristics can be combined with reinforcement learning to create even more powerful optimization strategies like DRL and SDRL.

A. FUTURE RESEARCH RECOMMENDATIONS

Future research directions may involve the development of new hybrid approaches that combine conventional methods and metaheuristics with advanced machine learning techniques to overcome the limitations of individual techniques and to achieve promising approaches for addressing the challenges and complexities of optimizing EV charging systems in real-world environments. Employing RL with human feedback may be used to enhance EV charging optimization. By learning from user input and preferences, RL algorithms can personalize charging schedules, ensuring efficiency while meeting individual needs. The fusion of cloud computing and RL holds the potential to significantly influence the development of future applications within EV charging systems. The cloud based smart charging networks have unveiled a lot of new challenges regarding security in data exchange. There is an urgent need for developing advanced fault and threat detection frameworks as modular solutions for security issues within smart charging platforms. A broad avenue of future research involves creating robust authentication mechanisms to prevent unauthorized data access EV charging systems, while upholding privacy and confidentiality by establishing interoperable universal standards for EV cybersecurity. Machine learning solutions can be explored to develop threat detection and monitoring tools to address the security challenges in EV communication networks. The charging scheduling algorithms to be developed in the future, addressing various optimization constraints, should try to incorporate security constraints regarding data exchange as well as energy trading as part of the optimization process. This could be achieved either by utilizing the encryption capabilities of existing blockchain technology or by exploring other novel opportunities. Integrating RES into existing charging stations and efficiently utilizing the V2G and V2V capabilities of EVs to employ them as mobile energy storage systems could transform the charging stations into grid-connected, small-scale microgrids. By tackling all these challenges addressed and fostering innovation, EV charging optimization could act as a key driver for widespread EV adoption and a greener transportation future.

IX. CONCLUSION

Electric vehicles play a pivotal role in energy transitions. This review provides a comprehensive examination of the current landscape in EV charging scheduling optimization. It emphasizes the critical role this field plays in enabling widespread EV adoption and enabling a more sustainable transportation future. The advantages of EVs over ICE vehicles in economic and environmental prospective are explained to highlight the necessity of employing EVs as the solution for greener transportation. A thorough examination of different methodologies and factors that have a crucial role in developing efficient charging strategies for EVs is provided. EV charging management is the prime focus of this review paper and the importance of coordinating charging schedules to balance between consumer demands, grid capacity, and economic factors is emphasized. The analysis highlights the essential role of EV charging management in maintaining grid stability, thus facilitating a smoother shift towards high penetration of EVs. It examined various EV charging scheduling optimization problems from the perspectives of power grid operators, aggregators, and individual EV owners. Different optimization techniques like mathematical programming, metaheuristics, and machine learning algorithms, that are employed for EV charging scheduling optimization are analyzed. The advantages as well as limitations of these techniques are evaluated, thus offering insights on their effectiveness in achieving diverse optimization objectives. The article thus provides valuable insights that could direct future research efforts to develop an efficient EV charging ecosystem. Future research is suggested to focus on constructing robust, adaptable, and secure optimization frameworks that utilize the power of hybrid techniques. Efficient utilization of V2G technology and RES integration could offer promising solutions for grid stability and sustainability. By strengthening the collaboration among stakeholders and adopting innovative optimization strategies, we can unlock the complete capabilities of EVs, paving the way for a more environmentally friendly and sustainable transportation infrastructure.

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