Review on Optimization of Forecasting and Coordination Strategies for Electric Vehicle Charging

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***Abstract*—The rapid development of electric vehicles (EVs) has benefited from the fact that more and more countries or regions have begun to attach importance to clean energy and environmental protection. This paper focuses on the optimization of EV charging, which cannot be ignored in the rapid development of EVs. The increase in the penetration of EVs will generate new electrical loads during the charging process, which will bring new challenges to local power systems. Moreover, the uncoordinated charging of EVs may increase the peak-to-valley difference in the load, aggravate harmonic distortions, and affect auxiliary services. To stabilize the operations of power grids, many studies have been carried out to optimize EV charging. This paper reviews these studies from two aspects: EV charging forecasting and coordinated EV charging strategies. Comparative analyses are carried out to identify the advantages and disadvantages of different methods or models. At the end of this paper, recommendations are given to address the challenges of EV charging and associated charging strategies.**

***Index Terms*—Electric vehicle (EV), forecasting, aggregator, coordination strategy, smart charging.**

I. Introduction

WITH the rapid development of decarbonization of the whole system and the wide adoption of electric vehicles (EVs), EV charging has posed a range of challenges to the power grid. In the past few years, several high-profile researchers have investigated the optimization of EV charging and vehicle-to-grid (V2G) applications to provide ancillary services to the electricity market [1]. The flexibility created by managed EV charging is mainly attributed to idled EVs, which are adopted as stationary energy storage systems [2]. Further, the charging time and mileage vary depending on the vehicle model, battery type, and power consumption.

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This paper will critically review the most concerning challenges with prioritized research in the context of the optimization of EV charging, including forecasting, scheduling, and aggregated charging optimization. The main motivations and contributions of this study are as follows.

1) EV charging demand forecasting

The EV charging demand in modern power systems is enormous. The power grid faces considerable challenges in meeting market demand, especially in the next 5-10 years when new registrations can no longer be internal-combustion-engine vehicles in the US and Europe. Demand forecasting is one of the biggest challenges in the management of EV charging. An accurate forecast for EV charging demand would alleviate uncertainties during the optimization of demand management. Very few studies have reviewed and investigated forecasting methods for coordinated EV charging strategies using practical field data. This study highlights the cooperation between forecasting techniques and coordinated charging. The available EV charging data and challenges in the forecasting process are also included in this review.

2) Coordinated EV charging and V2G applications

Smart charging is becoming legally bound in several countries including the UK. In the past, research has mainly focused on the optimization of a single entity, e.g., an EV, EV owner, EV charging station, or aggregator. More recently, there has been emerging research on the optimization of coordinated EV charging to ensure energy efficiency, viability, and system stability. This paper critically discusses coordinated and collaborative EV charging and V2G applications.

The remainder of this paper is organized as follows. Section II discusses forecasting strategies for EV charging, including various forecasting objectives, forecasting methods, and the methods for searching the historical data generated during the EV charging process. Section III presents the optimization of coordinated EV charging, in which various charging strategies and models are reviewed to identify their strength, weakness, and differences. Section IV presents a discussion and recommendations for future research, and conclusions are drawn in Section V.

II. Forecasting Strategies for EV Charging

The increase in the penetration rate of EVs will increase the load on the power grid, which means that it may be difficult for the original capacities of the power generation equipment and the power transmission and distribution facilities to meet the additional power demand. The stability of the power grid requires accurate forecasts for various data during the EV charging process. Section II-A reviews different types of forecasting data including the EV charging load, the error in the energy consumption, EV connection time, and the transition of the state of charge (SOC) distribution. In Section II-B, the methods and models used in the forecasting process are introduced. The advantages and disadvantages of different models and the types that can be adapted are analyzed by comparison. Moreover, accurate historical data are crucial in forecasting strategies, and how to obtain available real-world EV charging data is introduced in Section II-C. A detailed discussion of each part is provided below.

A. EV Charging Forecasting

1) EV Charging Load Forecasting

The increasing popularity of private electric cars has gradually increased the total daily electricity consumption. This poses challenges when forecasting the load for a collection of EVs, e.g., in a community. In [3], a random forest algorithm was proposed to forecast the EV charging load. Moreover, the factors such as charging stations at different scales and locations are considered. A large amount of historical data is learned by combining regression and classification algorithms to improve the accuracy of the random forest algorithm when forecasting the EV charging load. Reference [4] used four different forecasting algorithms: nearest neighbor, modified pattern sequence forecasting, support vector regression, and random forests. By comparing these algorithms, the charging load data are analyzed [5], which can improve the accuracy of forecasted EV electricity benchmark loads.

The above scenario is used to forecast short-term EV charging. In [6], a method for forecasting the additional load caused by the long-term charging of EVs was proposed. It consists of two parts: a probabilistic model for the charging curve of EVs and a model for forecasting the number of EVs in the future. To be more realistic, [6] divided the EVs in the charging state into three types: private EVs, electric taxis, and electric buses. The charging loads of these three types of EVs are then forecasted. The planning of EV charging uses long- and short-term machine learning predictions and high-dimensional data for machine learning during model building and data training. The charging behavior of EVs was analyzed and predicted using both supervised and unsupervised machine learning [7]. Most previous studies only considered historical data, including the arrival time, departure time, and energy consumption of EVs in machine learning models. In fact, there are many other types of data that could be included, e.g., traffic, weather, and local events, to refine and enhance the charging patterns and classification.

Forecasting the baseline load of the daily EV charging by users will effectively reduce the uncertainty and variance in the energy consumption by establishing a charging schedule.

2) Uncertainty and Error in Energy Consumption Forecasting

The energy consumption forecasting based on past charging data can be used to make the corresponding charging decisions. Various factors in the EV charging process result in different levels of uncertainty and errors in the energy consumption. The errors in the energy consumption forecasting will result in uncertainty in EV charging behavior and directly affect the contribution of an EV to the system, such as the battery capacity loss, V2G energy trading loss, and EV charging cost. The error in energy consumption forecasting is a link that cannot be omitted.

In [8], Gaussian distribution was used to represent the daily mileage of an EV and the error in the estimated consumption rate. In addition, an analysis of variance was used to explore the impact of different factors on the energy consumption and various errors. Figure 1 shows the distribution of the energy consumption rate of EVs [9]. However, the research situation in [8] is based on very limited cases. In [7], a linear regression (LR) model was used to predict the energy consumption, and this forecast was integrated into a smart charging algorithm to achieve grid stability. However, [7] did not consider the performance of this forecasting model, which will lead to an increase in the error in the energy consumption forecasting. Therefore, in [10]-[13], game theory was used to determine the optimal energy consumption schedule to reduce the uncertainty in the demand response caused by errors in the energy consumption forecasting.

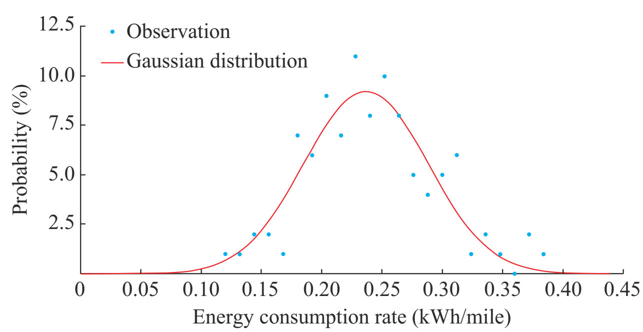

Fig. 1. Distribution of average energy consumption rate of EVs.

A convolutional neural network based on deep learning was used to predict the traffic flow and fully learn the uncertainty in the EV charging load [14], [15]. Then, different forecasting uncertainties were evaluated to formulate a forecast interval for the traffic flow. Finally, [16] used a fuzzy algorithm to control the EV schedule to reduce the waiting time for charging and balance the rate of requests for charging to avoid EV congestion at a charging station, thereby improving the charging performance of the power grid.

3) Forecast of EV Connection Time

The management of EV charging activities is a challenge when the grid load is high. To optimize the charging schedule of EVs, [17] used a discrete-time Markov chain to predict the EV connection time. In [18], a Poisson distribution was estimated based on historical datasets, and predictive model control for the optimization of scheduling was used.

Reference [19] input a larger volume of historical data into a model to train a support vector machine, which is a more complex LR model that improves the forecasting accuracy of the EV connection time. The method uses probability distributions to forecast the departure time, ignoring the impact of real-time electricity prices on users' charging behavior.

In [20], an autoregressive integrated moving average model was used to fit historical charging load data and obtain a day-ahead forecast. This model also proposes charging according to an EV user's price list to control EV charging according to the user's price preferences. On the user side, EV users can submit their price preferences and daily travel times themselves. The above methods forecast the user's charging schedule but do not evaluate and classify the EV user's charging habits. Reference [21] combined a time-of-use (TOU) tariff and user's charging behaviors to introduce a hybrid kernel density estimator. It uses a novel detection method to select different kernel density estimators. Accurate forecasts of the EV connection time may significantly minimize EV charging costs and load changes.

4) Transition of Combined SOC Distribution

The SOC of an EV battery is the percentage of the current remaining battery power to the maximum capacity of the battery. The SOC distribution must be considered when determining the power demand. Many factors affect the SOC distribution, e.g., the distance traveled by the EVs, the market share of different types of EVs, the charging rate, and the initial SOC after the EV is connected to the power grid [22]. Many studies have shown that a more accurate forecast of the SOC can significantly reduce the number of decision variables, reduce the time for formulating charging strategies, and maximize the energy utilization [23]. Moreover, an accurate SOC forecast can prevent the EV from being charged for a long time and prolong the service life of the EV battery.

The central limit theorem in [24] states that the combined SOC distribution of EVs is a Gaussian distribution at any given point in time, as shown in Fig. 2. Each EV unit has a Gaussian distribution for its SOC, confirming that the combined SOC distribution is Gaussian distribution. Historical data were used to calculate the dynamic combination of SOC distributions to estimate the maximum likelihood. However, it may take a considerable amount of time to calculate the SOC distribution and formulate a strategy. Reference [25] proposed another solution using Benders decomposition, which can reduce the calculation time to 11 s. However, the optimization performance of this method decreases as the number of EVs increases. On this basis, [26] used the alternating direction method of multipliers to reduce the calculation time.

The arrival and departure of EVs and the power required during the day are dynamic; therefore, the SOC distribution is dynamic [27]. Reference [23] showed the dynamics of the SOC distribution with a larger number of EVs. The proposed SOC fair charging strategy can reduce the calculation time and memory requirements by reducing the number of decision variables. References [28] - [30] considered adding the expected SOCs of EV users by combining the dynamic probability distribution when the EV is connected to the power grid and the expected SOC when a user leaves a charging point to predict the transition of the combined SOC distribution.

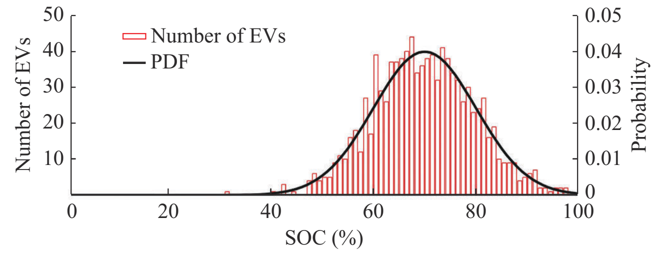

Fig. 2. Combined SOC distribution of EVs [24].

B. Forecasting Methods and Model Types

Section II-A describes the data that can be forecasted but did not analyze their applicability and characteristics in detail. This subsection will analyze and discuss some typical forecasting methods and models.

These methods/models may be applied to different practical users and forecast different objectives, which are listed in Table I. Reference [6] used the Bass model to forecast the future numbers of different types of EVs. The model considers several influencing factors including subsidy policies, oil prices, charging facilities, and industry maturity. The Monte Carlo method is used to eliminate random errors, simulating the future load demand generated by EV charging. The collection of historical EV charging data is indispensable. Reference [31] used a wavelet neural network to collect historical EV charging loads and predict the impact of fast charging on the power grid using the collected data. However, [6] and [31] only considered the impact of increases in the numbers of different types of EVs on the future load, and the EV charging forecasting based on the charging and driving habits of EV users need to be considered.

Reference [32] estimated the changes in the EV power demand based on the EV consumers' preferences, EV supply equipment (EVSE), and charging modes. The discrete choice experiment method was applied to analyze the preferences of EV consumers. Reference [32] assessed the potential market size of EVs based on consumers' preferences for passenger EVs and derived the probability of consumers choosing different types of EVs. They used discrete choice experiments to estimate the probability of using different forms of EVSE and combined consumers' preferences for passenger cars to estimate the total electricity demand. Machine learning and deep neural networks can analyze and forecast charging behaviors so that these data can improve the analysis of EV consumer charging patterns [7]. By combining this with the Markov decision process, the EV connection time was also taken into consideration in [15].

The forecasting methods presented in Table I do not consider real-time data; they only consider the behaviors of random EV users and the limitation on the power grid charging capacity. However, the impact of real-time electricity prices is also crucial. V2G technology provides a service in which the electrical energy stored in an EV battery is transferred back to the power grid, which means that energy flows in both directions between the EV and the power grid. Reference [33] proposed a multi-objective integrated independent solution based on a dynamic pricing model to coordinate the V2G scheduling of EVs. A nonlinear autoregressive neural network cyclic load predictor is used for effective load forecasting. These factors include the EV type (public/private), the SOC, the arrival and departure time of EVs (insertion time), the daily mileage, the driving frequency, the travel purpose, the charging rate, the battery capacity, and the dynamic charging price [34].

TABLE I
COMPARISON OF FORECASTING METHODS AND MODEL TYPES

No.	Method/model	Forecasting objective	Practical user	Reference
1	Bass model or probability theory	Future number of different types of EVs	Charging facilities and EV	[6]
2	Mixed-integer linear programming or Monte Carlo method	Error of energy consumption forecasting	Power grid	[35]
3	Discrete choice experiment	Choosing different types of EVSE, historical EV charging loads, and fast charging in power grid	EVSE, EV, and power grid	[32]
4	Wavelet neural network	Charging behavior	EV and EV users	[31], [34]
5	Nonlinear autoregressive neural network	Effective load and charging load forecasting	EV and EV users	[33]
6	Constrained Markov decision process	Demand response strategy and EV connection time	EV and power grid	[15]

C. EV Charging Data

In the forecasting strategy of coordinated EV charging, various optimization methods using real data can improve the forecasting accuracy. Therefore, real charging data are very important when making EV charging forecasting. In this subsection, we will focus on a method for searching the historical data generated during the EV charging process.

Reference [36] utilized "My Electric Avenue" (MEA), one of the largest EV trials in the world, to study how EVs and power grids work together and provide a large amount of detailed information on MEA trials. In [36], the available EV charging data included the charging habits of EV users and the impact of EVs on a low-voltage power grid. On the basis of these data, the suggestions for increasing the hosting capacity and methods by which EVs can provide various auxiliary services were proposed. Few studies have analyzed the number of EV charging instances per day. Reference [37] collected the number of charging events per day, and the results showed that approximately 70% of EVs are charged only once a day. Further, a rate density function based on a Gaussian mixture model was used to determine the time when an EV starts to charge and the initial and final SOCs of each EV battery. The number of cars in the MEA project was approximately 200. Another recent project in the UK, i.e., "Electric Nation" [38], [39], collected data on approximately 700 EVs, which includes charging transactions, the data communicated between EVs and charging stations, and vehicle database data. The results obtained by combining available real-world charging data with simulation models will be closer to reality and have smaller errors.

There are many challenges in this process, such as the uncertainty in EV charging, data collection security, and transaction risks. Reference [9] studied the uncertainty in EV charging and explained that this situation could affect the reliability of the system. Hence, [9] proposed a method to incorporate these uncertainties into a well-being analysis of the generating system to solve this problem, and [5] used the two-stage stochastic programming to model the problem of uncertainty. References [40] and [41] provided recourse decisions in the second stage according to the personal wishes of EV users for allocation to the parking lot of their choices. Reference [40] formulated the number of charging stations in a parking lot selected by consumers, and [41] used Boolean variables to represent the availability of charging points in the first stage. The two-stage optimization problem can reduce the expected operating cost of the charging station in a specific period and improve the stability of power system.

III. OPTIMIZATION OF COORDINATED EV CHARGING

The cost of EV charging using a smart grid cannot be ignored. Therefore, the optimization of the EV charging process is crucial [42]. In [43], it was explained that the smart grid must determine the price of EV charging. This can optimize its income while charging the EV and balance the charging revenue and related costs. Reference [44] evaluated the impact of different customers' charging behaviors on the economy and pointed out that the cost and revenue are not necessarily proportional to the popularity of EVs but depend on customer preferences to a large extent. The above research objectives focused on EV consumers and charging stations without considering the optimization of power grid. For example, the grid used V2G services to cut peaks and fill valleys, thereby reducing the load difference in the distributed grid system [45]. Table II presents a comparison of multi-objective optimization strategies.

A reasonable arrangement of the charging schedule for the purpose of avoiding excessive load can reduce the cost of power plant upgrades [51] and the energy loss in the distribution system [52]. Close integration of the power grid and charging station can minimize the operation cost of the power grid (including the operation of renewable energy and energy storage) [53], the risk of energy trading [54], etc. However, another focus of research is to optimize the aggregator, such as maximizing the profit of the aggregator [55] and reducing the imbalance caused by the energy purchased by the aggregator from the day market and the energy actually consumed [56].

TABLE II
COMPARISON OF MULTI-OBJECTIVE OPTIMIZATION STRATEGIES

No.	Optimization objective	Method/model	Drawback	Practical user	Reference
1	Capacity reserves in ancillary service market	CVaR-based risk management and sampling average approximation	No guarantee of global optimality	EV charging station operator	[46]
2	Qualified voltage by controlling EV demand	Multi-stage optimization and Monte Carlo simulation	No spatial uncertainty in EV load model	Adaptive distribution network operator	[47]
3	Frequency regulation (FR)	Fuzzy logic	Lack of simulation cases	Microgrid operator	[48]
4	Annual charging cost	Particle swarm optimization and Monte Carlo simulations	May not guarantee global optimum	Smart home	[49]
5	Total operating cost	Two-stage stochastic centralized dispatch scheme	Long computation time and may not guarantee global optimum	Distributed system operator	[50]

V2G technology can significantly increase the capacity of distributed storage [57]. Compared with the traditional one-way charging mode, V2G technology can promote the popularization of EVs and improve their economic efficiencies [58].

A. Ancillary Services

As participants in the V2G market, EVs play a vital role in ancillary services such as grid frequency modulation and power regulation. Table III presents a comparison of ancillary services, where the methods or models required for different optimization objectives are listed [58]-[63]. Each typical optimization target in auxiliary services is compared and analyzed as follows.

TABLE III
COMPARISON OF ANCILLARY SERVICES BASED ON SMART CHARGING

No.	Optimization objective	Method/model	Practical user	Reference
1	FR	Bilevel hierarchical control mechanism, stochastic dynamic programming, robust optimization, and fuzzy algorithm	EV charging station and power grid	[58]-[63]
3	Minimize renewable energy system loss	The maximum sensitivity selection (MMS)	EV charging station and power grid	[65]
4	Increase system profit	Unit commitment	EV aggregator (EVA) and EV owner	[66]
4	Control load mismatch risk	Two-stage stochastic linear program and L-shaped method	Power grid	[67], [68]

1) FR of Power Grid

FR is an auxiliary service that can maintain a balance between supply and demand in a smart grid. The deviation in the power grid frequency can be removed by adjusting the power generation and energy consumption for both supply and demand [59]. V2G technology has the potential to provide FR services. The power adjustment when the EV charging time is short has almost no impact on the EV itself. However, the receiving system requires frequency and voltage adjustments when there is a higher EV charging load in the receiving system. Thus, EVs can meet the requirements of FR, which means that the charging load of EV is of great significance to the FR [59]. Reference [60] used a bilevel hierarchical control mechanism, and the results show that the price difference between regulation up (discharge capacity) and regulation down (charge capacity) is very large. Many studies have focused on methods to directly handle uncertain input parameters through stochastic dynamic programming [61], robustness [62], stochastic optimization [63], [64], and fuzzy algorithms [16] to optimize the FR of power grid.

However, these methods require a large amount of historical data to deal with the uncertainty in the frequency and need to consider the operating time. Therefore, the deterministic method in [55] was developed to optimize the vehicle charging and frequency adjustment settings for evaluation.

2) Load Mismatch Risks

The mismatch between supply (planned load) and demand (actual load) may cause the regional frequency or voltage to deviate from its normal value [67]. Owing to the uncertainty in EV consumers' charging behaviors, the load mismatch between dispatches will incur other costs in addition to the electricity bills required for charging [68], [69]. EVs do not necessarily remain charged when they are connected to the power grid. EVs connected to the power grid can participate in the V2G strategy or remain still. Therefore, the charging time is usually less than the total time when an EV is connected to the power grid. The risk minimization of real-time load mismatch is a daunting challenge.

As mentioned in the Section II, the load forecasting during EV charging will increase energy utilization and reduce energy loss, and the risk of load mismatch can complicate the scheduling problem of advancing risk awareness (it involves nonconvex optimization). To solve this problem, [69] reproduced it as a two-stage stochastic linear program [70] and then used the L-shaped method [71] to solve it. By establishing the risk-aware advance scheduling, the EV charging cost and the risk of load mismatch are minimized.

3) Systems Integrated with Renewable Energy

Renewable energy, as a clean energy source, can be a solution to reducing energy costs and emissions. Most studies on renewable energy systems aimed to increase the rate of penetration of renewable energy in the EV charging process and reduce the cost of power generation [72]. When renewable energy participates in ancillary services, wind energy, solar energy, and EVs can be combined through V2G strategies to enhance the overall performance of the integrated system. Wind energy and solar energy are the main renewable energy sources, which can be combined with EVs to meet the needs of the power grid under various conditions [46], [73]-[75]. References [76] and [77] find that wind power, hydropower, photovoltaic power generation, and fuel cells can be used for distributed power generation in integrated systems, but it is difficult to integrate renewable energy into the power grid [78]. The ways in which EVs participate in ancillary services is shown in Fig. 3.

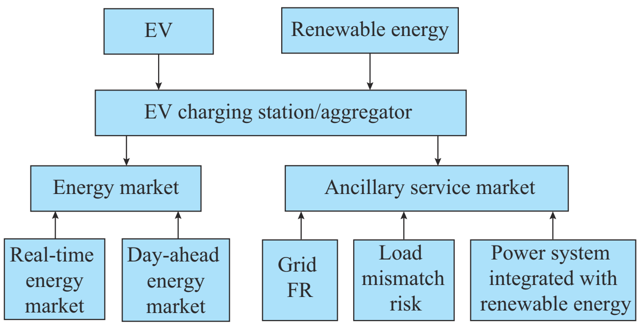

Fig. 3. EV's participation in ancillary service markets.

Reference [21] proposed suggestions to reduce the cost of the smart grid and reduce emissions by maximizing the use of grid-connected vehicles and renewable energy. The intelligent dispatch and control of grid-connected vehicles calculated by particle swarm optimization show its potential as a solution to developing sustainable integrated power and transportation infrastructure. The stochastic optimization methods were used in [79] to incorporate plug-in hybrid vehicles (PHEVs) as an energy-saving solution to address the variation in the time span of renewable energy and its limited predictability. However, [79] and [80] only maximized the use of renewable energy. In [78], the Lyapunov optimization algorithm was used to reduce the charging cost of EVs and delay the problem of satisfying the charging demand of EVs.

However, while meeting these requirements, it is also particularly important to ensure the stability of the power grid. Reference [81] built a PHEV charging station architecture and a quantitative random model based on queuing theory, which can maintain the stability of the power grid and provide the required quality of service.

B. Application of Game Theory in Vehicle-to-aggregator Methods

An EVA is a type of business entity. It can combine system operators and EV users to participate in the electricity market. The aggregator processes charging and collects the available capacity of the EVs connected to the power grid [82]. When the number of EVs in a geographic area is small, a single aggregator is sufficient for handling EV charging and grid services. However, multiple aggregators may be required in the overall system when the EVs in the system cover a large area or the penetration rate of EVs is high [9]. Table IV presents a comparison of strategies for the multi-objective optimization of EVAs, and a specific analysis and discussion will be given below.

TABLE IV
COMPARISON OF STRATEGIES FOR MULTI-OBJECTIVE OPTIMIZATION OF EVAS

No.	Optimization objective	Model/method	Technique evolution advantage	Practical user	Reference
1	Calculation of the optimal charging control	Dynamic programming algorithm and quadratic programming	Collect parameters of EV, the maximum battery capacity, SOC, and charging rate	Power grid, EV, and EV user	[17], [83]
2	Frequency adjustment provided	Quadratic programming	Minimize peak load and flatten overall load profile	EV and smart grid	[84]
3	Evaluation of the optimal bidding strategy for power reserve market	Monte Carlo method and stochastic programming	Provide flexibility for operating electricity market	Reserve market and EV user	[85], [86]
4	Risk measurement index and profits of aggregator and EV owner	Bilevel optimization mode and mixed integer linear programming	Consider financial risk management and market inferiority	EVA	[35]
5	Optimization bidding strategy of EV aggregators in electricity market	Bilevel optimization model, KKT method, and single-level linear program	Decompose problem to find global optimal solution	EV charging station, EV users, and renewable energy source owner	[87]
6	Effect of number of aggregators	Monte Carlo method	Increasing number of aggregators does not necessarily improve state of system	Power grid and EV	[9]

1) Coordinating Multiple Aggregators

The coordination of multiple aggregators can effectively utilize the distributed power of EVs to optimize the power grid [88]. A schematic of single aggregator and multiple aggregators is shown in Fig. 4.

Reference [17] applied a dynamic programming algorithm to calculate the optimal charging control for each vehicle. However, before this, the parameters must be collected. Through local and global control strategies based on quadratic programming [83], the aggregator was used to collect the parameters including the maximum battery capacity of the EV, the SOC, and the charging rate, which is the role of the aggregator. Another use of aggregators is to reduce load peaks. The coordination of multiple aggregators can enhance this effect. Reference [84] presented a smart energy control strategy based on quadratic programming for charging

PHEVs, aiming to minimize the peak load and flatten the overall load profile. However, the frequency adjustment provided by the aggregator is proportional to the number of EVs under its control. Considering the distributed storage capacity of V2G systems, a dynamic programming algorithm was used to design an optimal centralized control strategy for FR in the presence of aggregators [1], [57].

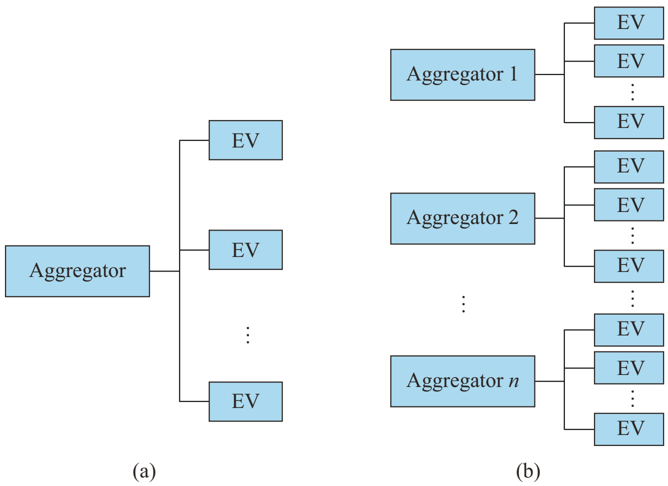

Fig. 4. Schematic of single aggregator and multiple aggregators. (a) Single aggregator. (b) Multiple aggregators.

The various studies above are based on ideal conditions without in-depth consideration of the energy loss factor. In [89], a real-time EV charging control strategy is proposed to minimize the total electricity generation cost and the associated grid energy losses. Two-stage optimization is used to demonstrate the competence of the distribution feeder reconfiguration (DFR) towards minimizing system losses in the presence of EVs. With an increase in the uncertainty in the aggregator scheduling process, [90] proposed the use of hybrid energy systems to optimize the bidirectional power flow so that an EV can obtain the optimal solution during the scheduling process, thereby minimizing the operating costs.

2) Market Transactions of Aggregators for Coordinated EV Charging

Owing to rapid increases in the popularity and use of EVs, the EV charging loads pose new challenges to the smooth operation of the power grid. The uncoordinated charging of EVs will increase the peak-to-valley load difference in the local power grid. Reference [22] stated that an EVA connects an independent system operator and a single EV to provide flexibility for operating the electricity market. However, there are uncertainties in the V2G market, the random aggregation behavior of EV owners, and the fluctuations in electricity market prices that incur financial risks to the operation of aggregators [91]. The aggregators must first evaluate the optimal bidding strategy for the power reserve market. Reference [85] used a Monte Carlo method to simulate this strategy, and stochastic programming was used in [86] to ensure that uncertain EV management is also taken into account.

These studies did not consider financial risk management and market inferiority. Hence, [35] used a bilevel optimization model to solve these problems. The conditional value of risk (CVaR) manages the financial risk caused by uncertainty and is used as a risk measurement index [42]. The aggregator maximizes the CVaR in upper-level problems, whereas lower-level problems minimize the operating cost of the system. In this model, the profits of the aggregator and EV owner are optimized. The Karush-Kuhn-Tucker (KKT) method was used to decompose the problem to obtain the global optimal solution [87]. Reference [92] combined the bilevel model and the CVaR, and the impact of the risk aversion parameters on the aggregator was evaluated to optimize the bidding strategy of the EVAs in the electricity market.

3) Challenges of Multiple Aggregators

Aggregators are considered essential for EV to participate in power grid services. To determine the influence of the number of EVAs on the operating conditions, [9] conducted simulations with different numbers of participating aggregators using Monte Carlo method, as shown in Fig. 5. It is found that an increase in the number of aggregators does not necessarily improve the state of the system.

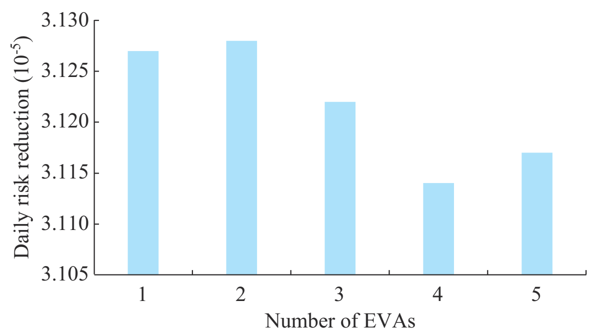

Fig. 5. Effect of number of EVAs.

The failure of an aggregator implies that it will have no contribution to the power grid, such as component failure in charging facilities, human error due to punctuality, time rounding, and the energy consumption forecasting [9]. In addition to the algorithmic challenge of dealing with uncertainties, the frequent discharge of EV batteries will also affect the optimization problem. Reference [93] proposed a new type of bidirectional control strategy for battery charger. The proposed control strategy can charge and discharge EV batteries in slow and fast modes. Combined with the loss of the battery, a reduction in the uncertainty in the bidirectional power flow during the charging of the aggregator is a new challenge. Temporary charging piles on the roadside or household mobile charging piles are a type of decentralized charging. The battery capacity of a single EV is limited, which limits its ability to participate in the energy market [94]. These scattered EVs can be dynamically combined to form a relatively fixed charging load. A service framework can solve this problem. EVs can subscribe to the services of aggregators (similar to telecommunications operators), and aggregators can coordinate the subscription of EVs at these charging stations through owned or cooperative charging stations [95]. Collaboration among aggregators is a research challenge.

C. Charging Behaviors of EV Users

The arrival and departure time of an EV and the electricity price are random; therefore, it is difficult to determine the best charging/discharging schedule to ensure that the electric car is fully charged when it leaves. Reference [15] formulated this scheduling problem as a constrained Markov decision process (CMDP) to ensure that EVs can be fully charged while minimizing the charging cost. In [96], a heuristic method is used to control the EV charging rate and time based on a TOU tariff.

References [15] and [96] did not clearly explain the possible effects of the charging behaviors of EV users, such as behaviors related to searching for charging, navigation behaviors, and the distribution of charging piles. The algorithms based on Bayesian inference were used to simulate these problems [97] and plan EV charging stations according to the users' charging behavior. On this basis, [98] added some daytime activity parameters including working, shopping, and traveling. These charging behaviors are intermittent and can last for several hours or longer. Therefore, charging stations around a driver's departure location or destination were regarded as potential locations for charging [99]. Owing to the limited driving range of a vehicle, the flow refueling location model in [100] can be utilized to plan the location of a charging station. The comparison of charging strategies based on behaviors of EV users is concluded in Table V.

TABLE V
COMPARISON OF CHARGING STRATEGIES BASED ON BEHAVIORS OF EV USERS

No.	Optimization objective	Model/method	Reference
1	Minimization of EV charging cost	CMDP	[15]
2	Control of EV charging rate and time	Heuristic method	[96]
3	EV charging station planning	Bayesian inference algorithm	[97]
4	Potential location for charging demand	An integer program	[99]
5	EV charging station planning	Flow-based methods	[100]

This section has reviewed the optimization methods or models for coordinated EV charging strategies and coordinated aggregator strategies. Moreover, multi-objective optimization has also been briefly discussed. The discussion and recommendations of this study will be presented in the next section. The authors propose conjectures and an outlook for infrastructure planning, data interaction, and incentive policies for V2G services.

IV. DISCUSSION AND RECOMMENDATIONS

Future charging scheduling algorithms are considered to be bidirectional, decentralized, and mobile [101]. Scheduling is a core area of EV charging management, and short- and long-term predictions and their impacts on scheduling need to be further considered. The optimization of EV charging strategies may be achieved through prediction using machine learning, bidirectional power flow aggregator charging schedules, and decentralized EV charging. The research publications reviewed in this paper are based on V2G technology, and V2G technology used in the intelligent charging process of EVs still faces many challenges. The following subsections will provide recommendations for potential problems arising in the future development of V2G technology.

A. Infrastructure Planning

The increasing number of EVs will lead to the inability of the existing charging infrastructure to meet the corresponding demand. Therefore, the government or related agencies need to plan for the expansion of the charging infrastructure. The planning of improper charging infrastructure may have a negative impact on the operation of the entire charging system [102] such as the unstable operation of power grid and the irrational use of electrical energy. The rationality of infrastructure planning is considered to be one of the challenges in ensuring the safe and stable operation of the entire system [103].

The cost associated with planning the EV charging infrastructure includes the maintenance cost, operating cost, distributed generation (DG) investment cost, and network loss cost. Figure 6 shows how the planning problem is optimized according to different types of EV charging stations including fast charging, battery swapping, and regulated charging [103]. Because of the similar uses of charging stations and gas stations, the planning of gas stations can be referred to in future research on the planning of EV charging infrastructure. The optimal planning of charging stations is the primary goal [104]. On this basis, the characteristics of the distribution lines, distributed generators, and road conditions also need to be considered. Reference [105] reviewed EV infrastructure development in the UK, in which the typical designs and business models are discussed for EV charging infrastructure as well as the challenges for the development of EVs and their charging infrastructure in the future.

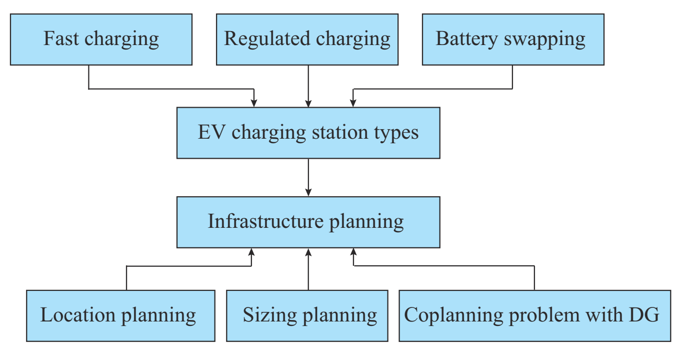

Fig. 6. Categories of charging infrastructure planning problem.

B. Data Flow and Management

In V2G applications, the efficiency of EVs with charging infrastructure, aggregators, the transmission of electricity market data, and the ability to process data is particularly important. Reference [106] proposed the application of a multi-agent model to the data interaction between EVs and the charging infrastructure (including the battery status of an EV, the location of the charging station, and the distance). In this model, the multiagent traffic simulation model can be used to evaluate the impact of the driving and charging processes of an EV on different electricity price strategies and charging priorities. Aggregators can be responsible for coordinating information for multiple targets, including the real-time status of EVs, electricity market data, and real-time information on charging stations. Reference [26] proposed an optimization framework based on the alternating direction method of multipliers to achieve computational scalability. Therefore, an increasing number of studies have begun to consider the issue of data interaction, which is essential for the future development of EVs.

C. Data Privacy

This paper discusses various challenges in EV charging forecasting. All of the predictive problems discussed need to collect a large amount of historical data to understand users' charging behaviors or driving preferences. For example, when consumers let their cars participate in V2G coordinated charging, these cars will send and receive a large amount of data including the charging location, the SOC, and personal user information. It is extremely important to observe and protect the privacy of these data [95]. Reference [107] solved the problem of data privacy when using the open charge point protocol to ensure the safe flow of data between charging stations and the control center. Reference [108] proposed that cyber infections may occur with this system. Therefore, their solution is to disconnect the infected EV supply equipment and formulate a linear program to offset the spread of network infections throughout the charging infrastructure while maintaining EV charging services.

D. Incentive Policies in V2G Systems

At present, EV owners receive very few benefits when participating in a V2G market, and some losses will also occur. For example, the number of EV battery cycles will increase during the V2G process, which will lead to an increase in the rate of battery degradation. Therefore, it is necessary to formulate a reasonable incentive policy. Most existing incentive policies are subject to government supervision, and the relevant departments can appropriately accelerate the speed of EV adoption in the transportation system. The formulation of future incentive strategies can be considered from multiple perspectives, such as determining the best incentives for EV owners from an EVA perspective and using incentive schemes to reduce communication delays in the field of EVAs.

V. Conclusion

The optimization of charging is a challenge for the development of EVs, which will affect the promotion of new EVs, the load on the power grid, and changes at the economic level. This paper reviewed previous research in this area in terms of EV charging forecasting strategies and coordinated EV charging strategies and hence provided recommendations, which are summarized as follows.

1) EV charging forecasting strategies: they need to combine various forecasting data such as the predicted charging load, energy consumption error, EV connection time, and SOC distribution. Simultaneously, different methods have different effects on the optimization objective. Available EV charging data can increase the accuracy of EV predictions. This paper also describes how to search for historical data generated during EV charging.

2) Coordinated EV charging strategies: the optimization of coordination strategies presented in this paper includes ancillary services, the application of game theory in vehicle-to-aggregator methods, and the charging behaviors of EV users. In ancillary services, the impacts of coordinated charging on the grid frequency, the load mismatch risk, and the combination of systems integrated with renewable energy and power grids have been analyzed. On this basis, game theory used in methods that model the transfer of energy from electric cars to aggregators has also been reviewed. Compared with a single aggregator, the coordination of multiple aggregators is a future research direction for smart grids. However, the coordination of multiple aggregators must be combined with market transactions, and different risk coefficients will lead to differences in returns. Moreover, it is necessary to accurately obtain the charging behaviors of EV users to ensure that an EV is fully charged when leaving and the charging cost is minimized.

3) Recommendations: the rationality of infrastructure planning is an important factor in ensuring safe and stable operation of the entire system. The charging infrastructure needs to be carefully planned and improved to reduce the impact on the power grid during the charging of EVs. Moreover, the data transferred between EVs and the charging infrastructure, aggregators, and electricity markets are complex, and the efficiency of data interaction and data processing capabilities are particularly important. Moreover, the formulation of reasonable incentive policies can effectively reduce the charging costs of EV owners and increase the participation of EV users in V2G markets.

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