

Status and Development of Research on Orderly Charging and Discharging of Electric Vehicles

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Abstract: As the scale of electric vehicles continues to expand, the charging load of electric vehicles into the network has become an issue that cannot be ignored. This paper introduces the concept and development of ordered charging based on the current background of ordered charging research. The application architecture of ordered charging is summarized, and the advantages and disadvantages of centralized, distributed, and hierarchical control architectures are introduced. The current status of research on orderly charging is analyzed at four levels: steps and methods of load modeling for orderly charging, optimization objectives of orderly charging, optimization methods of orderly charging, and practical projects of orderly charging. The methods of load modeling for orderly charging are summarized, different optimization objectives of grid operation for orderly charging are introduced, and the advantages and disadvantages of different optimization algorithms are compared and analyzed. Practical projects on orderly charging illustrate the great potential of orderly charging. This paper points out four problems of communication, data security, market mechanism, and the number of charging stations that orderly charging is currently facing and proposes feasible solutions. The development prospect of orderly charging being more environmentally friendly, energy-efficient, intelligent, and safe is proposed.

Keywords: orderly charging; V2G; optimization algorithm; virtual power plant; data security



Citation: Zhang, Z.; Lv, L. Status and Development of Research on Orderly Charging and Discharging of Electric Vehicles. *Electronics* **2023**, *12*, 2041. <https://doi.org/10.3390/electronics12092041>

Academic Editors: Dmitry Baimel and Inna Katz

Received: 21 March 2023

Revised: 24 April 2023

Accepted: 25 April 2023

Published: 28 April 2023



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1. Introduction

With the increasing frequency of global environmental problems, people's awareness of environmental protection has been raised to an unprecedented level, and countries have set their target years for achieving carbon neutrality. Vehicle emissions are an important cause of urban air pollution [1], and according to statistics, emissions from transportation in China totaled 950 million tons of CO₂ in 2020 and are expected to reach more than 1 billion tons in 2030 if growth continues and no measures are taken to limit them. If the growth continues and no measures are taken to limit it, it is expected to reach 1.2–1.7 billion tons in 2030. To limit the emission of greenhouse gases and eliminate the dependence on fossil energy, the development of electric vehicles has become a common choice of countries. Electric vehicles use electricity as an energy source, which has almost zero emission of greenhouse gases, and the running cost has obvious advantages compared with traditional fuel vehicles. With the support of national policies and environmental awareness, an increasing number of people choose to use electric vehicles. However, at the same time, the impact of electric vehicles on the power grid is becoming more obvious. If not guided, a large number of electric vehicles will have disorderly charging access to the grid; due to the use of electric vehicles with high simultaneity, it is easy to form the grid load “peak on peak” phenomenon [2]. This causes problems such as overloading of grid lines, voltage drop, and increased network loss [3]. The authors in [4] describe in detail the impact of large-scale electric vehicle charging on the security risk of the grid—the

greater the uptake of electric vehicles, the greater the operational risk of the distribution network. After considering the economic benefits, the risk to the grid is even more locally magnified. The authors in [5] analyzed that although the charging load of electric vehicles generally occurs at night, it can also bring new load peaks and put additional pressure on the operation of the grid. However, there are two sides to the coin. As a mobile load and with energy storage, electric vehicles, if properly guided and reasonably deployed grid resources, can greatly help the economy and stability of grid operation. This requires the coordination and optimization of charging strategies by charging stations to optimize the grid loss of the power grid, the charging cost of users, and the consumption of new energy. The authors in [6] introduced an orderly charging strategy with variable power regulation aiming at minimizing the peak-to-valley load difference and charging cost, which can effectively realize “peak shaving and valley filling” and reduce the charging cost of users. The authors in [7] proposed tariff guidance through the power generation characteristic curve of wind power to enable users to orderly charge according to the wind power, reduce the impact of charging load on the grid, and maximize wind power consumption.

After years of research and development, the research goal of orderly charging has changed from initially achieving “peak shaving and valley filling” for grid operation, to now allowing the grid to operate in the most stable and least loss state, allowing users to complete charging with the least cost and fastest time. To maximize the use of new energy generation, reduce carbon emissions, and achieve the goal of carbon neutrality. The research on orderly charging has matured and has been put into practice around the world. However, currently, there is still a lack of a comprehensive and up-to-date analysis of the research on orderly charging. Further summary and analysis are needed for the implementation structure, research methods, practical cases, key issues, and future development of orderly charging.

Based on the above background, this paper starts with the structure of the ordered charging strategy. The latest EV load modeling methods are analyzed, and different charging and discharging optimization strategies are investigated. The advantages of the ordered charging strategy are summarized, and the current problems and possible solutions are presented. Finally, the future development of ordered charging has been prospected. This paper aims to provide a systematic overview and evaluation of the principles, methods, and effects of orderly charging, to offer reference value for scholars and engineers who will engage in related research on orderly charging in the future, and to provide research ideas and suggestions for the development of orderly charging in the fields of electric vehicles and power grids.

2. The Concept of Orderly Charging

Due to the increasing scale of electric vehicles, the impact of charging load on the grid must be addressed when a large number of electric vehicles are connected to the grid for charging. It can lead to grid overload, increase the difficulty of grid dispatch, reduce power quality, and affect electrical equipment [8]. The quantitative assessment of the impact of large-scale electric vehicles on the grid and the study of charging control strategies aimed at reducing the negative impact have become increasingly popular issues, and Ref [9,10] have proposed charging interaction strategies between the grid and electric vehicles, while the concept of orderly charging has emerged. The authors in [11] propose a real-time power balancing strategy for electric vehicle charging loads. The authors in [12] propose that the orderly charging strategy uses practical and effective economic or technical measures to guide and control electric vehicle charging to meet the charging demand for electric vehicles; to reduce the variance of the load curve by “peak shaving and valley filling”; and to reduce the construction of installed power generation capacity to ensure the coordinated and interactive development of electric vehicles and the power grid. The authors in [13] propose that electric vehicles be considered as a new controllable load that participates in regulating grid operation for charging optimization. The authors in [14] developed

a charging scheduling strategy for electric vehicles considering traffic information and grid operation.

The OCPP protocol was developed by the OCA (Open Charge Alliance) in 2009, marking the establishment of the communication specification for V2G technology. With the update and application of V2G technology, the OCPP protocol has now been updated to version V2.0.1, which has a more standardized standard in terms of extended security and intelligent charging. With V2G technology, the unilateral consumption of electricity by electric vehicles is changed, and the two-way transmission of electricity between electric vehicles and the grid is achieved [15]. Smart V2G technology can benefit users while reducing battery losses [16]. The development of the ISO15118 protocol further ensures charging data security, realizes plug-and-charge and other functions, and provides convenience for the application of V2G technology. The authors in [17] pointed out the development potential of V2G technology. As long as users' "mileage anxiety" and "minimum mileage" are addressed, orderly charging can achieve high V2G participation. The authors in [18] proposed that through V2G technology, electric vehicles can be considered adjustable loads when charging. Peak load shifting is achieved through orderly charging management. Electric vehicle batteries can also be used as energy storage devices as the backup capacity for the distribution grid to optimize grid operation.

The development of today's orderly charging technology has become increasingly mature. By collecting the region's load data and analyzing the grid operation, the base load model of the grid is constructed. Then, based on the charging data of charging piles, the charging load model of electric vehicles is built. The two load models are used for day-ahead scheduling or real-time scheduling of power operations to prevent grid overload. In addition, the charging load of electric vehicles is involved in grid regulation through V2G technology by making appropriate task arrangements for charging orders from users at the control center level of charging piles or by guiding users at the level of distributed charging piles. Based on not causing grid overload, it controls the charging and discharging of electric vehicles to the "peak-shaving and valley-filling" of the grid, reduces network losses, and consumes new energy to benefit the grid. It enables users who choose not to accept the charging arrangement to complete charging at the fastest possible speed, depending on the needs of the different users. It also allows users who accept charging arrangements to complete charging at the lowest cost and at the right time, benefiting the user side. Appropriate charging deployment is made according to the profit demand and operation cost of charging stations so that the power station side can obtain enough profit to benefit the power station side. The optimization goal of an orderly charging strategy is the most suitable arrangement of a charging plan in the face of different actual situations and specific requirements. The sequential charging optimization is shown in Figure 1 below.

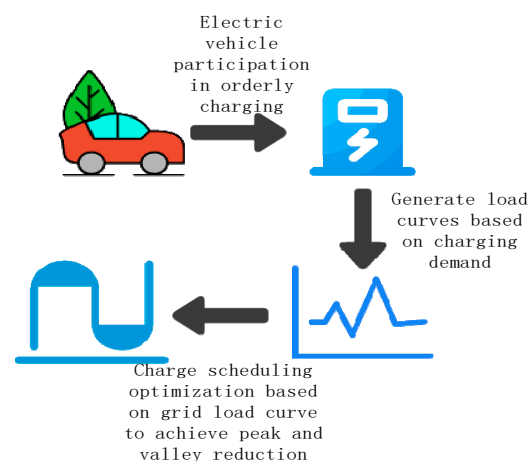


Figure 1. Sequential charging optimization concept.

3. Control Architecture for Orderly Charging

To better derive optimization solutions for different requirements, the researchers designed three control architectures for the control level of the charging pile, the user side of the pile, and the coordinated optimization of both aspects. They correspond to centralized optimization, distributed optimization, and hierarchical optimization, respectively. The three architectures have different characteristics, which will be introduced and compared from different perspectives.

3.1. Centralized Control Structure

The centralized control structure is a control center that directly controls the charging and discharging behavior of the charging piles. The control center collects the load data of the area and builds a load model. Charging orders from users are processed centrally, and charging tasks are scheduled according to different optimization objectives based on the base load model. The authors in [19] proposed an orderly charging scheduling strategy with centralized control to optimize the charging and discharging of electric vehicles by a local search and particle swarm algorithm, which realizes the “peak shaving and valley filling” of the grid and reduces the charging cost of users. The authors in [20] proposed an orderly charging optimization method based on the fuzzy heuristic algorithm and designed a public transportation operation system for centralized control of EV charging orders in public parking lots. The method optimizes the resource deployment of the grid and reduces the operating cost of charging piles. As seen from the above-referenced papers, the centralized optimization approach can leverage the control center’s ability to integrate data and centralize computational scheduling under different optimization objectives to derive a scheduling strategy with global optimization benefits. It can achieve the optimal solution for multiple objectives. However, the disadvantages are also apparent. On the one hand, there is the problem of computational difficulty. As the scale of electric vehicle charging increases, the difficulty and time for the control center to calculate the multi-objective optimal solution increase exponentially. This is different from the requirements for fast and convenient charging on the user side and has significant limitations for the optimization strategy of real-time scheduling. On the other hand, the user needs to send the charging request to the control center through the charging post or mobile app. Then, the control center sends the charging task to the charging port. This process requires high communication capability of the control system and can be slightly hindering to use in places where the signal is unstable. As shown in Figure 2.

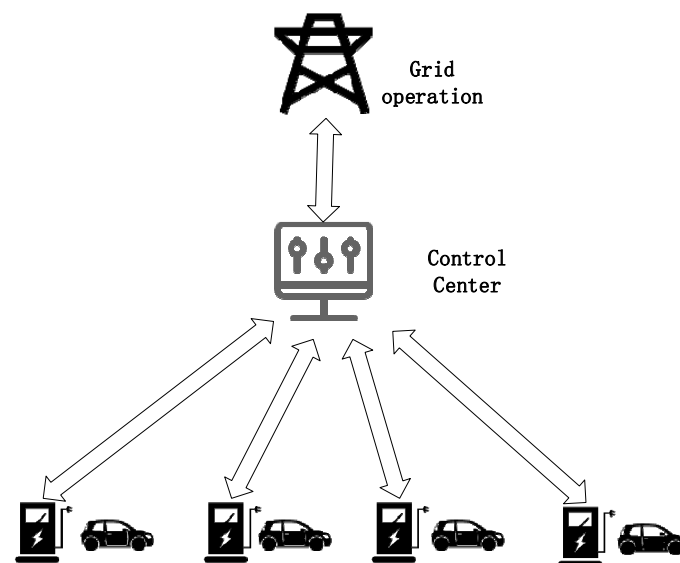


Figure 2. Centralized control architecture.

3.2. Distributed Control Structure

The core of the distributed control structure is to guide customers to orderly charging through time-of-use tariffs, allowing them to save on charging costs while relieving the operational pressure on the grid. The operation information of charging stations and charging tariff data are displayed to users, who make charging decisions based on their needs and the above information and send charging requests to charging stations, which arrange to charge after verifying charging orders. There are two time-sharing tariff approaches: day-ahead dispatch tariff guidance and real-time dynamic tariff guidance. The authors in [21] proposed a distributed control strategy based on the day-ahead tariff model. The day-ahead load curve and load forecasting model derives a time-of-day tariff model from guiding customers. It improves the operator's profit and reduces the users' charging costs. The authors in [22] proposed an orderly charging strategy based on deep learning and real-time tariff guidance. The scheduling structure is constructed using real-time electricity prices, and electric vehicle charging and discharging behaviors are optimized by deep learning to create a win-win situation for the grid and electric vehicle users. As seen from the above references, the distributed control structure uses the time-of-use tariff to guide and optimize the charging periods of the users. The advantages are (1) greater charging selectivity for users; (2) less computational difficulty for the control center, which can process users' subscriptions faster; and (3) less communication pressure on the system. The disadvantage is that it depends more on the user's responsiveness to the time-of-use tariff. If the user's response is low, the goal of orderly charging cannot be achieved. In addition, the regulating role of distributed optimization is relatively singular and cannot achieve the purpose of multi-objective optimization through the guidance of a time-sharing tariff. It cannot achieve the same effect as centralized optimization regarding new energy consumption and network loss reduction. As shown in Figure 3.

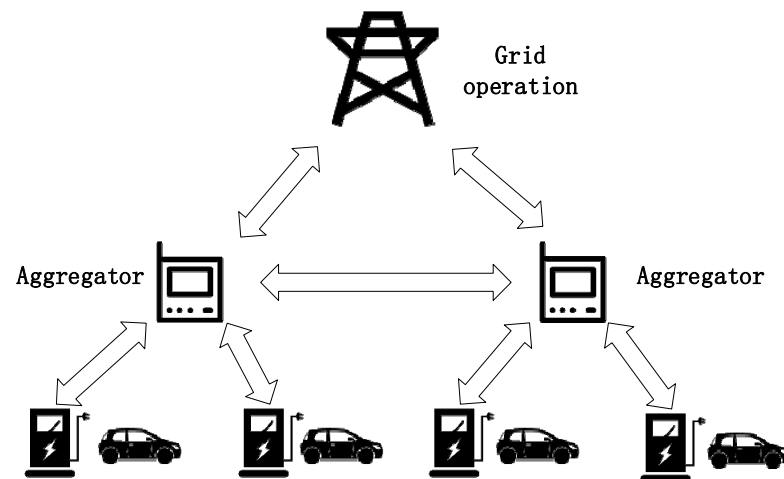


Figure 3. Distributed control architecture.

3.3. Hierarchical Control Structure

The hierarchical control structure combines the features of centralized and distributed control. The time-of-use tariff of distributed control guides users' charging choices and combines users' charging requests and optimization goals at the control center. The most suitable EV charging order arrangement is derived from reaching the optimization goal and benefiting multiple parties. The authors in [23] proposed a two-tier optimization model based on the real-time load of the grid. The real-time electricity price model is constructed based on the regional load. The lower layer model is aimed at optimizing the EV charging load, and the upper layer is aimed at optimizing the charging price in real time. The results of the two-tier optimization are combined to optimize the multi-objective ordered charging strategy. The objective of "peak shaving and valley filling", reducing user charging costs and promoting new energy consumption, is achieved. The authors

in [24] proposed an overall architecture of the master station and energy controller in hierarchical cooperative control. The first level of optimization is to control the charging cost of users, and the second level is to reduce the fluctuation of the grid load. The charging cost of users is reduced, and the operation of the grid is optimized. As seen from the above references, the hierarchical control structure combines the user-side guidance of distributed control with the control center optimization of centralized control. It reduces the computational pressure on the control center and the transmission pressure on the communication lines while achieving global multi-objective optimization and avoiding the extreme case of low user responsiveness. It combines the advantages of both control structures and compensates for the disadvantages of each. As shown in Figure 4.

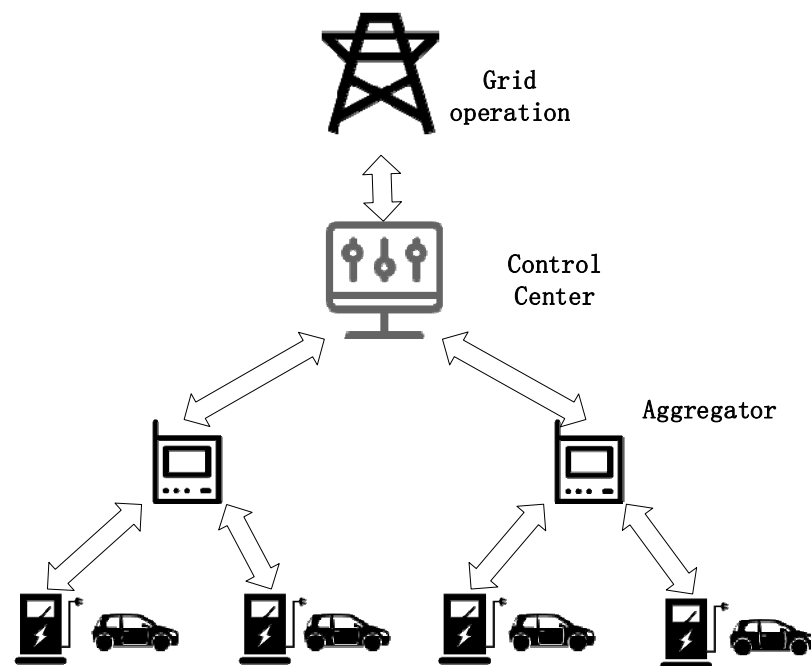


Figure 4. Hierarchical control architecture.

3.4. Application Analysis

The characteristics of the three orderly charging control structures are suitable for application environments in different scenarios. The centralized control structure requires the majority of users to respond to orderly charging and sufficient scheduling time, but it achieves better optimization results with a relatively small investment. This approach is more suitable for small-scale charging stations, such as a collection of charging posts in residential communities, and can make full use of users' parking time at night for orderly charging scheduling. The distributed control structure relies on the responsiveness of users and can provide them with freer charging options. This model is more suitable for small and medium-sized commercial charging stations, such as those in office buildings, and can guide users to participate in orderly charging through the economic benefits of time-of-use tariffs, which take advantage of users' working hours for optimal scheduling of orderly charging. The hierarchical control structure is the most optimized of the three approaches, but it is also the most expensive. This approach is more suitable for charging stations in large-scale and high-traffic areas, such as optical storage charging stations in commercial centers. Through the optimal scheduling of orderly charging, we can strive for economic benefits for users during their parking hours, and we can fully consume PV power and make full use of energy storage equipment to assist in peak shaving and valley filling. The analysis of the three structures is shown in Table 1.

Table 1. Comparison of three control structures.

Control Structure	Advantages	Disadvantages	Applicable Scenarios
Centralized control structure [19,20]	Can find the global optimal solution, good optimization effect, small investment	Need for adequate scheduling frequency and user responsiveness	Small-scale charging stations or a collection of charging stations in residential areas
Distributed control structure [21,22]	Provide users with more free charging options for a wider range of scenarios	Poor optimization when customer responsiveness is low, more dependent on time-of-use tariff strategy	Small and medium-sized charging stations, such as commercial charging stations in office buildings
Hierarchical control structure [23,24]	The best optimization effect can achieve multi-objective optimization, to achieve the goal of multi-benefit	Large investment, difficult operation, and higher requirements for optimization strategies	Large-scale charging stations, such as optical storage charging stations in commercial centers

4. Orderly Charging Strategy for Electric Vehicles

The strategy for the orderly charging of electric vehicles consists of three parts. The first is modeling, which requires a base load model based on the local base load and a charging load model based on the charging load of EVs. Then, the optimization objectives of orderly charging need to be determined. According to the actual demand, the optimization is carried out with minimum charging cost, the minimum peak-to-valley difference of the power grid, or maximum new energy consumption. Finally, the optimization method is determined. Different load models and optimization objectives are suitable for different optimization methods. Genetic algorithms, particle swarm algorithms, or other intelligent algorithms must be determined according to the actual demand or several experiments.

4.1. Electric Vehicle Charging Load

The charging load must first be modeled to analyze the impact of electric vehicle charging on the grid. Three main factors determine the charging load model: 1. The type of electric vehicle. Electric vehicles consume different amounts of electricity per 100 km and have different travel patterns and ranges. 2. Number of electric vehicles. The number of electric vehicles determines the size of the charging load and the amount of space available for grid dispatch. 3. The charging method of electric vehicles. Electric vehicles have three main charging methods: fast, slow, and battery swapping. The power required for different charging methods, charging time, and impact on the grid are all different.

After determining the above three points, it is also necessary to analyze realistic car travel data to derive data such as the probability density function of electric vehicle travel miles and the density function of electric vehicle's access moment to the grid. The load prediction model is then developed using the Monte Carlo method or travel chain spatiotemporal analysis. It simulates the charging power curve and spatiotemporal distribution of electric vehicles.

The Monte Carlo simulation method is the most commonly used method in the study of ordered charging, which constructs a probabilistic process of car trips based on the data of car trips by statistical simulation and then samples from the probabilities to obtain a load model for simulation prediction. The data model for the 2018 release of the National Household Vehicle Survey results (NHTS2017), which is currently being used more frequently, is the Monte Carlo method for load prediction. Some of the data from the NHTS2017 model are shown in Figure 5. This model is cited in references [25,26]. Some studies have combined Markov chain and Monte Carlo methods to solve the problem of

Monte Carlo simulation that requires many samples to construct a probabilistic model. Samples that conform to a stable probability distribution are obtained so that the EV charging load prediction for the current day is only related to the charging load of the previous day. The authors in [27] utilized a Markov chain approach to develop a load model for the ordered charging of electric vehicles.

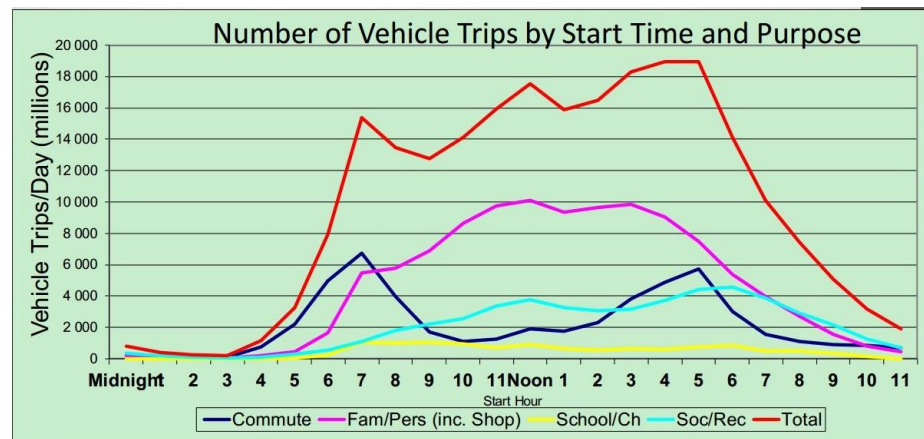


Figure 5. NHTS2017 car user trips.

Probability density distribution of daily miles driven

$$f(x_s) = \frac{1}{x_s \sigma_s \sqrt{2\pi}} \exp \left[-\frac{(\ln x_s - u_s)^2}{2\sigma_s^2} \right]$$

where x_s represents the daily mileage of the car and u_s represents the expected value.

Some scholars have also chosen the trip chain spatiotemporal distribution method for load forecasting. In contrast to the Monte Carlo method, this method introduces the user's travel purpose as an influencing factor. It combines both temporal and spatial distributions for load forecasting of electric vehicles. The authors in [28] collected real driving data of 1000 electric vehicles in Zhengzhou, China, for analysis. The charging load model of electric vehicles is derived based on the data of the number distribution of electric vehicles, the parking time distribution, and the state distribution of the vehicle SOC. Then, the orderly charging strategy is optimized by a genetic algorithm to best fit the local load situation, which improves the stability and economy of grid operation. The authors in [29] collected EV data from a North American campus network and a portion of the London metropolitan area to describe a charging model for EVs. The road congestion and the spatiotemporal distribution of EVs were considered, and the charging capacity of charging stations was significantly increased by predicting the load of EVs and controlling the charging behavior of users. It also improves user satisfaction and enables charging stations to increase their profits. The above studies indicate that although most studies have used the NHTS2017 data model, researchers in different countries have started collecting automobile occurrence data in their own countries or regions. Future orderly charging research will definitely be based on local data, and the research goals will be refined applications that are most suitable for the local context.

4.2. Optimization Goals for Orderly Charging

The optimization goal of orderly charging is the core of developing an orderly charging strategy. From the most straightforward charging operation, the charging process for the user is that the grid provides the energy, the charging station provides the tools, and the user consumes to complete the charging process. In this process, all three parties have different demands, which promote the development of orderly charging. From the grid perspective, the purpose of orderly charging is to improve the operation of the grid, improve power

quality, and consume more new energy [30]. From the charging station's perspective, the purpose of orderly charging is to obtain the maximum profit with the lowest operating cost. From the user's perspective, orderly charging aims to achieve the desired charging goal with the lowest charging cost and the shortest time. The above charging objectives can be roughly divided into three categories: grid operation, economic efficiency, and environmental issues. The optimization objectives are shown in Figure 6 below.

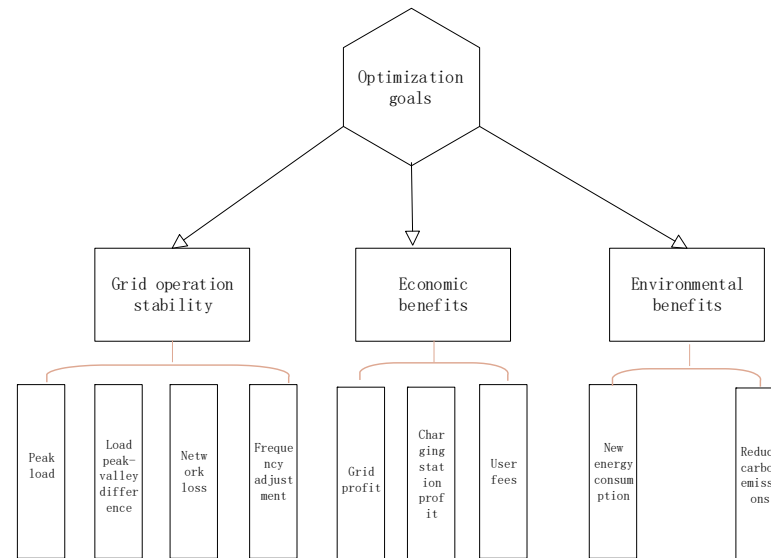


Figure 6. Hierarchical control architecture.

4.2.1. Optimization Objectives for Grid Operation

With the development of EV charging technology, the impact of EV charging load on the grid is becoming increasingly prominent, especially with the gradual maturity of V2G technology. An increasing number of EV loads are involved in the regulation process of the grid. Guiding the charging load to play a positive role in the operation of the grid is the optimization goal of orderly charging in the direction of grid operation [31]. Currently, the following optimization objectives are mainly used in optimizing grid operation: prevention of overload, reduction in load peak–valley difference, reduction in network losses, and frequency adjustment.

(1) Prevention of overload

Preventing grid overload is the initial optimization objective of orderly charging and a necessary constraint for almost all orderly charging strategies. The large number of electric vehicle load accesses during peak periods can lead to grid overload, which can cause interference and damage to the grid's electrical equipment and affect or even interrupt the normal electricity consumption of other users in the area [32]. To prevent grid overload phenomena, differently ordered charging strategies incorporate power constraints or have load peak minimization as the optimization objective.

Minimum load objective function:

$$f = \min (\max P'_L(t))$$

where $P'_L(t)$ represents the total load of the distribution network at time t after superimposing the EV charging load.

The authors in [33] performed orderly charging optimization with the goal of safe operation of the distribution network. Evaluating the impact of each indicator of electric vehicle entry on the distribution network, the distribution transformer capacity allocation model was used as the optimization target constraint to reduce the load fluctuation of the distribution network, resulting in a 3.7% reduction in the maximum load factor in

the commercial area and keeping the voltage excursion within the allowable range. The method effectively reduces unnecessary investment while maintaining the security of the distribution network. The authors in [34] constructed a multi-objective coordinated optimization control model with a minimum peak load and peak-to-valley load gap as the optimization objectives. Optimizing the orderly charging of electric vehicles with the minimum peak load is guaranteed. This reduced the charging cost for users, decreased the peak load by 6.7%, promoted the consumption of distributed energy, and ensured the safety of the power grid. The above literature indicates that orderly charging can effectively reduce the peak load of the power grid, prevent overloading, and has significant benefits for the safe operation of the power grid.

(2) Peak-to-valley load gap

To minimize the impact of EVs on the grid operation and optimize the grid operation by making full use of the charging load. Many studies on orderly charging have taken the optimization objective of minimizing the peak-to-valley load difference to reduce the charging power of EVs during peak electricity consumption periods. The charging of electric vehicles is arranged during the low period of electricity consumption to achieve the purpose of “peak shaving and valley filling” of the grid operation. Achieving “peak shaving and valley filling” of the power grid can smooth the load curve, reduce the electricity demand, reduce the cost of generating units, and stabilize the power grid operation for energy savings [35].

Minimum load peak–valley difference objective function:

$$f = \min \left(\frac{\max P'_L(t) - \min P'_L(t)}{\max P'_L(t)} \right)$$

where $P'_L(t)$ represents the total load of the distribution network at time t after superimposing the EV charging load, and $\max P'_L(t)$ and $\min P'_L(t)$ represent the maximum and minimum values of the total load of the distribution network, respectively.

The authors in [36] used a time-of-use tariff as a means to rationalize the charging load of electric vehicles by a genetic algorithm with the load peak–valley difference as the optimization objective. The load fluctuation was reduced, which decreased the peak-to-valley difference of the load by 20% and improved the stability and economic efficiency of the power grid. The authors in [37], from the perspective of the power grid, fully considered the stable operation requirements of the distribution network and carried out large-scale EV centralized charging optimization with the objectives of “peak shaving and valley filling” and charging economy. This realizes the stable operation of the distribution network, reduces the peak-to-valley difference of the regional distribution network by 5%, avoids the risk of supply–demand imbalance caused by electric vehicle charging load, reduces the risk of line congestion, and lowers the charging cost. The regulation effect of the load peak–valley difference by ordered charging depends on the time-of-use electricity price strategy and user behavior characteristics. If the electricity price strategy is not specifically tailored to the local user behavior characteristics, the optimization effect of ordered charging will be poor or even counterproductive.

(3) Grid loss

As the load of electric vehicles connected to the grid increases, the current in the grid changes; if left uncontrolled, the losses in the transmission lines, transformers, and other grid components will increase to the point of affecting the normal operation of the grid [38]. To reduce grid losses, some studies [39] proposed using electric vehicles to compensate for reactive power to reduce network losses. However, the method has difficulty considering the complex grid topology when large-scale electric vehicles are on the network. It has also been shown [40] that the flatter the load curve is, the smaller the network losses. The optimization of orderly charging takes the regulation of the load curve or nodal reactive

power compensation as the optimization goal to reduce the network losses and ensure the stable operation of the grid.

Grid loss minimum objective function:

$$f = \min \sum_{t=1}^T \sum_{s=1}^{s_{max}} R_s I_{t,s}^2 t$$

where R_s represents the resistance of line s , $I_{t,s}^2$ represents the current phase of line s for time period t , and s_{max} represents the number of lines.

The authors in [41] established a real-time tariff model for guiding users' decisions with the objectives of network losses, load peak–valley differences, and new energy consumption. Additionally, as the number of electric vehicles participating in orderly charging increases, the network losses of the system decrease significantly, and in simulation experiments, the network losses can be reduced by up to 14%. The authors in [42] established an orderly charging strategy based on V2G technology to realize bidirectional active and reactive power flow between EVs and the grid, analyzed the interests of users and the grid, and controlled the charger for reactive power compensation as a means. This benefits both users, and the grid reduces the cost of charging for users, and significantly reduces the network loss rate. The authors in [43] defined the ordered charging problem as minimizing the charging price and the load peak-to-valley difference. Additionally, to reduce the impact of the EV charging load on the distribution network, EVs were modeled as reactive power compensation devices. The purpose of controlling the node voltage within the allowed range and reducing the charging cost for users is achieved. With the maturity of V2G technology, the efficiency of reducing network losses through electric vehicles as reactive power compensation devices is constantly improving. Electric vehicles, as flexible load devices, will have an increasingly expanding impact on the power grid under the optimization of the orderly charging strategy.

(4) Frequency adjustment

In the process of grid operation, the frequency of the AC grid is one of the important signs of power quality. It is also the core parameter used to control the operation of the power system in grid dispatch [44]. The grid's frequency can maintain the rated frequency only when the power generation of the power plant and the power consumption of the user side are kept in real-time balance. When the amount of either side is too large, resulting in the balance being broken, the grid frequency will shift the rated power. Not being adjusted in time will damage the equipment on the grid, causing normal operation of the power generation equipment off the grid or even leading to serious consequences such as grid unlisting. To prevent the occurrence of frequency shift conditions, the orderly charging strategy combined with the participation of V2G technology in frequency regulation can play a significant role in grid regulation.

The objective function of frequency adjustment:

$$P_t^{AG} = K \times \begin{cases} \max \left(S_t, -C_t^{up}, \Delta f \leq 0 \right) \\ \min \left(S_t, C_t^{down}, \Delta f > 0 \right) \end{cases}$$

where S_t represents the area control error or area regulation requirement signal for time t , P_t^{AG} represents the dispatch regulation task undertaken through a single EV aggregator, K is a ratio that determines the dispatch proportion based on which the EV aggregator undertakes frequency regulation, taking values between 0 and 1, and C_t^{up} and C_t^{down} represent the total capacity of the regulation rise and fall, respectively, uploaded by the EV aggregator to the control center.

The authors in [45], starting from the grid side, fully considered the grid frequency deviation and EV charging power deviation, and used a self-learning particle swarm algorithm with the minimum frequency deviation and charging power deviation as the

optimization objectives. The minimized frequency shift was achieved by allowing charging to be suspended or reduced during charging. It provides the optimal charging solution for electric vehicle users while meeting the grid operation requirements. The authors in [46] proposed a V2G control strategy based on reinforcement learning. Based on user requirements and the benefits of charging stations, deep learning was used to dynamically adjust V2G power scheduling to meet the needs of charging users and perform frequency adjustment tasks simultaneously. The power grid reduced the frequency deviation by 22.07% and improved the operational environment. The above literature shows that electric vehicles still have great potential in regulating the frequency of the power grid. V2G technology can allow electric vehicles to participate in frequency regulation while meeting the driving needs of users. Moreover, as more electric vehicles participate in the regulation, the frequency of the power grid becomes more stable.

4.2.2. Economic Benefits

In the charging process of electric vehicles, the grid, charging stations, and users all have their economic benefits to consider. In the case of disorderly charging, not only is it difficult to control the charging cost of users, but charging stations are also unable to gain maximum profit by adjusting the charging time. The grid side also faces the problem of the safe operation of the grid. Therefore, coordinating the economic benefits of all parties through an orderly charging strategy and V2G technology is one of the vital optimization goals. The grid side can reduce the operating cost of the grid by time-sharing tariffs, reducing the number of engine starts and stops, and introducing new energy generation. The authors in [47] solved the time-sharing tariff model by a nondominated ranking genetic algorithm. The subregional and time-of-day pricing strategy enables the grid side to obtain the maximum charging profit. However, the grid is more concerned with using load regulation of electric vehicles in orderly charging to make the grid operate stably. The economics of orderly charging research focuses on reducing charging costs for users and maximizing profits for charging stations.

(1) Economic benefits of charging stations

The charging station needs to consider the time-of-day tariff given by the grid side, the operating cost of the charging station, and the revenue obtained from the order of user charging. The charging station sets the time-of-day tariff for the charging station based on the grid's time-of-day tariff and the customer charging load forecast. It is used for day-ahead scheduling or real-time time-of-use tariff scheduling. The operating cost will be reduced while the charging profit of the charging station will be increased.

Charging station operating cost minimum objective function:

$$f = \min(C_{pur} + C_{ope} + C_{pun})$$

where C_{pur} represents the total cost of electricity purchased by the charging station unit, C_{ope} represents the total unit operation and maintenance cost, and C_{pun} represents the cost of PV and wind turbine abandonment and abandonment penalties.

The authors in [48] proposed an interaction strategy based on time-of-use tariffs to guide charging stations and electric vehicle users. Taking into account the operating costs of charging stations and users' willingness to charge at different electricity prices, the orderly charging strategy reduced the peak-to-valley load difference by 32.52%, decreased the operating cost of charging stations by 9.93%, significantly lowered the charging cost for users, and helped charging stations maximize their profits. The authors in [49] established an optimal power regulation calculation model and designed the driving demand judgment module to ensure users' travel demand. The method seeks the maximum profit of the aggregator as the goal in the aggregator's participation in grid frequency regulation. Charging station profit is an important factor that drives charging station operators to participate in orderly charging. In the optimization of orderly charging, the response rate of users, the time-of-use electricity price strategy of the grid, and the orderly charging

scheduling strategy of the charging station are the key links for optimization and scheduling. The scheduling strategy of the charging station has the greatest impact. Therefore, in the optimization of orderly charging, whether to reduce the operating costs of the charging station or to increase the service fee income of the charging station, ensuring the interests of the charging station is a prerequisite for the smooth implementation of orderly charging.

(2) User economic benefits

The economic benefit to the user is one of the most intuitive indicators of a user's willingness to participate in an orderly charging strategy. Usually, users have two indicators when seeking EV charging: satisfying driving demand and minimum charging cost. The lower the charging cost, the higher the user's willingness to participate in an orderly charging strategy, and the more beneficial to the grid's scheduling operation.

User charging cost minimization objective function:

$$f = \min \sum_{k=1}^{N_{ev}} \sum_{t=1}^T X_{t,k}$$

where N_{ev} represents the total number of EVs to be charged and $X_{t,k}$ represents the electricity bill to be paid by the k th EV in time period t .

After charging model prediction with Monte Carlo, sampling fuzzy cluster analysis is used to classify the load. An adaptive genetic algorithm is used to optimize the charging scheme to obtain an ordered charging method with optimal time-sharing pricing demand response in [50]. Reduced customer charging costs by 11% and reduced grid operational risk. The authors in [51] proposed the willingness index to quantify users' willingness to participate in orderly charging. A genetic algorithm was used to minimize charging costs, and the real-time dynamic electricity price guided users to participate in orderly charging. We analyzed the relationship between the different charging intentions of users and the fees for orderly charging, resulting in a 12% reduction in users' charging costs. The results show that both charging and grid purchasing costs influence users' willingness index. In addition to the power target, the charging cost is the most concerning issue for users, and the reduction in charging cost is an important advantage of electric vehicles over fuel vehicles. The above-literature shows that as long as there is a suitable pricing strategy for ordered charging, the more users participate in ordered charging, the lower their charging costs will be. As the charging cost for users decreases, more users will participate in ordered charging until the maximum value of the full user response is reached.

4.2.3. Environmental Objectives

The key for electric vehicles to replace traditional fuel vehicles is that they can reduce the emission of air pollution gases. To solve the problem of carbon emissions, various countries have introduced policies to support the development of electric vehicles. However, the use of electric vehicles does not mean that there is no pollution. Research [52] shows that if all the electricity of electric vehicles is derived from coal-fired power plants, then the emission of polluting gases by coal-fired power plants would not be much less than the exhaust emissions of fuel cars. Therefore, future electric vehicle power sources will join wind, light, nuclear energy, and other new energy generation sources. However, wind power and photovoltaic power generation are not stable, so how a load of electric vehicles is regulated so that the charging strategy can maximize the consumption of new energy is the environmental goal of orderly charging.

New energy consumption objective function:

$$f_1 = \min \sum_{d=1}^{N_{DG}} \left(P_{DG_d}^{max} - P_{DG_d} \right) \quad (d \in N)$$

where N_{DG} represents the number of DG, d represents the serial number of DG, $P_{DG_d}^{max}$ represents the maximum output of the d th DG run, and P_{DG_d} represents the actual grid-connected active power of the d th DG.

The authors in [53] proposed a centralized management strategy to orderly dispatch electric vehicles at charging stations. To promote the grid-connected consumption of wind power and photovoltaic power, a multi-objective optimization model with minimum grid load variance, minimum abandoned scenery solar power, and maximum benefit of charging stations is established. The orderly charging strategy is obtained by solving with the genetic algorithm. It achieves “peak shaving and valley filling” of the grid, promotes new energy consumption, and reduces the cost of power stations and customers. The authors in [54] proposed an extended coordinated scheduling algorithm that resides in power prediction. The learning and generalization ability of the generalized regression neural network is used to learn uncertainty information from historical data by fully considering the consumption and uncertainty of renewable energy. A combination of the genetic algorithm and the Stackelberg game algorithm is used to develop an orderly charging strategy for electric vehicles. It promotes the local consumption of renewable energy in the microgrid and accurate new energy generation and load forecasting of the grid. Compared to traditional power plants, the advantages of distributed new energy generation lie in lower generation costs and significant environmental benefits. However, due to the fluctuation of new energy generation and issues with electrical energy quality, if not properly planned, a large amount of wasted resources, such as unused solar and wind energy, can occur. The above literature shows that orderly charging planning can solve the problem of new energy consumption to the greatest extent possible, allowing investors to obtain sufficient returns, reducing the pressure on the power grid, and making new energy charging stations an important driver of national energy transformation.

4.2.4. Multi-Objective Optimization

Some of the above optimization goals are contradictory, but more can be complementary. Coordinating the demands of different parties and developing a charging strategy that satisfies all parties is the ultimate goal of orderly charging optimization. The future orderly charging strategy will develop toward multi-objective optimization. The weights of critical parameters with complementary optimization objectives are enlarged, and the parameters with conflicting optimization objectives are analyzed according to the actual situation to obtain optimal strategies acceptable to multiple parties. For example, the two objectives of minimizing the peak-to-valley load difference and saving user charging costs are separate. The user charging cost can be reduced while pursuing the minimum peak-to-valley load difference. The weights of critical parameters with complementary optimization objectives are enlarged, and the parameters with conflicting optimization objectives are analyzed according to the actual situation to obtain optimal strategies acceptable to multiple parties. For example, the two objectives of minimizing the peak-to-valley load difference and saving user charging costs do not conflict. The user charging cost can be reduced while pursuing the minimum peak-to-valley load difference. The authors in [55] constructed a computational model for orderly charging optimization with economic incentives and technical control to measure the coordinated effect of orderly charging and discharging of electric vehicles on carbon emissions and grid security economics. The results show that this optimization method can significantly reduce carbon emissions, save project investment costs, and reduce coal material consumption. The authors in [56] fully considered the maximization of the interests of the grid, charging stations, and users and carried out multi-objective optimization from the perspective of a win-win situation for both supply and demand, resulting in a time-sharing tariff scheme for orderly charging optimization. The results show that the reasonableness of the tariff directly affects the comprehensive satisfaction of users, which determines the charging behavior of users and affects the interests of all parties. The reference shows that a win-win situation can be achieved for all three parties involved, but it requires a multifaceted consideration of the charging strategy.

Furthermore, in the context of the article, using dynamic time-of-use electricity prices can lead to better optimization results. The authors in [57] established an orderly charging model with the participation of grid companies, charging station operators, and electric vehicle users. The method analyzes the demand and decision-making behavior characteristics of each party, considers the different objective functions of each party, proposes the concept of tariff regulation cost, and establishes a tariff subsidy mechanism. It effectively avoids the problem that the profit demand of charging station operators contradicts the demand for grid security and satisfies the demand of all parties to participate in orderly charging. The authors showed that with the appropriate scheduling strategy, the demands of grid stability, user charging cost, and charging station operating profit can all be met. However, the drawback of the strategy is that it requires the grid to provide additional risk improvement subsidies to charging stations beyond the time-of-use pricing strategy to ensure the profit of the charging station in the optimization process. This is equivalent to using the economic benefits of the grid to reduce the operational risk of the grid.

4.3. Optimization Algorithm for Orderly Charging

The optimization process of orderly charging has a large scale of computational data and many decision variables. If V2G technology is used, the impact of charging and discharging on the grid must also be considered. With such computational difficulties, it is challenging to come up with an optimal solution within a specified time. Among the existing studies, the algorithms used for ordered charging are the exact algorithm, convex optimization algorithm, metaheuristic algorithm, hybrid algorithm, and deep learning algorithm. The overall algorithm comparison is shown in Table 1.

4.3.1. Precise Algorithm

Precise algorithms, including dynamic and linear programming, are often used in combinatorial optimization to find optimal solutions. However, when facing the optimization problem of sequential charging of electric vehicles with large data sizes, the “combinatorial explosion phenomenon” occurs. The optimization process consumes too many cases and storage space, is computationally inefficient, and cannot be solved in the specified time. Therefore, few studies use the exact algorithm alone to optimize the ordered charging. The authors in [58] used the mixed integer linear programming algorithm in the exact optimization algorithm to combine PV power generation and electric vehicle exchange power stations and modeled the maximum net profit of the power station as the goal. The optimization efficiency and stability are ensured, and the consumption of new energy power is also increased. However, the optimization object in the literature is the operation of battery-swapping charging stations. This algorithm is not applicable in many scenarios for the more common plug-in charging stations.

4.3.2. Convex Optimization Algorithm

The convex optimization algorithm is a continuous optimization algorithm. It solves some practical problems by converting them into convex optimization problems and can find the solution to the problem with high efficiency for problems that can be optimized convexly. However, this approach has two limitations. First, it is challenging to transform the problem into a convex optimization problem. In addition, the traditional convex optimization algorithm is a single-objective optimization, which requires additional improvements to be applied to the ordered charging of electric vehicles. The authors in [59] transformed the ordered charging problem by convex optimization and solved the objective function using the Lagrangian relaxation method. The user charging cost is reduced, and the convergence speed of the algorithm is significantly improved. However, during the optimization process, since convex optimization algorithms can only find the global optimum or prove that the problem has no solution, it is difficult for convex optimization algorithms to handle cases with multiple local optima. Therefore, in the process of solving ordered charging, other algorithms need to be used in conjunction.

4.3.3. Metaheuristic and Hybrid Algorithms

The most commonly used optimization algorithm for ordered charging is the metaheuristic algorithm. Compared with the many limitations of exact and convex optimization algorithms, metaheuristic algorithms can handle the problems of many parameter variables and large data sizes in the optimization process of ordered charging. Genetic and particle swarm algorithms are the most commonly used metaheuristic algorithms in ordered charging research.

Genetic algorithms obtain the optimal global solution by crossover, mutation, and interindividual merit. The genetic algorithm is also the most applicable of all search algorithms. In optimizing ordered charging, the optimal charging scheme is obtained by the genetic algorithm through the superiority of different charging plans according to the optimization objective. The authors in [60] proposed a dynamic probabilistic genetic algorithm that changes the probability of change as the number of iterations increases. A combined model of charging station selection and EV charging optimization is established and solved by an improved genetic algorithm. An improved genetic algorithm solves the model to minimize users' charging time and the grid's peak-to-valley load difference. The authors in [61] used the genetic algorithm as an optimization method to perform multi-objective optimization and guide owners to regulate and orderly charging. The objectives of reducing charging time, reducing cost, and reducing load peak-to-valley differences are achieved. The genetic algorithm can achieve good optimization results, but it has a high computational complexity and slow convergence speed, and it is easy to become trapped in local optima when facing large-scale ordered charging optimization. Therefore, genetic algorithms still need to be improved in terms of optimization efficiency to avoid becoming trapped in local optima in practical applications.

The particle swarm algorithm simulates the foraging behavior of birds to find better solutions around the current optimal individual and iterate continuously to finally obtain the optimal global solution. The particle swarm algorithm is simpler in principle and faster in convergence than the genetic algorithm. The authors in [62] constructed a multi-energy dispatching strategy including electric vehicles, distributed energy sources, and grid loads, using a typical urban residential low-voltage substation area as the application scenario. It solved the optimization scheme with a multi-objective particle swarm algorithm using the optimization objectives of total load variance and minimum charging cost. The goal of regulating the grid's peak load, reducing the charging cost of users, and improving the profit of charging station operation is achieved. The authors in [26] proposed an optimization strategy for the orderly charging of electric vehicles based on an individual differential evolutionary particle swarm optimization algorithm. The objective is to reduce the wind abandonment rate of the grid system and further improve the degree of wind power consumption while effectively reducing the fluctuation and amplitude of wind power output. A dynamic time-sharing tariff is derived according to the optimization strategy to guide users to orderly charging. The purpose of smoothing the fluctuation of wind power output and improving the wind power consumption rate is achieved. Particle swarm optimization (PSO) has strong global search capabilities with relatively less complexity, and it is faster than genetic algorithms in terms of searching for solutions. However, in regard to multi-objective optimization in ordered charging, it is prone to becoming trapped in local optimal solutions, and its local search ability is weak. Therefore, PSO is more suitable for single-objective optimization in ordered charging. When dealing with multi-objective optimization problems, multi-objective particle swarm optimization (MOPSO) or the nondominated sorting genetic algorithm (NSGA) are better choices.

Since the performance of the metaheuristic algorithm depends mainly on the quality of the initial solution, a good initial solution can save much time and many computational steps for the algorithm to find the optimal solution. To improve the operational efficiency of the algorithm, some studies combine the metaheuristic algorithm and the heuristic algorithm to obtain a hybrid algorithm. The heuristic algorithm seeks a high-quality initial solution, and then the optimal solution is sought by the metaheuristic algorithm. There

are also studies combining metaheuristic algorithms and metaheuristics. The advantages of different algorithms are exploited to offset the disadvantages of each to achieve better optimization. The authors in [63] combined the gravitational search and particle swarm algorithms to propose a hybrid improved GSA-PSO method, which optimizes the load scheduling of microgrids containing electric vehicles. PSO is characterized by global search and fast convergence, but searches in a small range are not effective, whereas the GSA algorithm has a strong search capability in a small range but no global search capability. The MGSA-PSO algorithm can avoid these defects and implement optimal global scheduling of electric vehicle loads to improve grid security and economy.

4.3.4. Deep Learning Algorithms

In recent years, with the development of algorithmic techniques, increasing research has been conducted to apply deep learning algorithms to optimize ordered charging. Deep learning is developed based on machine learning, essentially solving an unconstrained nonconvex optimization problem. Deep learning is used in the application of orderly charging to obtain an optimized charging strategy or a pricing scheme for time-of-use tariffs by analyzing and computing the characteristic model of electric vehicles. The authors in [64] proposed deep reinforcement learning based on dual-depth Q-networks for an electric vehicle charging arrangement strategy. It can fully consider the uncertainty of the travel pattern and charging demand of EVs and achieve the minimum charging cost of charging stations. Furthermore, the difficulty of model training does not increase with increasing electric vehicle scale. The authors in [65] proposed a virtual power plant considering flexible resources such as charging stations, distributed units, energy storage, and renewable energy. A reasonable power sales strategy is developed based on deep reinforcement learning to guide the orderly grid integration of electric vehicles and achieve coordinated complementarity and overall optimization among new energy sources. Deep learning algorithms can adaptively adjust charging strategies based on real-time data from charging stations and electric vehicles to meet different charging needs. Compared to other algorithms, deep learning algorithms have good performance in optimization efficiency and optimization results. However, training deep learning algorithms requires a large amount of data and higher hardware requirements. The application of deep learning algorithms needs to be trained with local user data in different regions, making it difficult to be widely promoted. The algorithm comparison is shown in Table 2.

Table 2. Comparison of algorithms used in sequential charging optimization.

Algorithm Category	Advantages	Disadvantages	Applicable Optimization Objectives
Precise Algorithm [58]	Capable of finding the optimal global solution and accurate calculation results when dealing with small-scale data	Difficult to handle for large-scale data, needs to be used with other algorithms	Reduced power loss, minimized user cost, voltage regulation
Convex optimization algorithm [59]	High efficiency for suitable model solving and mature algorithm development	It is only applicable to the solution of some problems, and it is not simple to transform the problem into a convex optimization problem	Minimize user cost, maximize charging station profit, reduce power loss, frequency adjustment
Meta-heuristic algorithms [60–62]	Capable of solving global optimal solutions, with excellent performance when facing large-scale data	More dependent on the quality of the initial solution, the algorithm does not run efficiently	Applicable to most targets

Table 2. Cont.

Algorithm Category	Advantages	Disadvantages	Applicable Optimization Objectives
Hybrid Algorithm [63]	Excellent calculation efficiency, accurate calculation results	Need the right combination of algorithms	Applicable to all targets
Deep learning algorithms [64,65]	Adaptable and can be applied to most problems. Data-driven, with high computational upper limits	High hardware requirements, difficult model training, and complex model design	Ability to handle uncertainty in EV travel and charging demand, minimizing user costs

5. Practice of Orderly Charging

Ordered charging technology has been researched and developed over the years and has gradually been applied to charging practices to find problems and solutions. As early as 2011, Nissan and Hawaii collaborated on JumpSmartMaui (JSM), an orderly charging pilot project in Maui. Shifting charging loads that would otherwise be at peak off-hours to early morning hours reduces grid load, prevents peak coincidence, and consumes excess wind power [66]. The authors in [67] analyzed the transformation and optimization of the island energy system with the addition of an orderly charging strategy with V2G technology. BMW partnered with California to launch the forward charge program in 2015. The project uses V2G technology for charging management and renewable energy integration to optimize charging strategies to minimize charging costs, “peak shaving and valley filling”, and new energy consumption. V2G technology and orderly charging optimization have proven to greatly impact grid regulation and increase user satisfaction [68]. China also carried out the practice of orderly charging in 2019, based on IoT and V2G technologies, in the North China Power Grid by deploying a load regulation platform to enable the interconnection and sensing of resources such as electric vehicles, distributed energy storage, virtual power plants, and power grids for integrated and coordinated optimal operation [69]. The goals of grid operation regulation, coordinated distributed energy operation, and improved customer experience are achieved. Currently, the practice of ordered charging has been carried out all over the world, such as the Smart Charging and Discharging Demonstration Project of the Ubiquitous Electric Power Internet of Things in Jiading District, Shanghai, which has already brought real economic benefits to electric vehicle users. Even in regions with relatively developed new energy, such as the Netherlands and California, ordered charging participating in power regulation has formed a preliminary commercial model. As shown in Table 3, the above practical projects show the great potential of orderly charging technology in grid regulation. By improving and optimizing the technology, satisfying the interests of all parties, and allowing more people to participate in orderly charging, a win-win situation can eventually be formed for all parties.

Table 3. Orderly charging practice.

Project	Start Time	Characteristic	Meaning
JumpSmartMaui (JSM)	2011	To combine the scheduling of electric vehicle charging load and the consumption of new energy sources, and to explore the promotion effect of electric vehicles on clean energy and the regulation effect on power grids	The first large-scale orderly charging time, the experimental method and the experimental results provided valuable reference value for later research.

Table 3. Cont.

Project	Start Time	Characteristic	Meaning
iChargeForward	2015	The further combination of charging load scheduling and new energy consumption, using intelligent orderly charging optimization scheduling, and adding the application of retired battery energy storage.	Different orderly charging optimizations were practiced in various environments, and the results showed that different orderly charging strategies were needed in different environments. The various incentive methods used also proved that economic benefits were the most effective in stimulating users to participate in orderly charging.
Load control platform of North China Power grid	2019	Combining technologies such as V2G, virtual power plant, distributed energy storage, etc., to optimize and schedule the electric vehicle charging load of different operators in a unified way.	This practice realized for the first time in China the real-time connection and data sharing between the scheduling automation system and the load aggregator operation system, breaking through the multi-level barriers, and achieving the power aggregation perception monitoring of electric vehicles and distributed energy storage.
Smart charging and discharging demonstration project of Ubiquitous Power Internet of Things	2020	To explore in depth the connection between virtual power plants and electric vehicles, to achieve more efficient peak shaving and valley filling through V2G and other technologies, and to promote the consumption of more distributed new energy sources.	The wide application of orderly charging technology and virtual power plant technology, affecting the intelligent power dispatching of thousands of users.

6. Challenges to Orderly Charging

With the influence of people's concept of environmental protection and policy support, electric vehicles will gradually become popular in people's daily lives and replace fuel cars. How to solve the charging problem of electric vehicles, make the electric vehicle load have a positive impact on the grid, make the charging pile profit from the charging process, and reduce the user's charging expenses are the research goals of orderly charging. After years of research and development, orderly charging technology has been gradually applied in practice in different regions. For example, the "special charging" project of China's "TELD" company and the pilot project of orderly charging in Zhengzhou, a residential district in China, have shown the advantages of regulating the power grid and reducing costs, but they have also revealed some problems and challenges. In these practices, the orderly charging strategy has demonstrated the advantages of regulating the grid and reducing costs but also revealed some problems and challenges.

6.1. Communication Problems of Orderly Charging

Information exchange between electric vehicles, power grids, and charging stations is the basis for orderly charging. Whether the control structure of orderly charging is centralized, distributed, or hybrid, a stable communication structure is needed. However, the current level of communication in many areas does not meet the communication requirements of orderly charging. One reason is that there is no uniform communication method for charging piles. Different companies produce charging piles with different communication methods: some charging piles use Ethernet communication [70], some use wireless network communication for convenience [71], and others use carrier wave communication for communication stability [72]. To achieve the communication requirements of orderly charging, the distribution network needs to be equipped with communication methods compatible with the charging piles. Different communication methods not only add to the construction cost of the distribution network but also add to the construction

difficulty. The other reason is that the information level of the regional distribution network itself is insufficient. Regardless of whether the charging piles are built in the parking lot of the residential area or the charging stations in the commercial area, the information level of many regional distribution grids needs to meet the requirement of real-time information. It is challenging to ensure stable transmission of information in the face of large-scale EV charging and discharging control. In the future, if we want to realize orderly charging optimization, we should first improve the information level of the distribution network and establish a smart grid. In addition, to solve the communication problem, the construction of a ubiquitous power IOT can provide some reference. 5G technology's ultra-high-speed transmission, high reliability, low power consumption, low latency, and other characteristics are all needed to communicate orderly charging. The application of 5G technology is an excellent solution to the charging communication problem in the future.

6.2. Data Security Privacy Issues

Protecting user information security is the premise of orderly charging optimization. In most of the orderly charging optimization solutions, the user's vehicle usage information and trip information need to be collected, and some optimization solutions even need to collect the user's driving habits and routes for analysis. To a certain extent, this increases the danger caused by user data leakage. User data leakage can lead to unnecessary losses for users on the one hand and discourage them from participating in orderly charging on the other hand. The authors in [73] introduced possible network security issues such as payment security, electricity metering, and camping data in the charging process, summarized the possible attack patterns, and proposed two intrusion detection methods based on the model and data. Therefore, developing orderly charging technology, protecting the security of user data, and establishing a cyber-attack defense mechanism for the charging system is the future development direction of the charging system.

6.3. Reasonable Market Mechanism

A rational market mechanism is the best motivation to promote the participation of all parties in orderly charging. The pricing issue for orderly charging optimization becomes particularly salient after electric vehicles regulate the grid through V2G technology. Some studies have argued that the grid should give up some of its profits to supplement customers and charging stations. The grid is the most profitable party because it improves operational stability through EV load regulation, increases new energy consumption, and sells surplus power. Some studies argue that charging stations should reduce charging tariffs because they reduce equipment losses through orderly charging and gain additional profits. There are also studies that the government should give more subsidies because the social benefits of orderly charging electric vehicles are significant, promoting new energy consumption and reducing carbon emissions. Developing a market mechanism that satisfies all parties is an issue the government needs to improve. Blockchain technology can solve the market mechanism problem due to its security, transparency, traceability, and bidding method. One study applied blockchain technology to the orderly charging of electric vehicles and participated in the smart contract and tariff transaction of V2G regulation to achieve a reasonable benefit distribution among all parties [74].

6.4. Number of Charging Piles

The number of charging piles is a constraint for orderly charging optimization scheduling. Most orderly charging optimization methods are based on the ideal condition that the number of charging piles is sufficient and the user's electric vehicle can be connected to the charging piles and wait for the charging order from the control center. However, in the reality of charging station usage, many EVs are often connected to charging piles during peak power consumption periods, while some are still waiting for charging positions. Therefore, coordinating the optimal scheduling of orderly charging and user charging demand is a problem that must be solved. The authors in [75] proposed a charging station

capacity and pricing scheme that considers user behavior uncertainty. Charging station operation is optimized by changing the tariff to guide uncertain user charging behavior. Is it by physically increasing the construction of charging posts? Or is it through charging optimization, which expands the capacity of charging stations by scheduling appropriate EVs for early charging when charging demand is excessive? Is there a need to compensate for vehicles scheduled to charge in advance? These questions need to be considered for future research on orderly charging. Combining virtual power plant technology with charging stations, the charging stations within a region can be centrally coordinated, making full use of idle charging piles within the region and effectively solving the problem of insufficient charging piles in individual charging stations.

6.5. Problems with V2G Technology

There is no doubt that the emergence of V2G technology will take the optimization and scheduling of orderly charging to a higher level. With the support of V2G technology, electric vehicles are no longer just consumers of electricity but become flexible energy storage devices, as shown in Figure 7. On the premise of ensuring users' charging needs, idle energy can be used to provide energy to the grid, achieving bidirectional transmission of energy between the grid and electric vehicles [76]. The application of V2G technology expands the impact of electric vehicles on the grid, providing greater scheduling space for orderly charging in terms of grid frequency, new energy consumption, and user charging costs [77]. In the aforementioned Shanghai Jiading District's ubiquitous electric power Internet of Things smart charging and discharging demonstration project, electric vehicle users have already gained profits through V2G technology. They charge their cars when the electricity price is low at night and discharge to the grid when the power is in short supply during the day, solving the problem of power supply shortage while providing economic benefits to users.

However, there are still some problems in the practical application and research of V2G technology. First, there are technical problems. To apply V2G, it is necessary to equip bidirectional charging and discharging interfaces, which involves updating the hardware equipment of charging stations, protocol formulation of software, data security, and other issues [78]. In addition, the introduction of V2G technology means that the optimization scenarios faced by orderly charging are more complex, and the requirements for optimization programs are higher. Therefore, upgrades in hardware and software are necessary, which bring investment costs. Second, there is the issue of battery wear [79]. Adopting V2G technology for bidirectional charging and discharging will accelerate the aging of the battery. The aging of the battery will lead to a decrease in battery capacity, which is most intuitively reflected by the reduction in driving range for car owners. Most electric vehicle users have range anxiety, and new energy vehicle companies have invested a lot of money in battery research to increase driving range. However, due to the use of V2G technology, the performance of the battery is decreasing. Is it worth it? Finally, there is the market problem [80]. Knowing that V2G technology will cause battery degradation, additional economic compensation may not necessarily increase user response. In such a market environment, charging stations and car companies also find it difficult to invest in V2G technology. Therefore, suitable V2G service strategies and government policy support are needed to promote V2G technology. For example, the "Regulatory Sandbox" policy in the UK is worth learning from. At the same time, it is also necessary to improve the optimization problem of V2G technology and solve the problem of battery aging caused by V2G technology. Aging retired batteries can be recycled to reduce losses caused by V2G technology.

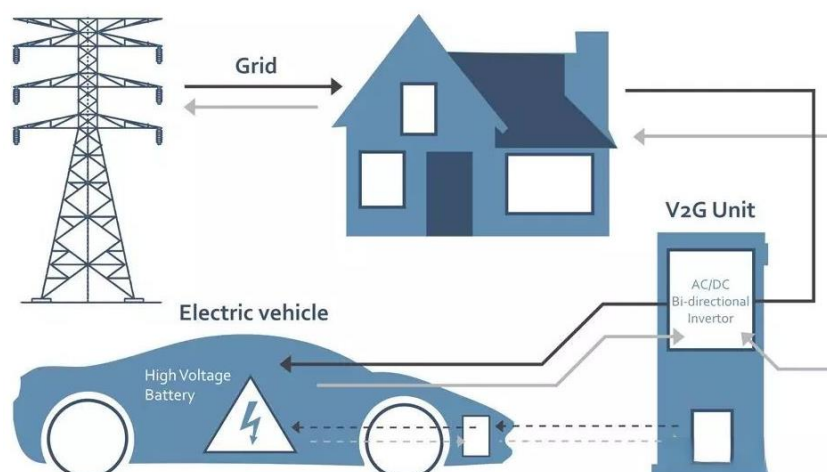


Figure 7. V2G technology application [81].

7. The Future of Orderly Charging

Research on orderly charging technology has become hotter with the popularity of electric vehicles in recent years, and scholars' continuous innovation and improvement in modeling, algorithms, and optimization objectives have gradually improved and matured orderly charging technology. Many research results have been obtained in distributed charging and V2G bidirectional charging, as foreseen in [82]. However, research on orderly charging still has great development prospects. With the innovation of algorithms, the improvement in people's environmental awareness, the enhancement of processor computing power, and the mature application of IoT technology, future orderly charging technology will develop in the direction of environmental protection, more energy savings, more intelligence, and more safety.

- (1) More environmentally friendly orderly charging optimization: Fully stimulating the user's environmental awareness and the corresponding government policies will become the new direction of orderly charging development. The significance of promoting electric vehicle popularity is replacing traditional fuel vehicles with electric ones. Reduce the dependence on fossil energy and reduce carbon emissions to achieve the goal of carbon peaking and carbon neutrality: Because of the carbon emissions that coal-fired power plants also produce, future electric vehicle charging must necessarily be combined with distributed generation, such as wind and photovoltaics. Some current studies on orderly charging have already considered new energy sources, and controlled, orderly charging through charging stations maximizes the consumption of new energy generation [83]. However, more than just the efforts of charging stations alone are needed; they should also fully stimulate the environmental awareness of users so that people can contribute to environmental protection together. The carbon emissions generated by charging decisions will be made in future orderly charging optimization: Users will be able to see the carbon emissions reduced by that decision in the process of making charging decisions, allowing them to feel the positive feedback of the environmental benefits. The government should also introduce corresponding policies to limit carbon emissions or incentivize environmental behavior through carbon quotas. For example, Ref [84] uses carbon quota restrictions to optimize bus charging and discharging.
- (2) More energy-efficient orderly charging optimization: The participation of retired batteries in orderly charging optimization will be another development direction that benefits many parties. The disposal of retired batteries for electric vehicles is a controversial issue. Due to the long-term charging and discharging of the battery, the battery's performance in all aspects, such as storage capacity, will gradually decline. The electric vehicle battery will be retired when its performance is depleted to below

the standard value. The retired batteries are put into the optimization of orderly charging, playing the role of energy storage and regulating power distribution [85]. Users can reduce the cost of battery replacement: Charging stations can reduce the cost of building energy storage devices. The grid can be operated more stably and efficiently. Socially, pollution from waste batteries can be reduced.

- (3) A more digital and intelligent optimization of orderly charging: The participation of electric vehicles in regulating virtual power plants is a popular project for current research. Many studies have shown that electric vehicles, as mobile energy storage devices, can benefit multiple parties by participating in the regulation of virtual power plants through the optimization of ordered charging and by taking advantage of the flexible energy storage of electric vehicles [86]. Integrating regional distributed renewable energy and optimized charging into the regulation of virtual power plants: Through the resource integration of virtual power plants and the fine-tuned scheduling of electric vehicle loads, the efficiency of distributed renewable energy integration can be effectively improved. With the development of IoT technology and digital twin technology, future orderly charging optimization will utilize a more refined digital twin model and smart city technology to breakdown professional data barriers and realize collaborative management of the whole value chain combining urban transportation, distributed power generation, virtual power plant regulation, and orderly charging optimization [87]. Realizing cluster and intelligent management and decision-making, from global optimization to full control of individual charging decisions.

8. Conclusions

It is foreseeable that with the improvement in people's environmental awareness, policy guidance, and the development of digital technology, the future electric vehicle charging load will no longer be the initial obstacle to grid operation after the optimization of orderly charging. Instead, it will play an important role in regulating the grid, reducing user travel costs, and ultimately achieving the dual carbon goal. This paper summarizes the research on orderly charging technology in recent years and presents some perspectives on orderly charging technology from the following aspects.

- (1) This paper summarizes the application architecture of ordered charging from the concept of ordered charging and introduces the advantages and disadvantages of centralized, distributed, and hierarchical control architectures.
- (2) The current research status of orderly charging is analyzed from three levels: the steps and methods of load modeling, the optimization objectives of orderly charging, and the optimization methods of orderly charging. The methods of load modeling for orderly charging are summarized, and the optimization of grid operation, economic optimization, environmental optimization, and multi-objective optimization for orderly charging are introduced. The advantages and disadvantages of the exact, convex optimization, metaheuristic, hybrid, and deep learning algorithms are compared. Several practical projects of orderly charging are presented to illustrate the importance of orderly charging for the benefit of all parties.
- (3) The article points out the challenges and prospects of orderly charging technology. Feasible solutions are proposed for communication problems, data security issues, market mechanism problems, a limited number of charging piles, and the application of V2G technology. To solve the communication problem of charging piles, the automation level of regional distribution networks should be improved, and IoT technology and 5G communication should be combined to realize orderly charging scheduling of charging piles. To address the data security issue, network defense systems should be strengthened, and encryption technology and user agreements should be improved. For market mechanism issues, a blockchain transaction system led and supervised by the government should be established to leverage the government's scheduling advantages and stimulate market vitality. To address the limited number of charging piles, virtual power plant technology should be utilized to allocate charging stations

in the region uniformly and make full use of idle charging piles. To overcome the current developmental difficulties faced by V2G technology, pilot projects should be launched with the government's support to reduce the cost of battery loss caused by V2G technology using retired battery recycling methods. The potential development direction of orderly charging technology is also pointed out, and it is expected that with the development of technology and the joint efforts of all parties, orderly charging optimization will have unique advantages in environmental protection and social construction and form a more environmentally friendly, energy-saving, and intelligent orderly charging system.

Author Contributions: Formal analysis, Z.Z.; methodology, Z.Z.; writing—original draft, L.L.; writing—review and editing, Z.Z. and L.L. All authors have read and agreed to the published version of the manuscript.

Funding: The research was supported by the Department of Education of Guangdong Province (2022ZDZX1029).

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Wu, Y.; Zhang, S.; Hao, J.; Liu, H.; Wu, X.; Hu, J.; Michael, W.; Timothy, W.; Zhang, K.; Svetlana, S. On-road vehicle emissions and their control in China: A review and outlook. *Sci. Total Environ.* **2017**, *574*, 332–349. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Putrus, G.A.; Suwanapongkarl, P.; Johnston, D.; Bentley, E.; Narayana, M. Impact of electric vehicles on power distribution networks. In Proceedings of the 2009 IEEE Vehicle Power and Propulsion Conference, Dearborn, MI, USA, 7–11 September 2009; IEEE: Piscataway, NJ, USA, 2009; pp. 827–831.
3. Khalid, M.R.; Alam, M.S.A.; Jamil Asghar, M.S. A Comprehensive review on electric vehicles charging infrastructures and their impacts on power-quality of the utility grid. *eTransportation* **2019**, *1*, 100006. [\[CrossRef\]](#)
4. Hou, H.; Xu, T.; Ke, X.; Xue, M.; Li, Z.; Wang, C. Research on risks of electric vehicle charging to distribution network. *Power Syst. Prot. Control* **2019**, *47*, 87–93.
5. Liu, Z.; Wang, D.; Jia, H. Power system operation risk analysis considering charging load self-management of plug-in hybrid electric vehicles. *Appl. Energy* **2014**, *136*, 662–670. [\[CrossRef\]](#)
6. Ji, Y.; Zhang, J.; Li, S.; Deng, Y.; Mu, Y. Variable power regulation charging strategy for electric vehicles based on particle swarm algorithm. *Energy Rep.* **2022**, *8*, 824–830. [\[CrossRef\]](#)
7. Jundong, D.; Gaoshang, L.I.; Yishi, L.I.; Fu, Z.; Huang, H. Coordinated charging control for EV charging stations considering wind power accommodation. *Energy Storage Sci. Technol.* **2021**, *10*, 630.
8. Xiao, H.; Huimei, Y.; Chen, W.; Hongjun, L. A survey of influence of electric vehicle charging on power grid. In Proceedings of the 2014 9th IEEE Conference on Industrial Electronics and Applications, Hangzhou, China, 9–11 June 2014; IEEE: Piscataway, NJ, USA, 2014; pp. 121–126.
9. Han, H.; Xu, H.; Yuan, Z. Research of interactive charging strategy for electrical vehicles in smart grids. In Proceedings of the 2011 International Conference on Electrical Machines and Systems, Beijing, China, 20–23 August 2011; IEEE: Piscataway, NJ, USA, 2011; pp. 1–6.
10. Wu, C.; Mohsenian-Rad, H.; Huang, J. Vehicle-to-aggregator interaction game. *IEEE Trans. Smart Grid* **2011**, *3*, 434–442. [\[CrossRef\]](#)
11. Adhikari, S.; Halgamuge, S.K.; Watson, H.C. An online power-balancing strategy for a parallel hybrid electric vehicle assisted by an integrated starter generator. *IEEE Trans. Veh. Technol.* **2010**, *59*, 2689–2699. [\[CrossRef\]](#)
12. Xu, Z.; Hu, Z.; Song, Y.; Luo, Z.; Zhan, K.; Shi, H. Coordinated charging of plug-in electric vehicles in charging stations. *Autom. Electr. Power Syst.* **2012**, *36*, 38–43.
13. Zhang, L.; Zhang, M.; Lin, W. Design and discussion of a unified EV-grid integration structure. *Mod. Electr. Power* **2014**, *31*, 34–39.
14. Luo, Y.; Zhu, T.; Wan, S.; Zhang, S.; Li, K. Optimal charging scheduling for large-scale EV (electric vehicle) deployment based on the interaction of the smart-grid and intelligent-transport systems. *Energy* **2016**, *97*, 359–368. [\[CrossRef\]](#)
15. Yuhuan, H.E.; Xiuyuan, Y.; Qiyu, C.; Siqi, B.; Zhiqiang, X.; Tianying, X. Review of Intelligent Charging and Discharging Control and Application of Electric Vehicles. *Power Gener. Technol.* **2021**, *1*, 180–192.
16. Qiyu, C. Research on Implementation Strategy of Ubiquitous Power Internet of Things. *Power Gener. Technol.* **2019**, *40*, 99–106.
17. Geske, J.; Schumann, D. Willing to participate in vehicle-to-grid (V2G)? Why not! *Energy Policy* **2018**, *120*, 392–401. [\[CrossRef\]](#)
18. He, Y.; Chen, Y.; Yang, Z.; He, H.; Liu, L. A review on the influence of intelligent power consumption technologies on the utilization rate of distribution network equipment. *Prot. Control Mod. Power Syst.* **2018**, *3*, 18. [\[CrossRef\]](#)
19. Yin, W.J.; Ming, Z.F. Electric vehicle charging and discharging scheduling strategy based on local search and competitive learning particle swarm optimization algorithm. *J. Energy Storage* **2021**, *42*, 102966. [\[CrossRef\]](#)

20. Wu, H.; Pang GK, H.; Choy, K.L.; Lam, H.Y. Dynamic resource allocation for parking lot electric vehicle recharging using heuristic fuzzy particle swarm optimization algorithm. *Appl. Soft Comput.* **2018**, *71*, 538–552. [\[CrossRef\]](#)
21. Rui, T.; Hu, C.; Li, G.; Tao, J.; Shen, W. A distributed charging strategy based on day ahead price model for PV-powered electric vehicle charging station. *Appl. Soft Comput.* **2019**, *76*, 638–648. [\[CrossRef\]](#)
22. Wang, K.; Wang, H.; Yang, J.; Feng, J.; Li, Y.; Zhang, S.; Onyeka, O.M. Electric vehicle clusters scheduling strategy considering real-time electricity prices based on deep reinforcement learning. *Energy Rep.* **2022**, *8*, 695–703. [\[CrossRef\]](#)
23. Yang, X.; Niu, D.; Sun, L.; Ji, Z.; Zhou, J.; Wang, K.; Siqin, Z. A bi-level optimization model for electric vehicle charging strategy based on regional grid load following. *J. Clean. Prod.* **2021**, *325*, 129313. [\[CrossRef\]](#)
24. Shen, G.; Chen, G.; Zhao, Y.; Li, X.; Geng, A.; Yuan, H.; Liu, F. Orderly charging optimization strategy of an electric vehicle based on double objective hierarchical optimization and TOPSIS ranking. *Power Syst. Prot. Control* **2021**, *49*, 115–123.
25. Zhang, L.; Sun, C.; Cai, G.; Huang, N.; Lv, L. Two-stage optimization strategy for coordinated charging and discharging of EVs based on PSO algorithm. *Proc. CSEE* **2022**, *42*, 1837–1852.
26. Zhang, L.; Yin, Q.; Zhang, Z.; Zhu, Z.; Lyu, L.; Hai, K.L.; Cai, G. A wind power curtailment reduction strategy using electric vehicles based on individual differential evolution quantum particle swarm optimization algorithm. *Energy Rep.* **2022**, *8*, 14578–14594. [\[CrossRef\]](#)
27. Li, J.; Yang, D.; Lai, W.; Lin, Z.; Zhang, S.; Li, J.; Guan, W. Orderly charging method of electric vehicle in charging station of residential area. *Demand Side Manag.* **2021**, *23*, 31–35.
28. Tao, Y.; Huang, M.; Chen, Y.; Yang, L. Orderly charging strategy of battery electric vehicle driven by real-world driving data. *Energy* **2020**, *193*, 116806. [\[CrossRef\]](#)
29. Fotouhi, Z.; Hashemi, M.R.; Narimani, H.; Bayram, I.S. A general model for EV drivers' charging behavior. *IEEE Trans. Veh. Technol.* **2019**, *68*, 7368–7382. [\[CrossRef\]](#)
30. Cui, J.; Li, Y.; Zhang, W.; Chen, C. Research on impact and utilization of electric vehicle integration into power grid. In Proceedings of the 2018 Chinese Control And Decision Conference (CCDC), Shenyang, China, 9–11 June 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1594–1597.
31. Qiushuo, L.; Xiangning, X.; Jing, G.; Lin, L. Research on scheme for ordered charging of electric vehicles. *Power Syst. Technol.* **2012**, *36*, 32–38.
32. Ma, L.; Yang, J.; Fu, C.; Liu, P.; Sun, Y. Review on impact of electric car charging and discharging on power grid. *Power Syst. Prot. Control* **2013**, *41*, 140–148.
33. Zou, M.; Yang, Y.; Liu, M.; Wang, W.; Jia, H.; Peng, X.; Su, S.; Liu, D. Optimization Model of Electric Vehicles Charging and Discharging Strategy Considering the Safe Operation of Distribution Network. *World Electr. Veh. J.* **2022**, *13*, 117. [\[CrossRef\]](#)
34. Liu, Z.; Sheng, W.; Du, S.; Su, J.; Sun, R. Coordinated Optimal Control Method for Smart Distribution Network Considering Orderly Charging of Electric Vehicles. *Trans. Chin. Soc. Agric. Mach.* **2021**, *52*, 377–384.
35. Yin, W.J.; Wen, T.; Zhang, C. Cooperative optimal scheduling strategy of electric vehicles based on dynamic electricity price mechanism. *Energy* **2023**, *263*, 125627. [\[CrossRef\]](#)
36. Ou, M.; Cheng, Z.; Tan, Y.; Wen, M.; Zhou, Z. Optimization of electric vehicle charging load based on peak-to-valley time-of-use electricity price. *J. Electr. Power Sci. Technol.* **2021**, *35*, 54–59.
37. Tian, J.; Lv, Y.; Zhao, Q.; Gong, Y.; Li, C.; Ding, H.; Yu, Y. A charging plan generation method for EV clusters considering the operation of regional distribution network. *Energy Rep.* **2022**, *8*, 135–143. [\[CrossRef\]](#)
38. Bradley, W.G. Electric vehicle battery charger-power line interface. In Proceedings of the Region 3 Conference and Exhibit, SOUTHEASTCON'81, Huntsville, AL, USA, 5–8 April 1981; pp. 430–434.
39. Yong, J.Y.; Ramachandaramurthy, V.K.; Tan, K.M.; Mithulananthan, N. Bi-directional electric vehicle fast charging station with novel reactive power compensation for voltage regulation. *Int. J. Electr. Power Energy Syst.* **2015**, *64*, 300–310. [\[CrossRef\]](#)
40. Queiroz LM, O.; Roselli, M.A.; Cavellucci, C.; Lyra, C. Energy losses estimation in power distribution systems. *IEEE Trans. Power Syst.* **2012**, *27*, 1879–1887. [\[CrossRef\]](#)
41. Shi, W.; Lu, L.; Gao, H. Economic dispatch of active distribution network with participation of demand response and electric vehicle. *Autom. Electr. Power Syst.* **2020**, *44*, 41–51.
42. Yao, L.; Zhang, Y.; Yang, J. Voltage Control Considering Electric Vehicle Orderly Charging and Discharging. In Proceedings of the 2021 IEEE Sustainable Power and Energy Conference (iSPEC), Nanjing, China, 23–25 December 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 3513–3518.
43. Mazumder, M.; Debbarma, S. EV charging stations with a provision of V2G and voltage support in a distribution network. *IEEE Syst. J.* **2020**, *15*, 662–671. [\[CrossRef\]](#)
44. Luo, A.; Xu, Q.; Ma, F.; Chen, Y. Overview of power quality analysis and control technology for the smart grid. *J. Mod. Power Syst. Clean Energy* **2016**, *4*, 1–9. [\[CrossRef\]](#)
45. Dechanupaprittha, S.; Jamroen, C. Self-learning PSO based optimal EVs charging power control strategy for frequency stabilization considering frequency deviation and impact on EV owner. *Sustain. Energy Grids Netw.* **2021**, *26*, 100463. [\[CrossRef\]](#)
46. Alfaverh, F.; Denai, M.; Sun, Y. Optimal vehicle-to-grid control for supplementary frequency regulation using deep reinforcement learning. *Electr. Power Syst. Res.* **2023**, *214*, 108949. [\[CrossRef\]](#)
47. Xu, X.; Niu, D.; Li, Y.; Sun, L. Optimal pricing strategy of electric vehicle charging station for promoting green behavior based on time and space dimensions. *J. Adv. Transp.* **2020**, *2020*, 8890233. [\[CrossRef\]](#)

48. Song, X.; Lv, Q.; Sun, Y.; Liu, X. Interactive Strategy of Electric Vehicles and Integrated Energy System Based on Electricity Price Guidance. *High-Volt. Technol.* **2021**, *47*, 3744–3756.
49. Peng, C.; Zou, J.; Lian, L.; Li, L. An optimal dispatching strategy for V2G aggregator participating in supplementary frequency regulation considering EV driving demand and aggregator's benefits. *Appl. Energy* **2017**, *190*, 591–599. [\[CrossRef\]](#)
50. Goh, H.H.; Zong, L.; Zhang, D.; Dai, W.; Lim, C.S.; Kurniawan, T.A.; Goh, K.C. Orderly Charging Strategy Based on Optimal Time of Use Price Demand Response of Electric Vehicles in Distribution Network. *Energies* **2022**, *15*, 1869. [\[CrossRef\]](#)
51. Xu, X.; Peng, M.; Li, S.; Chen, J.; Zhu, Y. A Personalized Orderly Charging Strategy for Electric Vehicles Considering Users' Needs. In Proceedings of the 2018 International Conference on Power System Technology (POWERCON), Guangzhou, China, 6–8 November 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1190–1195.
52. Lindly, J.K.; Haskew, T.A. Impact of electric vehicles on electric power generation and global environmental change. *Adv. Environ. Res.* **2002**, *6*, 291–302. [\[CrossRef\]](#)
53. Wang, H.; Ma, H.; Liu, C.; Wang, W. Optimal scheduling of electric vehicles charging in battery swapping station considering wind-photovoltaic accommodation. *Electr. Power Syst. Res.* **2021**, *199*, 107451. [\[CrossRef\]](#)
54. Hao, Y.; Dong, L.; Liang, J.; Liao, X.; Wang, L.; Shi, L. Power forecasting-based coordination dispatch of PV power generation and electric vehicles charging in microgrid. *Renew. Energy* **2020**, *155*, 1191–1210. [\[CrossRef\]](#)
55. Zhou, C.-B.; Qi, S.-Z.; Zhang, J.-H.; Tang, S.-Y. Potential co-benefit effect analysis of orderly charging and discharging of electric vehicles in China. *Energy* **2021**, *226*, 120352. [\[CrossRef\]](#)
56. Cui, J.; Luo, W.; Zhou, N. Research on Pricing Model and Strategy of Electric Vehicle Charging and Discharging Based on Multi View. *Proc. CSEE* **2018**, *38*, 4438–4450.
57. Lin, X.; Qian, B.; Xiao, Y.; Luo, X.; Yang, J. Ordered charging of electric vehicles considering grid-station-user multi-party demands and decision-making behavior characteristics. *Electr. Power Autom. Equip.* **2021**, *41*, 136–143.
58. Cheng, Y.; Zhang, C. Configuration and operation combined optimization for EV battery swapping station considering PV consumption bundling. *Prot. Control Mod. Power Syst.* **2017**, *2*, 26. [\[CrossRef\]](#)
59. Cai, L.; Zhang, Q.; Dai, N.; Xu, Q.; Gao, L.; Shang, B.; Xiang, L.; Chen, H. Optimization of Control Strategy for Orderly Charging of Electric Vehicles in Mountainous Cities. *World Electr. Veh. J.* **2022**, *13*, 195. [\[CrossRef\]](#)
60. Liang, S.; Zhao, Q.; He, J.; He, S. Optimization of community electric vehicle charging schemes with balanced load time distribution under shared charging hubs. *Appl. Res. Comput.* **2022**, *39*, 3688–3693.
61. Hou, S.; Jiang, C.; Yang, Y.; Xiao, W. Electric Vehicle Charging Scheduling Strategy based on Genetic Algorithm. *J. Phys.* **2020**, *1693*, 012104. [\[CrossRef\]](#)
62. Wang, N.; Li, B.; Duan, Y.; Jia, S. A multi-energy scheduling strategy for orderly charging and discharging of electric vehicles based on multi-objective particle swarm optimization. *Sustain. Energy Technol. Assess.* **2021**, *44*, 101037. [\[CrossRef\]](#)
63. Zhang, X.; Wang, Z.; Lu, Z. Multi-objective load dispatch for microgrid with electric vehicles using modified gravitational search and particle swarm optimization algorithm. *Appl. Energy* **2022**, *306*, 118018. [\[CrossRef\]](#)
64. Chen, G.; Wang, X.; Yuan, C.; Shuai, X.; Zhou, Q. Coordinated Charging Strategy Applicable to Large-scale Charging Stations Based on Deep Reinforcement Learning. *Autom. Electr. Syst.* **2023**, *47*, 88–95.
65. Wang, J.; Guo, C.; Yu, C.; Liang, Y. Virtual power plant containing electric vehicles scheduling strategies based on deep reinforcement learning. *Electr. Power Syst. Res.* **2022**, *205*, 107714. [\[CrossRef\]](#)
66. Ku, A. EVs to Reduce Dependence on Imported Oil: Challenges and Lessons from Maui. In *Electric Vehicle Business Models*; Springer: Cham, Switzerland, 2015; pp. 229–247.
67. Lee, T.; Glick, M.B.; Lee, J.H. Island energy transition: Assessing Hawaii's multi-level, policy-driven approach. *Renew. Sustain. Energy Rev.* **2020**, *118*, 109500. [\[CrossRef\]](#)
68. Spencer, S.I.; Fu, Z.; Apostolaki-Iosifidou, E.; Lipman, T.E. Evaluating smart charging strategies using real-world data from optimized plugin electric vehicles. *Transp. Res. Part D Transp. Environ.* **2021**, *100*, 103023. [\[CrossRef\]](#)
69. Ning, J.; Jiang, C.; Zhang, Z. Thinking and technical practice of adjustable load resources participating in dispatching and control of power grid. *Autom. Electr. Power Syst.* **2020**, *44*, 1–8.
70. Zhang, J.; Liu, C.; Yuan, R.; Li, T.; Li, K.; Li, B.; Li, J.; Jiang, Z. Design scheme for fast charging station for electric vehicles with distributed photovoltaic power generation. *Glob. Energy Interconnect.* **2019**, *2*, 150–159. [\[CrossRef\]](#)
71. Wang, Y.; Su, Z.; Li, J.; Zhang, N.; Zhang, K.; Choo, K.-K.R.; Liu, Y. Blockchain-based secure and cooperative private charging pile sharing services for vehicular networks. *IEEE Trans. Veh. Technol.* **2021**, *71*, 1857–1874. [\[CrossRef\]](#)
72. Wu, X.; Dong, Y.; Ge, Y.; Zhao, H. A high reliable communication technology in electric vehicle charging station. In Proceedings of the 2013 IEEE Seventh International Conference on Software Security and Reliability Companion, Gaithersburg, MD, USA, 18–20 June 2013; IEEE: New York, NY, USA, 2013; pp. 198–203.
73. Abedi, S.; Arvani, A.; Jamalzadeh, R. Cyber security of plug-in electric vehicles in smart grids: Application of intrusion detection methods. In *Plug In Electric Vehicles in Smart Grids*; Springer: Singapore, 2015; pp. 129–147.
74. Luo, Q.; Zhou, Y.; Hou, W.; Peng, L. A hierarchical blockchain architecture based V2G market trading system. *Appl. Energy* **2022**, *307*, 118167. [\[CrossRef\]](#)
75. Dong, H.; Wang, L.; Wei, X.; Xu, Y.; Li, W.; Zhang, X.; Zeng, M. Capacity planning and pricing design of charging station considering the uncertainty of user behavior. *Int. J. Electr. Power Energy Syst.* **2021**, *125*, 106521. [\[CrossRef\]](#)

76. Kempton, W.; Letendre, S.E. Electric vehicles as a new power source for electric utilities. *Transp. Res. Part D Transp. Environ.* **1997**, *2*, 157–175. [[CrossRef](#)]
77. Ghazanfari, A.; Perreault, C. The path to a vehicle-to-grid future: Powering electric mobility forward. *IEEE Ind. Electron. Mag.* **2021**, *16*, 4–13. [[CrossRef](#)]
78. Kempton, W.; Tomić, J. Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy. *J. Power Sources* **2005**, *144*, 280–294. [[CrossRef](#)]
79. Bhoir, S.; Caliendo, P.; Brivio, C. Impact of V2G service provision on battery life. *J. Energy Storage* **2021**, *44*, 103178. [[CrossRef](#)]
80. Tan, K.M.; Ramachandaramurthy, V.K.; Yong, J.Y. Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques. *Renew. Sustain. Energy Rev.* **2016**, *53*, 720–732. [[CrossRef](#)]
81. zhihu.com. Available online: <https://zhuanlan.zhihu.com/p/88059977> (accessed on 14 April 2023).
82. Mukherjee, J.C.; Gupta, A. A review of charge scheduling of electric vehicles in smart grid. *IEEE Syst. J.* **2014**, *9*, 1541–1553. [[CrossRef](#)]
83. Bhatti, A.R.; Salam, Z.; Aziz MJ, B.A.; Aziz, M.; Yee, K.P. A critical review of electric vehicle charging using solar photovoltaic. *Int. J. Energy Res.* **2016**, *40*, 439–461. [[CrossRef](#)]
84. Yang, S.X.; Wang, X.F.; Ning, W.Q.; Jia, X. An optimization model for charging and discharging battery-exchange buses: Consider carbon emission quota and peak-shaving auxiliary service market. *Sustain. Cities Soc.* **2021**, *68*, 102780. [[CrossRef](#)]
85. Sharma, P.; Naidu, R.C. Optimization techniques for grid-connected PV with retired EV batteries in centralized charging station with challenges and future possibilities: A review. *Ain Shams Eng. J.* **2022**, *14*, 101985. [[CrossRef](#)]
86. Yang, X.; Zhang, Y. A comprehensive review on electric vehicles integrated in virtual power plants. *Sustain. Energy Technol. Assess.* **2021**, *48*, 101678. [[CrossRef](#)]
87. Zhaoyun, Z.; Linjun, L. Application status and prospects of digital twin technology in distribution grid. *Energy Rep.* **2022**, *8*, 14170–14182. [[CrossRef](#)]

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