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Review

Integrating Electric Vehicles to Power Grids: A Review on Modeling, Regulation, and Market Operation

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Abstract: Fossil energy consumption and environmental protection issues have pushed electric vehicles (EVs) to become one of the alternatives to traditional fossil-fuel vehicles. EV refers to a vehicle that uses electric energy as power and is driven by an electric motor. The electric energy of EVs is stored in batteries. When the EV is not traveling, the battery can provide power for other loads. Therefore, with the increase in the number of EVs and the load of the power grid, the EV-to-grid (V2G) mode, which uses EVs to supply power to the power grid, has gradually entered the field of vision of researchers. The physical connection mode, charge and discharge technology, and energy management strategy are the main topics of the current review papers; however, there is a lack of systematic research on V2G modeling, framework, and business models. This paper describes the concepts of the spatio-temporal distribution model and the adjustable capacity of EVs. In addition, common constraints and methods in optimization are introduced. Moreover, this paper introduces the interactive relationship among power grids, load aggregators, and EV users. Furthermore, the business model of V2G is introduced and analyzed from various perspectives. Finally, the future development of V2G is pointed out. This paper's goal is to provide an overview of the present V2G application scenarios and to identify any challenges that must be overcome.

Keywords: vehicle-to-grid; electric vehicle; load aggregator; adjustable capacity; electricity market

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1. Introduction

With the increasing global attention towards environmental protection, EVs have gradually become one of the alternatives to traditional fossil-fuel vehicles due to their low emission and low pollution characteristics. By the end of 2022, there were more than 27 million EVs on the road, which could store about 1.35 billion kilowatt-hours of electricity. EVs equipped with large-scale energy storage devices have attracted the attention of the energy sector [1]. Their huge energy storage capacity enables them to participate in power grid regulation as virtual energy storage [2]. Some researchers have pointed out that many EVs spend most of their time in parking spaces during use. Therefore, during EV parking, the EV battery can be used to supply power to the surrounding load. EVs charge load/energy storage units, which can assist in more stable operation of the power grid and make the power grid system more flexible, efficient, and balanced [3].

EVs that obtain electricity from the grid are called grid to vehicle (G2V) [4]. Vehicle to grid (V2G) refers to the power grid using the batteries of EVs to cushion the volatility [5]. This volatility is brought about by excessive load [6]. Mahela et al., through calculation, verified that the V2G system can effectively keep system parameters such as frequency and voltage within the allowable range [7]. Based on bidirectional converters, V2G and G2V can be converted between EVs and the grid [8]; when the load curve of the grid approaches the peak, the EVs feed the power grid as an energy storage unit. When the load curve of the grid approaches the valley, EVs can reduce the peak−valley difference of the grid by storing the excess power generation of the grid. Due to the existence of time-of-use electricity prices, EV users can sell electricity when the price is high and buy electricity from the grid when the price is low. In this way, EV users can obtain certain subsidies and reduce charging costs [9]. EVs can supply power to the connected buildings, compensate for the instantaneous electricity demand of the buildings by using battery discharge [10], reduce the additional power generation of the grid, and meet the power demand of the power side and the balance demand of the grid [11]. Many references have shown that it is effective and feasible for response EVs to operate as virtual energy storage auxiliary power grids, and they can reduce the impact of disorderly charging of large-scale EVs on power grids [12].

A battery is an important component to achieve V2G, and in the current research on EV batteries, lithium batteries and supercapacitors are hot topics. Lithium batteries have the advantages of a high specific energy [13,14], good cycle performance [15], and no memory [16,17]. Lithium batteries are often used as power supplies for EVs, portable electronic devices, distributed energy storage systems, and other devices [18]. The supercapacitor is a kind of power supply between the traditional capacitor and the battery. No chemical reaction occurs during the charging process, so its charging and discharging process is reversible [19]. The supercapacitor can be repeatedly charged and discharged, and can be quickly charged and discharged at a great current. However, the battery has a higher energy density than the supercapacitor, and can store more energy in the same volume. Song et al. described the functions of each part of the lithium battery, and described the composition of the battery in detail [20]. Considering the whole life cycle of EVs and battery reuse after the end of vehicle life, Chengjian et al. showed that by 2050, the participation rate of EVs needs to reach 12–43% to meet the global short-term grid storage demand. If half of the batteries are used as stationary storage after the end of the vehicle's life, the participation rate of EVs will be less than 10% [21]. At present, supercapacitors have reached the level of meeting the needs of portable and wearable electronic devices [22], but there is still a gap for the application of EVs.

In existing studies, many authors are studying the energy management method, optimization method, operation mode, and topology of EVs in V2G mode. Van Binh and Long Bao considered the cost of battery degradation and EV charging optimization [23]. Niphon K et al. described several energy management methods to reduce the impact of EV entry on the grid [24]. Luo et al. mainly focussed on the influence of large-scale EVs on the distribution grid and proposed a multistage sequential load recovery method to ensure the safe and stable operation of the grid [25]. Hou et al. mainly focused on the cooperation mechanism and basic framework under the Internet of vehicles. In addition, researchers also put forward an energy management method based on the Internet of vehicles [26]. At the same time, researchers also proposed that the disorderly charging of EVs will affect the energy management of smart buildings with renewable energy, and thus proposed a method to limit the disorderly charging behavior of EVs. Faran and Ibrahim focused on the development of EV infrastructure and comprehensively described the standards and specifications for infrastructure implementation. In addition, Razi Faran also introduced the existing charging technologies and predicted the future development direction and challenges that EVs will face [27]. Tao Ye introduced three kinds of EV energy supply facilities, namely charging piles, charging stations, and changing stations, and expounded on the method for determining charging demand points according to different methods of charging infrastructure planning. In addition, Tao et al. also introduced a model and algorithm for optimizing the layout of charging infrastructure and put forward some suggestions for optimizing the layout of the EV charging infrastructure [28].

In addition, some research reviews have described charging topology and the related technologies involved in the process of response EVs. Sunddararaj Suvetha et al. mainly focussed on the various standards of EVs, photovoltaic systems, and the interconnection equipment of grid-connected systems [29]. Abraham Dominic et al. mainly focused on related standards of EV charging stations [30]. The reference also discussed different levels and types of charging stations used for EV charging. Mierlo Joeri et al., [31] introduced a variety of new EV technologies and analyzed potential technical challenges. From the perspective of car users and EV users, Ali M B et al. proposed a new energy management strategy for optimizing the operation of mobile charging stations [32].

In the current review studies, most of the existing references in the field of V2G explore the integration of V2G, such as the equipment in V2G, active and reactive power algorithms, the connection mode in V2G, lower fuel consumption and CO_2 emissions, and the impact of EV access on the power grid. İnci Mustafa et al. [33] presented a comprehensive introduction to the structure of the charge and discharge system and the use of converters. Reasonable active and reactive power can enable EVs to provide frequency and voltage regulation services; Alicia T provided a review of wireless charging technology for EVs [34]. Abdulgader et al. described an EV technology, charging topology, and energy management strategy [35]. Das H et al. reviewed the impact of electric vehicles on the power grid, and summarized the international standards for EV charging and grid interconnection, as well as the charging infrastructure [36].

Several review articles that describe V2G connection, wireless charging technologies, and energy management strategies are analyzed in this paper. However, the spatio-temporal distribution, multi-subject interaction framework, and business model of V2G are not taken into account. Therefore, in this paper, the adjustable capacity modeling of EVs, common optimization objectives, the multi-subject interaction framework, and the multi-type V2G business model are presented. In Section 2, this paper elaborates on the existing models of the spatiotemporal distribution and the adjustable capacity of EVs. The limits of the adjustable energy, the objective function, and the constraint conditions are described in this paper. In Section 3, the interactive relationship among the power grid, load aggregator, and EV user is introduced. This paper describes the role of each subject and the framework among the subjects. In Section 4, this paper introduces the business model of V2G from the perspectives of demand response, ancillary services, and green power transactions. Finally, the future development prospect of V2G is analyzed and the full text is summarized. This paper's goal is to provide an overview of the present V2G application scenarios and to identify any challenges that must be overcome.

The databases this paper uses are Web of Science, IEEE Xplore, and Scopus, with keywords such as vehicle-to-grid, EV, and adjustable capacity. This paper focuses on papers from the last 5 years. In this work, the bibliography has been compiled based on the fundamentals of integrating EVs into power grids by using >80 journal research papers, reviews, conference proceedings, book chapters, theses, and web pages.

2. Response Modeling of EVs

2.1. Spatio-Temporal Distribution Model of EV Charging Load

The primary issue regarding integrating EVs in power grid regulation and control is the impact of the driving behavior and charging and discharging behavior of large-scale EVs in the traffic network [37]. Factors such as travel rules of EV users, the structure of the traffic network, and the distribution of charging facilities affect EVs' driving behavior and charging and discharging behavior [38]. Therefore, the analysis of the spatial-temporal distribution of EVs is the premise and foundation for the study of the virtual energy storage of EVs. This section will introduce several commonly used research methods of spatio-temporal distribution of EVs. This section describes two methods used to characterize user trips. Both methods require Monte Carlo sampling. Therefore, the process of Monte Carlo sampling will be briefly described at the end of this section.

Original-destination (OD) matrix analysis is usually used to study the urban road network, where O represents the starting point, D represents the destination, and OD point refers to the longitude and latitude coordinates of the trip's starting point and arrival point. The OD matrix analysis divides the selected traffic plane into different spatial grids according to the spatial scale, and takes these spatial grids as the research area [39]. The OD spatio-temporal matrix can be used to obtain the charging and discharging characteristics of EVs under different charging and discharging modes. After the OD matrix describes the travel characteristics of users, it is necessary to use Monte Carlo sampling to predict the time and space of EVs. In reference [40], by extracting the road topology of the city, the OD matrix is used to establish the travel probability matrix describing the user's travel characteristics.

The Monte Carlo method is an approximate inference method to solve problems such as expectation, mean value, area, and integration [41]. According to the characteristics of the spatiotemporal distribution of EVs, EVs can be regarded as particles and cities as a plane. The Monte Carlo method can be used to predict the spatiotemporal distribution of EVs [42]. The Monte Carlo simulation flow diagram is shown in Figure 1. The first step is to generate the quantity of EVs, the number of simulation cycles, the initial state of charge (SOC), the start time, the beginning node, the destination, and to compute the mileage energy consumption. SOC refers to the usable state of the remaining charge in the battery [43]. If SOC is less than the threshold value, an emergency charging requirement is generated and the charging location is taken as the starting node. If SOC is greater than the threshold value, the estimated travel time and arrival time are considered. Second, if the destination is home, start the next cycle or end the simulation. If the destination is not home, the EV owner chooses whether to fragment time charging. If so, no emergency charging requirement is generated; otherwise, it is generated. In reference [44], based on the central limit theorem and travel chain theory, the Monte Carlo method is adopted to simulate the time distribution of charging loads at different functional stations.

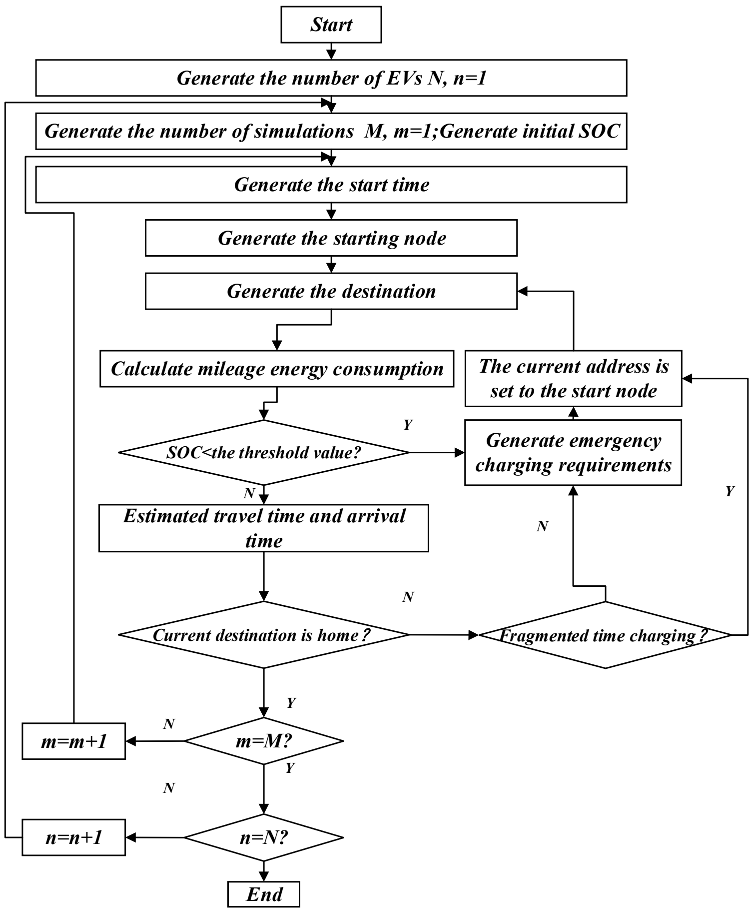

Figure 1. The Monte Carlo simulation flow diagram.

The travel chain model effectively describes the spatial and temporal distribution of EVs, which includes both time and space feature quantities [45]. The time characteristic quantity records the travel time distribution of EVs, including the departure time, arrival time, waiting time, and other time information. The spatial characteristic quantity records the spatial displacement of EVs, including the departure location, destination location, travel distance, and other spatial information [46]. The resident travel chain and Markov process are introduced to describe the spatial transfer characteristics of user trips, and then Monte Carlo sampling is used to obtain the temporal and spatial distribution of the charging load.

2.2. Modeling Analysis of EV Adjustable Capacity

2.2.1. Scenario Analysis of Adjustable Capacity

The adjustable capacity of EVs refers to the space for adjusting the charging load up and down. Considering the constraints of the battery capacity, charging power, and driving time, the adjustable capacity specifically reflects the change ability of the charging power of EVs in different periods [47].

As shown in Figure 2, the X-axis is time and the Y-axis is the *SOC*, taking the adjustable capacity of the unidirectional charging EV as an example. ABCDE is the area with the adjustable capacity of the unidirectional charging EV. The slopes of AE and BC represent the rising rate of *SOC* when the EV is charged at the rated charging frequency. To prevent excessive battery discharge, EV users will set SOC_{min} and stop discharging when it is lower than this value. SOC_t is the battery state when EV enters the grid. SOC_{pm} meets the lower limit of off-grid *SOC* for EV users in the next stroke; SOC_e is the expected off-grid power of EV users. If the off-grid power is not lower than SOC_e, user satisfaction will not be reduced. If the off-grid power is within the range of $[SOC_{pm}, SOC_e)$, user satisfaction will be reduced; SOC_{max} is the upper limit of battery capacity. $[t_{in}, t_{out}]$ is the on-grid period; t_{in} and t_{out} are the on-grid and off-grid time of EV, respectively; and t_{pm} is the latest charging time of EV after on-grid, ensuring that the off-grid electric quantity is not lower than SOC_{pm}.

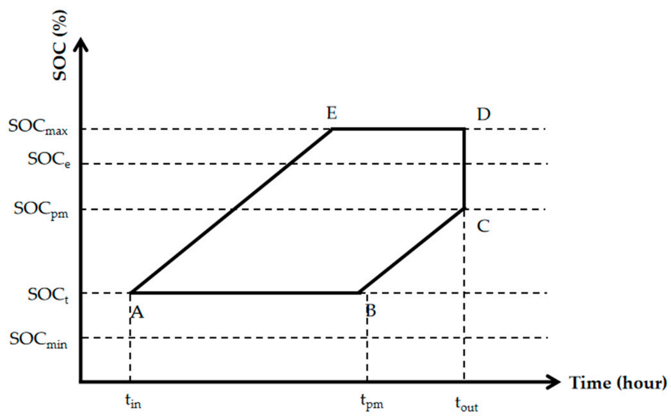

Figure 2. Unidirectional charging EV adjustable capacity range.

Segment BC represents the mandatory charging constraint, point B is the latest charging time; the latest charging time t_{pm} and line BC can be expressed as follows:

$$t_{pm} = t_{out} - \frac{(SOC_{pm} - SOC_{in})C}{P_{rated,c}\eta_c} \quad (1)$$

$$SOC = \frac{P_{rated,c}\eta_c}{C}(t - t_{out}) + SOC_e \quad (2)$$

where

$P_{rated,c}$ = the rated charging power of EV;
C = the battery capacity;
η_c = the charging efficiency.

In the scenario of V2G, the EV can be charged and discharged. Compared with the adjustable range of the unidirectional charging EV from ABCDE to AA1B1BCDE, the *SOC* value of EV should be included in the above area. Line segment B_1C still represents the forced charging constraint, and the latest charging time is $t_{pm,d}$. In Figure 3, line segment AA_1 represents the process of EV discharging from SOC_t to SOC_{min} at a rated discharge power after the EV is connected to the network. The slope is the SOC change rate under the rated discharge power.

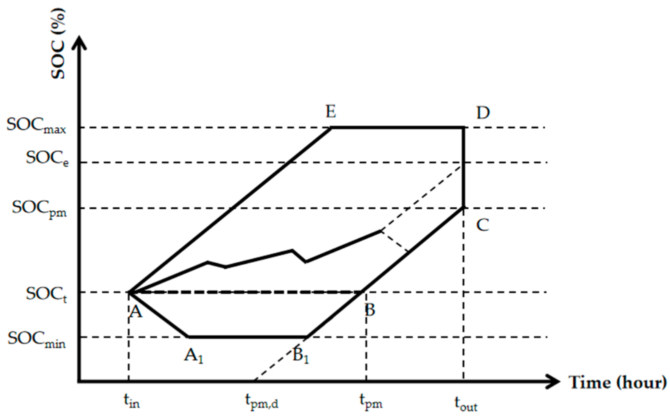

Figure 3. EV adjustable capacity area in V2G.

The mathematical expression of line AA_1 is as follows:

$$SOC = \frac{P_{rated,d}\eta_d}{C}(t - t_{in}) + SOC_{in} \tag{3}$$

where

$P_{rated,d}$ = the rated discharging power of EV;

η_d = the charging efficiency.

The lower limit of SOC should be satisfied in the charging process:

$$SOC_{in} + \frac{\sum_{t_{in}}^{t} p_t\eta_t\Delta t}{C} \geq \max\left(\frac{P_{rated,d}\eta_d}{C}(t - t_{in}) + SOC_{in}, \frac{P_{rated,c}\eta_c}{C}(t - t_{out}) + SOC_e, SOC_{\min}\right) \tag{4}$$

The upper limit shall meet the following:

$$SOC_{in} + \frac{\sum_{t_{in}}^{t} p_t\eta_t\Delta t}{C} \leq \min\left(\frac{P_{rated,c}\eta_c}{C}(t - t_{in}) + SOC_{in}, 100\%\right) \tag{5}$$

where

p_t = the charging and discharging power at time t. A positive power indicates charge, while a negative power indicates discharge.

η_t = the charging and discharging efficiency at time t.

According to the deformation of Equations (4) and (5), the dynamic constraint of SOC in the charging process can be written as follows:

$$\sum_{t_{in}}^{t} p_t\eta_t\Delta t \geq \max(P_{rated,d}\eta_d(t - t_{in}), P_{rated,c}\eta_c(t - t_{out}) + C(SOC_e - SOC_{in}), C(SOC_{\min} - SOC_{in})) \tag{6}$$

$$\sum_{t_{in}}^{t} p_t\eta_t\Delta t \leq \min(P_{rated,c}\eta_c(t - t_{in}), C(100\% - SOC_{in})) \tag{7}$$

In this case, the adjustable capacity of the EV at time t is:

(1) Upward capacity:

$$\Delta p_t = \begin{cases} 0\ , p_{t,0} > 0 \\ P_{rated,c}, p_{t,0} = 0 \end{cases} \tag{8}$$

(2) Downward capacity:

$$\Delta p_t = \begin{cases} -P_{rated,c}\ , p_{t,0} > 0 \\ -P_{rated,d}\ , p_{t,0} = 0 \end{cases} \tag{9}$$

where

$p_{t,0}$ = EV's reference charging power.

2.2.2. Objective Function

The optimization goal is to minimize the load fluctuation of the power grid.

$$\min \frac{\sum_{t=1}^{24} \left(Q_{grid,t} + \sum_{i=1}^{N} p_t^i - Q_{avg} \right)}{Q_{avg}^2} \tag{10}$$

where

$Q_{grid,t}$ = the operating load of the power grid at time t;

$p_t{}^i$ = the charging power of EV_i at time t by the optimal charging scheme;

Q_{avg} = the average load of the total operating load of the grid in a day when EVs are charged according to the optimal charging scheme.

2.2.3. Constraint Condition

(1) Charging power constraint

$$P_{rated,d}^i \leq \overline{p_t^i} \leq P_{rated,c}^i \tag{11}$$

(2) Charging time constraint

$$t_{in}^i \leq t \leq t_{out}^i \tag{12}$$

(3) SOC lower bound at the off-grid time

$$SOC_{\min} + \frac{d^i w^i}{C^i} \leq SOC_{out}^i \leq 100\% \tag{13}$$

where

d^i = estimated mileage for the next trip;

$w^{\ i}$ = power consumption per kilometer.

(4) During the charging process, the constraints are (6) and (7).

2.3. Common Constraints in Optimization

2.3.1. Renewable Energy Generation

Renewable energy includes photovoltaic, wind power, etc. Photovoltaic power plants are scattered, and their output power characteristics are determined by the characteristics of light resources and power generation equipment. Influenced by weather and seasonal factors, the output power of photovoltaic power generation is regular, intermittent, and fluctuating. The output power model of photovoltaic power generation can be approximated as follows [48]:

$$P_{\rm pv}(t) = P_{\rm STC} \frac{G(t)}{G_{\rm STC}} [1 + k(T(t) - T_{\rm STC})] \tag{14}$$

where

P_{STC} = the maximum output power under standard test conditions;

G_{STC} = the illumination intensity under standard test;

$G(t)$ = the light intensity at the time of the test;

$T(t)$ = the surface temperature at the time of the test.

Wind speed changes with season and day and night, which makes the wind power output present certain randomness and periodicity. When the wind turbine is running, only when the wind speed is greater than the inlet wind speed and less than the outlet wind speed, the wind turbine can generate electricity normally. When the wind speed is too low, the fan will not work. When the wind speed is too high, the fan will stop to prevent damage to the internal components. The relationship between its output power and wind speed is as follows:

$$P_{\mathrm{wt}} = \begin{cases} 0 & v < v_{\mathrm{in}} \\ \frac{v - v_{\mathrm{in}}}{v_{\mathrm{r}} - v_{\mathrm{in}}} p_{\mathrm{r}} & v_{\mathrm{in}} < v < v_{\mathrm{r}} \\ p_{\mathrm{r}} & v_{\mathrm{r}} < v < v_{\mathrm{out}} \\ 0 & v_{\mathrm{out}} < v \end{cases} \tag{15}$$

where v_{in}, v_{out}, and v_{r} are the inlet wind speed, cutting wind speed, and rated wind speed of the fan, respectively, and p_{r} is the rated output power.

2.3.2. Spatial Transition Probability

The time interval between each grid-connected charging and the next trip will directly affect the flexibility of charging optimization. Spatial transition probability refers to the probability of a car traveling from a destination D_m to the next destination D_{m+1} in a specific period of time. The spatial transition probability can be written as follows [48]:

$$P(D_m \to D_{m+1}) = P(D_{m+1} \mid D_m) \tag{16}$$

The spatial transition probability can be transformed into a three-dimensional matrix $M \times N \times N$, where M is the number of discretized time intervals and N is the number of destination types. When the time interval is determined, the spatial transformation probability matrix becomes a two-dimensional matrix, as follows [48]:

$$P_{t_i} = \begin{bmatrix} p_{t_i,D_1,D_1} & \cdots & p_{t_i,D_1,D_N} \\ \vdots & \ddots & \vdots \\ p_{t_i,D_N,D_1} & \cdots & p_{t_i,D_N,D_N} \end{bmatrix} \tag{17}$$

where $P_{ti,Di,Dj}$ is the probability of driving from the current location D_i to the next destination D_j during time interval t_i. The sum of the probabilities in the same column is 1. The diagonal probabilities are not necessarily 0, indicating some round trips.

2.3.3. Node Voltage

To ensure the safe operation of the power grid, the node voltage constraint of the line and the load constraint of the distribution transformer should be satisfied during the charging and discharging process of EVs.

$$\mathrm{U_{i,min}} \le \mathrm{U_{i,t}} \le \mathrm{U_{i,max}} \tag{18}$$

$$\sum_{i=1}^{N} P_{i,t} \le \alpha S_{\mathrm{T}} \tag{19}$$

where $\mathrm{U_{i,min}}$, $\mathrm{U_{i,max}}$ are the upper and lower limits of voltage operation of node I, respectively, and α and S_{T} are the efficiency and rated capacity of the transformer, respectively.

2.4. Common Problems and Methods in Optimization

With the introduction of large-scale EVs into the grid, simple EV responses have been unable to achieve the expected peaking and valley-filling effect, and may even form new peaks. Therefore, to reduce the possibility of a peak value caused by large-scale EV entry into the grid, it is necessary to optimize the scheduling of a reasonable EV response.

Current research focuses on tracking day-ahead scheduling [49–51], reducing load curve variance [52–61], improving wind power consumption [62,63], etc. Robust optimization, sparrow search algorithm, and moth fire-extinguishing algorithms are adopted to solve the problem, The specific Optimization Objective and Optimization Method is shown in Table 1.

Table 1. Summary of EV response optimization.

Optimization Objective	Optimization Method	Reference
Solve the effect of wind random output	Stochastic programming, robust optimization, enhanced-interval linear programming, and distributed robust optimization are introduced to deal with the uncertainty problem.	[49–51]
Reduce the variance of the load curve	Coupled Monte Carlo simulation and multi-objective modified Sparrow search algorithm were used to solve the multi-scenario and multi-objective optimal scheduling model.	[52–55]
Alleviate the peak phenomenon caused by EV	Based on the response motion theory and random probability algorithm, a cooperative EV charging scheduling strategy is proposed.	[56–59]
Minimize the active power loss and total voltage amplitude deviation of the grid	The optimal dispatching interval optimization model of EVs considering the uncertainty of renewable energy generation and the load was established, and the optimal interval optimization method was used to determine the optimal interval EV power of the previous day.	[60,61]
Increase consumption of new energy	The multi-objective function was transformed into a linear weighted single objective function using the Max min method and analytic hierarchy process, and the improved moth extinguishing algorithm was used to solve the problem.	[62,63]

3. EVs Participating in the Grid Regulation Framework

3.1. Positioning of Each Subject in the Regulation Framework

(1) EV users

EV users are important participants in V2G. Power grids can improve the enthusiasm of users through a price mechanism, contract mechanism, and incentive mechanism [64]. EV users are encouraged to participate in the regulation of power system independently, which can provide certain economic benefits for users while reducing the load of the power grid [65].

(2) Load aggregators

The individual capacity of EVs is too small to participate in power exchange independently. Therefore, it is necessary to introduce load aggregators to aggregate EVs so that they can reach the capacity threshold in order to participate in power exchange. Load aggregators usually optimize the charging behavior of EVs to meet the travel demand of users, thus reducing the peak−valley difference. In [66], based on EV's orderly charge−discharge and carbon emission limitations, load aggregators are introduced as energy managers to purchase and dispatch energy, which improves the flexibility of energy consumption in the community. In the optimal power dispatching strategy proposed in [67], a load aggregator is introduced as the dispatching center to improve the economy and security of energy use.

(3) Power grid

A power grid connects power plants, substations, and loads to form a national or regional power system for unified management and commands [68]. In the framework, the grid is responsible for transmitting price information, compensation information, current load conditions to load aggregators, and electricity to power users.

3.2. The Interactive Hierarchical Relationship among Different Subjects

The interaction between EV users, load aggregators, and the grid is shown in Figure 4. The power grid transmits the price information and the compensation information to the load aggregator. According to the travel demand and participation willingness of EV users, the load aggregator enables EV users to adjust their charging behavior through incentives such as the time-of-use electricity price. In this way, it can assist the power grid in reducing the peak−valley difference. The load aggregator uploads relevant information such as power consumption characteristics and load curves in the process of regulation to the power grid. After the adjustment is completed, a transaction settlement is carried out with the EV users and charging stations.

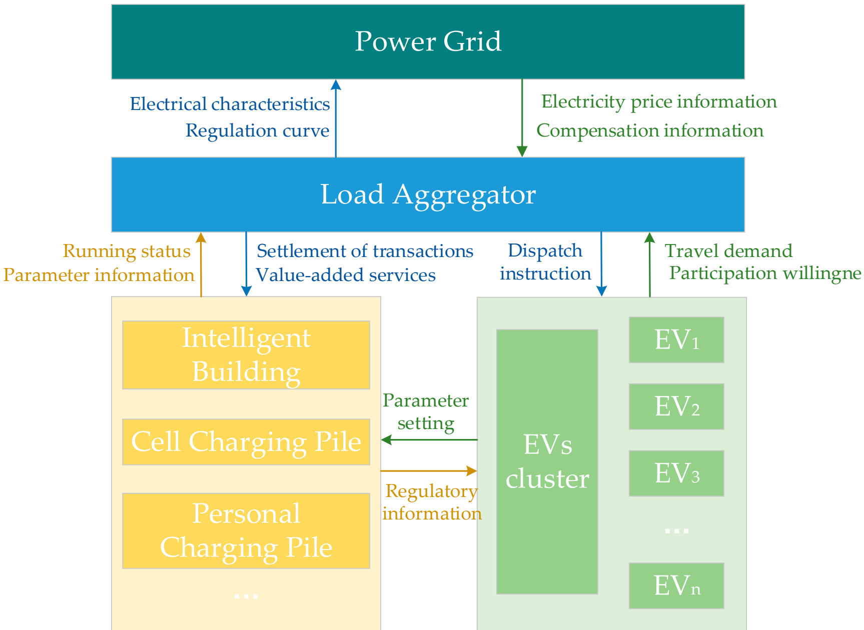

Figure 4. Multi-subject interaction framework.

4. EVs in Electricity Market Operation

V2G is jointly promoted by the government and the power grid, so V2G has strong investors, and with the gradual increase in the number of EVs, it has large customer resources. V2G has high requirements for the response rate, so it has advanced coordination control technology, communication technology, and associated equipment. The above attributes support the operation of V2G. In the V2G model, the load aggregator participates in the ancillary market transactions of the electricity market and the ancillary service market. Within the load aggregator, the load aggregator encourages EV users through time-of-use electricity price or dynamic electricity price, so that EV users can participate in ancillary services, demand response, and green power trading independently, the V2G business canvas is shown in Figure 5.

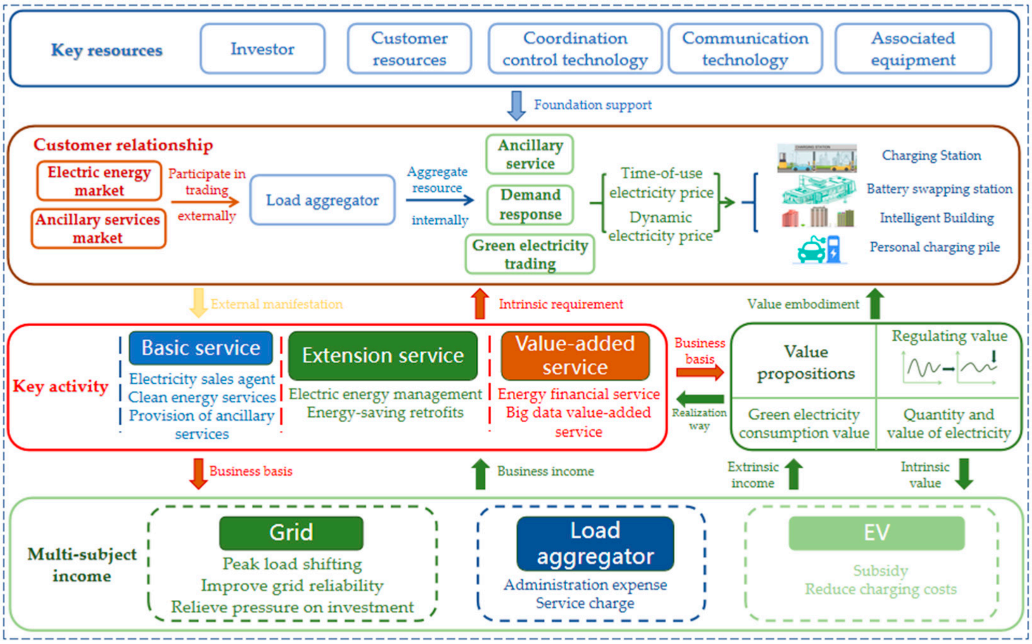

Figure 5. V2G business canvas.

The key services of V2G are divided into basic services, extended services, and value-added services. The basic business of V2G is to sell electricity on behalf of the power grid and power users. When an EV needs to be recharged, it buys power from the grid, and when the EV has surplus power, it sells it to the grid. In addition, V2G can also assist in clean energy consumption and control the charging of EVs at night when wind power generation is redundant.

V2G enables multi-subject coexistence and mutual benefits. Traditional thermal power generation can ensure the controllability of the power generation side of the grid, but with a great amount of wind power and photovoltaic access to the grid, the power generation side of the grid becomes unstable. The power grid can only meet the load demand by increasing the size of the power grid or reducing the peak load. V2G can reduce the investment cost of the power grid by reducing the peak load. Load aggregators can obtain management fees and service fees by responding to grid commands, EVs can obtain demand response subsidies, and charging in valley time can reduce charging costs through time-of-use price (TOU).

4.1. Demand Response

Demand response means that when the load rises (falls) sharply or the generation side fluctuates, EV users temporarily change their electricity consumption behavior and reduce (increase) electricity consumption after receiving electricity prices or incentives. The purpose of demand response is to promote the balance of power supply and demand, ensure the stable operation of the power grid, and restrain the short-term behavior of electricity price increases [69].

The operating subject of the EV demand response is the load aggregator, and the participants are EV users, photovoltaic power stations, and buildings inside the load aggregator. According to the operation requirements of the power grid and its own situation, the load aggregator integrates internal resources and participates in demand response transactions to optimize energy efficiency [70]. EV participates in the demand response type is shown in Table 2.

Table 2. EV participates in the demand response type.

Types of Demand Response	Response Mode	Features
Price Response	Time-of-use electricity price	Uncertainty is strong and new load peaks may form.
	Real-time electricity price	Easy to cause user response fatigue, the formation of a new load peak.
Incentive response	Sign a contract or agreement	Better timeliness and stability.

(1) Price response

The price response includes time-of-use price (peak−valley price mechanism), real-time price (price change per hour or less), etc. Users can actively change their electricity consumption behavior according to the change in real-time electricity price [71]. The decision-making power of the price response is the user, and it is difficult to guarantee the speed and quantity of the EV response. Price response is suitable for businesses with long regulation time scales and great EV response participation, such as peak shaving and reactive power regulation.

(2) Incentive response

The incentive response is to directly use incentives and compensation to induce users to change their charging behavior and reduce the load of the power grid [72]. For example, when the grid requires load reduction, users can adjust or reduce their electricity consumption. After changing the charging behavior, users will receive discounts or subsidies on electricity charges. In other words, the grid pays customers to reduce their load over time.

(3) Day-ahead response

Day-ahead response is divided into one day before demand response execution (day-ahead response) and several hours before demand response execution (hour-level response) [73]. The power grid sends response invitations to participants through platform announcements, short messages, and telephone calls. The content includes response scope, demand, cycle, invitation deadline, etc. Before the invitation deadline, the participants feedback the information through the platform, and the power grid determines the participants and the response quantity according to the principle of "giving priority to the users with early response time and giving priority to the users with large response quantity". The user completes the load adjustment by themself during the response period [74].

(4) Real-time response

The real-time response is divided into two categories. In the first category, 30 min before the execution of demand response (minute-level response), the grid issues adjustment instructions to participants through the platform [75]. The scheduling information includes information such as response range, demand, and time. The platform automatically completes the confirmation of the response capability. In the second category, one minute before execution (second-level response), the provincial platform directly sends control instructions to the participants. The equipment involved in real-time demand response will have the characteristics of rapid interruption or remote interruption. Participants use demand response terminals to link with their own power energy efficiency monitoring system [76].

In this way, participants can automatically complete the load adjustment within 30 min. For the secondary response, the provincial power company automatically completes the load control of the participants through the provincial platform.

4.2. Ancillary Services

Ancillary services refer to the services provided by power sources, loads, and storage to maintain the safe and stable operation of the power system. The main contents of EVs participating in grid ancillary services include frequency modulation, reactive power compensation, peak shaving, and reserve. The process of EVs participating in ancillary services is as follows. After determining the ancillary services that EVs need to provide, the dispatching center first defines the response mechanism and control strategy of EVs. Secondly, according to the type of ancillary services, the control strategy of the grid layer is selected to generate the corresponding control signal. Finally, it is sent to the load aggregator for control and implementation [77].

Taking frequency modulation as an example, as shown in Figure 6, the load aggregator sends power instructions and power adjustment instructions to the charging pile operator or private charging pile, and the charging pile operator or private charging pile feeds back the response feedback and vehicle information such as the battery charging state, whether to receive regulation or not, and travel plan to the load aggregator. The load aggregator feeds back the adjustable capacity, benchmark load quantity quotation, and response results calculated by the relevant functional modules to the market, and the market sends the checked results, electricity price information, V2G control instructions, power control instructions, and settlement information to the load aggregator. The market sends the clearance result to the grid before the safety check, and the grid sends the electricity demand, auxiliary service demand, and the clearance result to the market after the check, EV participation auxiliary service type is shown in Table 3.

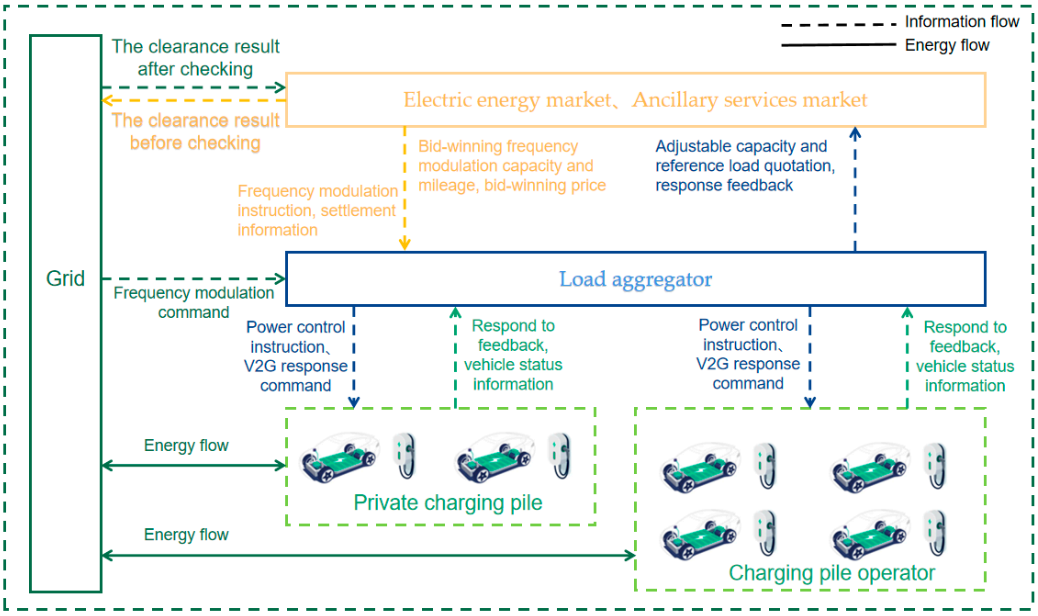

Figure 6. Schematic diagram of information flow and energy flow of EV participating in frequency modulation.

Table 3. EV participation auxiliary service type.

EV Participation Auxiliary Service Type	Concrete Type	Compensation Mode
Active balancing service	Frequency modulation Peak regulation Backup power supply	Fixed compensation, market mode (centralized bidding, public bidding/listing/auction, bilateral negotiation).
Reactive power balancing service	Reactive power compensation	Fixed compensation, market mode (centralized bidding, public bidding/listing/auction, bilateral negotiation).

4.3. Green Electricity Trading

In addition to the types of transactions mentioned above, EVs can also participate in green electricity trading. By researching the charging and discharging information of EVs, a cooperative wind abandonment agreement can be reached with wind farms [78]. The business model's participants include EV users, aggregators, and wind farms. The three main objectives of the model are as follows, with each subject benefiting from its interests. (1) For EV users, they can charge at a lower price by participating in the charging and discharging schedule of the aggregator, while ensuring their own charging needs. If EV users do not participate in the charging and discharging schedule, they can charge at the normal price. (2) For aggregators, they can maximize the profits of the aggregators. (3) For the wind farm, they can cooperate with the aggregator to increase the on-grid electricity and share the power generation income with the aggregator.

Similarly, EVs can also participate in absorbing surplus photovoltaic energy. As photovoltaic power generation advances, solar radiation is strongest at noon. However, the power demand may not be enough to match the photovoltaic power generation. To address this, the charging time of EVs can be adjusted through incentive means, so that its charging behavior and photovoltaic power generation curve match, resulting in the consumption of excess photovoltaic energy.

4.4. V2G Benefit Analysis

4.4.1. Grid Benefits

(1) Reduction in peak load [79]. When the power load is at its peak, the power grid needs to dispatch the generating units at a high cost through the dispatching center to participate in the generation. If the power generation side has reached the limit and cannot supply power continuously, there may be power rationing and regional rolling blackouts, which could even lead to the collapse of the power system, thus causing social, economic, and industrial losses. The peak load can be reduced by starting the demand response at the peak time and guiding the non-emergency EV users to change their charging and discharging behavior through pricing or incentives.

(2) Improve power system reliability [80]. The stability of the power system is measured by the frequency and time of the power supply failures. Leading EV users to participate in the demand response can reduce the peak of the load curve, reduce the frequency of power supply failures, and thus improve the reliability of the power system.

(3) Reduce the pressure to expand the power grid scale [81]. As the electricity demand continues to rise, the pressure on the grid to build new power plants and transmission lines is also increasing. Demand response can alleviate the pressure of insufficient capacity of the power system.

4.4.2. Load Aggregator Benefits

(1) The cost of services to support the operation of the grid [82]. In the process of demand response, load aggregators sign contracts with the power grid and users individually to obtain demand response compensation from the power grid. When EV users participate in the demand response, they provide EV users certain response compensation. The amounts of the two are different, and the load aggregator benefits from it.

(2) Management fees paid by the user [83]. EV users need to participate in the demand response through the load aggregator to obtain compensation fees. Therefore, during the implementation of the demand response, EV users need to pay the management fees to the load aggregator.

4.4.3. User Benefit

(1) Compensation costs for participating in the response [84]. EV users can obtain certain compensation expenses for participating in the demand response.

(2) Reduce the cost of electricity [85]. In the implementation process of demand response, EV users are required to suspend the charging behavior at the peak of electricity consumption and charge when the electricity load is low, and the electricity price at the valley value is lower than the peak value. Therefore, EV users' participation in the demand response can reduce the electricity cost of EV users.

5. Conclusions and Prospect

This paper focuses on the subjects involved in EV and V2G. In this paper, the common models of EVs are analyzed, and the current spatio-temporal distribution models of EVs are introduced. The common optimization objectives and optimization methods of EVs are summarized. In V2G mode, the load aggregator controls the EVs to discharge when the load curve of the power grid approaches the peak value and to charge when the load curve of the power grid approaches the valley value. V2G can effectively reduce the peak−valley difference of the power grid. This paper also reviews the framework and business model of V2G, including demand response, ancillary services, green power trading, and other models. Load aggregators use differentiated price signals and incentive mechanisms to guide EVs to participate in grid dispatching. This paper summarizes the ways EVs participate in the power grid from many aspects. Although the frequent charging and discharging process in V2G mode may affect the battery life of EVs and shorten their service life, it is more economical for EV owners and the grid. In V2G mode, the power grid can balance the difference between the peak and valley. Load aggregators can obtain corresponding subsidies in the process of dispatching. Because of the time-of-use electricity price, EVs participating in V2G can be charged at a lower price to reduce the charging cost, and, at the same time, they can obtain subsidies to participate in demand response.

Although the V2G model is very promising, there are still some problems to be solved.

(1) Impact on battery life. Frequent charging and discharging will affect the battery life, which will affect the willingness of EV users to participate in V2G. Therefore, future research needs to conduct more in-depth research on battery protection, including battery safety boundary, optimization of charging and discharging strategies, battery material optimization, and so on.

(2) Unstable income. The income of EVs will be affected by the demand of the power grid and electricity price, so it is necessary to study how to formulate a stable electricity price policy and establish a reliable market mechanism.

(3) Affect user travel. In V2G mode, the charging and discharging behavior of EVs is controlled by the load aggregator. This may affect users' travel. It is necessary to study and optimize the charging strategy and to improve the power of charging and discharging equipment.

(4) Safety risk. In V2G mode, there are electricity and information interactions between EVs and the power grid, and there may be security risks such as information leakage and power grid failure.

In summary, V2G still faces some problems in practical applications, including the impact of battery life, unstable income, the impact of user travel, and security risks. Further research and analysis are needed in future studies.

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