Optimal Scheduling Strategy for Photovoltaic Charging Stations Participating in the Electricity Market based on Transactive Energy Mechanism

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Abstract. Regarding the optimization and management of energy in photovoltaic charging stations, existing research mostly focuses on the power grid, with little consideration given to its characteristics as a producer and consumer. This paper proposes an optimized scheduling strategy for photovoltaic charging stations that considers transactive energy mechanisms. Firstly, under the premise of ensuring the safe operation constraints of the distribution network, a distributed transaction model for photovoltaic charging stations was established. Secondly, the optimization model is solved using the Lagrangian decomposition principle and Subgradient method to obtain the scheduling plan of the photovoltaic charging station. The simulation results indicate that the scheduling strategy proposed in this article can promote the on-site consumption of renewable energy and improve the economy of photovoltaic charging stations.

1. Introduction

Environmental pollution and energy issues have become increasingly serious. In the current strategic environment of promoting the development of a low-carbon economy, electric vehicles (EVs) have also received significant support in the development of the automotive industry due to their energy-saving and emission reduction characteristics [1-2]. Charging facilities are the hub for achieving electric vehicle energy supply and interaction [3]. The random charging and load characteristics of large-scale electric vehicles will inevitably have an impact on the stable operation of the power grid. Reasonably configuring a certain capacity of distributed power sources with charging stations can not only suppress the randomness of charging loads but also promote the nearby consumption of renewable energy generation and the low-carbon development of electric vehicles [4-6]. Therefore, it is necessary to study the optimization scheduling method for EV charging stations (EVCS) that include renewable energy.

The existing research on optimization scheduling methods for charging stations mainly includes orderly charging control methods [7-9] aimed at regulating and controlling demand on the grid side, charging station power distribution methods [10,11], etc. Reference [7] proposes a charging and discharging optimization model for EVCSs to participate in the carbon emission trading market and peak shaving auxiliary service market to minimize the grid load fluctuation, which can reduce the load fluctuation while optimizing the operating costs of charging stations. Reference [8] established a charging and discharging optimization strategy for EVs based on the double-layer dynamic game theory with the objective function of minimizing the voltage deviation of the power grid. In reference [9], an optimization scheduling strategy based on the dynamic electricity pricing mechanism was designed to guide EVs charging and discharging, taking into account various interests and achieving multi-objective optimization. As the number of electric vehicles and charging stations increases, centralized control in the above research would significantly raise the computational load and construction control cost of the dispatch center, while neglecting the use of renewable energy. References [10,11] proposed energy management strategies for renewable energy charging stations, which improved the service efficiency of charging stations and reduced the impact of charging loads on the power grid. However, the transaction mechanisms designed in the research are optimized based on the power grid, with less consideration given to the characteristics of the producers and consumers of charging stations. When charging stations reach a certain scale, they can participate in electricity market transactions.

The transactive energy mechanism (TE) has the advantages of distributed regulation and giving economic benefits to participating entities. By integrating economic and power grid control methods, "value" is used as a coordination tool to manage and optimize energy dispatch for producers and consumers [12]. Reference [13] proposes a two-layer hybrid robust stochastic framework based on an transactive energy mechanism,

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which verifies the feasibility of energy trading for high-penetration electric vehicle populations in networked microgrids. Reference [14] proposes a distributed EV charging scheduling strategy based on an transactive energy mechanism, with the optimization goal of peak shaving and valley filling. This strategy not only achieves grid regulation requirements but also improves the economic benefits of electric vehicle charging. Reference [15] proposes an economic scheduling method based on an transactive energy mechanism for the economic scheduling problem of multi-user and consumer clusters.

The above research mainly focuses on the optimization of power grid objectives and establishes energy management and optimization scheduling strategies for producers and consumers, with less consideration given to the characteristics and autonomy of photovoltaic charging stations. Therefore, based on the interactive energy mechanism, this article takes the power grid and photovoltaic charging stations (PVCS) as research objects, considers the uncertainty of photovoltaic output and the charging load characteristics of each charging station, and proposes an optimized scheduling strategy for photovoltaic charging stations.

2. Distributed Trading Strategy

2.1. Structure of PVCS

The research objects are fast charging stations (FCS) and photovoltaic charging stations, Fig.1 and Fig.2 are structural diagrams. The CS includes AC charging stations and DC charging stations, which can meet the charging needs of different types of EV users. The PVCS includes photovoltaic power generation systems, AC/DC converters, and other equipment, with energy sources coming from the power grid and photovoltaic system.

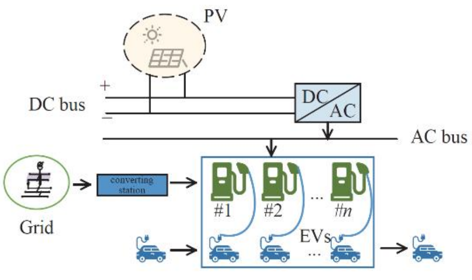

Fig. 1. Structure of photovoltaic charging station for EV

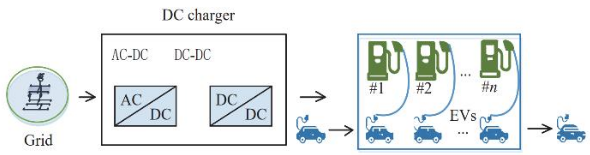

Fig. 2. Structure of quick-charging station for EV

2.2. Distributed Trading Framework for CSs

Considering the information exchange and energy trading between the power grid, trading platforms, CSs, and EV users, a charging station energy trading mechanism framework is proposed as shown in Fig. 3.

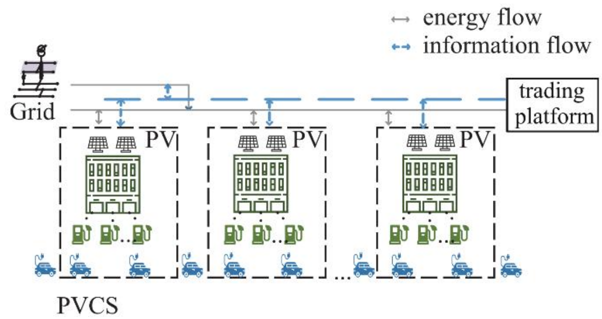

Fig. 3. Framework of energy trading mechanism of EVCS

Considering the randomness of the number of electric vehicles with charging needs at each moment in the charging station, Monte Carlo simulation is used to obtain their quantity. The energy sources of photovoltaic charging stations are photovoltaic power generation systems, trading platforms, and power grids. When the photovoltaic output in the charging station meets the charging needs of electric vehicle users and there is still a surplus, the remaining electricity can be sold to the trading platform; When the photovoltaic output in the charging station cannot meet the charging needs of electric vehicle users, the charging station first purchases electricity from the trading platform, and finally considers the power grid. The distributed trading framework for electric vehicle charging stations established in this paper adopts an interactive energy mechanism, which weakens the dominant position of the power grid in the electric vehicle charging market. It transforms one-way transactions between charging stations and the power grid into multilateral transactions dominated by transactions between charging stations, enhancing the flexibility of charging stations participating in power market transactions, avoiding long-distance transmission, and improving economic efficiency. It also promotes the on-site consumption of distributed power sources.

3. Mathematical model

3.1. PV model

Set the number of EVCS as N_{evcs}, and the PV model of the charging station n is

$$0 \le P_{n,t,s}^{pv} \le P_{n,t,s}^{pv,\max} \tag{1}$$

where $P_{n,t,s}^{pv}$ represents the PV power generation within n of the CS in the s-th scenario; $P_{n,t,s}^{pv,\max}$ is the maximum value of PV output.

The cost function of PV power generation system is

$$C^{pv} = \frac{C^{\prime\mathrm{pv}}}{P^{pv,ave}T^{pv}} \tag{2}$$

where C^{pv} is the unit price of PV power generation cost; $C^{'pv}$ is the cost of PV equipment; $P^{pv,ave}$ is the average annual power generation of PV equipment; T^{pv} is the service life of the PV equipment.

3.2. PV uncertainty model

This paper uses the Monte Carlo method to generate scenarios for PV power generation systems. The multi-scenario method solves the uncertainty problem of PV output. The synchronous backpropagation reduction method is used to cluster and generate typical scenarios [16]. Assuming the initial number of scenes is Ns, the sample distances of scenes Q_i(t) and Q_j(t) is $\left\|Q_i(t)-Q_j(t)\right\|_2$, and the clustered scenes need to meet the probability distance constraint condition $D_{di}=\pi_i \min\left\|Q_i(t)-Q_j(t)\right\|_2$ to obtain the final number of clustered scenes.

3.3. EV model

The charging demand of EVs is influenced by factors such as the state of charge (SOC) of the battery at the time of grid connection, the SOC at the time of grid disconnection, and the charging time. The charging process model is

$$\begin{cases} P_{i,t}^{Ev,\min} \leqslant P_{i,t}^{Ev,ch} \leqslant P_{i,t}^{Ev,\max} \\ Q_i S_{i,t}^{\mathrm{SOC}} = Q_i S_{i,t-1}^{\mathrm{SOC}} + P_{i,t}^{Ev,ch}\Delta t \\ M = \begin{cases} 1, t \in \left[T_{\mathrm{start}}, T_{\mathrm{depart}}\right] \\ 0, t \in \left[0, T_{\mathrm{start}}\right] \cup \left[T_{\mathrm{depart}}, T_{\mathrm{end}}\right] \end{cases} \\ S_{i,\min}^{\mathrm{SOC}} \leqslant S_{i,t}^{\mathrm{SOC}} \leqslant S_{i,\max}^{\mathrm{SOC}} \end{cases} \tag{3}$$

where $P_{i,t}^{Ev,ch}$ is the average charging power; $P_{i,t}^{Ev,\max}$ and $P_{i,t}^{Ev,\min}$ are the upper and lower limits of the charging power; $S_{i,t}^{\mathrm{SOC}}$ represents the state of charge of the EV, $S_{i,\min}^{\mathrm{SOC}}$ and $S_{i,\max}^{\mathrm{SOC}}$ represent the upper and lower limits of SOC for the EV; *M* represents the grid connection status of EVs during period *t*.

The EV cluster charging model is

$$P_{n,t}^{\mathrm{EV,ch}} = \sum_{i=1}^{N_{\mathrm{ev}}} P_{i,t}^{\mathrm{ch}} \tag{4}$$

4. Electric vehicle charging station transaction model supported by interactive energy mechanism

4.1. Transaction model

Based on the TE mechanism, PVCS purchase energy through their PV power generation system, trading platform, and power grid to meet the charging needs of EV users. The PVCS prioritizes the use of electricity generated by the PV system. When there is excess PV output, the remaining electricity is sold to the trading platform for profit.

The purchasing power of CS is $P_{n,t,s}^{\mathrm{buy}}$, the selling power is $P_{n,t,s}^{sell}$. Among them:

$$P_{n,t,s}^{\mathrm{buy}} = P_{n,t,s}^{\mathrm{bfp}} + P_{n,t,s}^{\mathrm{bfg}} \tag{5}$$

where $P_{n,t,s}^{\mathrm{bfg}}$ and $P_{n,t,s}^{\mathrm{bfp}}$ are the electricity purchased by the CS from the power grid and trading platform.

The time-of-use electricity price model of the power grid is

$$y_t = c_t + \beta_t P_t^{\mathrm{bfg}} \tag{6}$$

where c_t is the initial electricity price issued by the platform at time *t* before the day; β_t is the electricity price adjustment coefficient; P_t^{bfg} represents the electricity purchased by all CSs on the grid.

Distributed PV output has strong uncertainty. This paper uses the multi scenario method to cluster and reduce the initial scenarios, ultimately retaining N_{pv} typical scenarios. Divide the previous 24 hours into N_T time intervals, and each CS adopts the electricity price model represented by equation (6). Establish an objective function to maximize the revenue of all charging stations

$$F = \max \sum_{s=1}^{N_{\mathrm{pv}}} \pi_s \sum_{t=1}^{T} \sum_{n=1}^{N_{\mathrm{evcs}}} \left\{ \begin{aligned} &[-c_t P_{n,t,s}^{\mathrm{bfg}} - \beta_t \left(P_{n,t,s}^{\mathrm{bfg}}\right)^2] - \\ &g_h \left(P_{n,t,s}^{\mathrm{bfp}}\right)^2 + [c_t E_{n,t,s}^{\mathrm{b}} / \eta - C_n^{\mathrm{pv}}] \end{aligned} \right\} \tag{7}$$

where π_s is the probability of scenario *s* occurring, N_{evcs} represents the number of EVCSs, η is the charging efficiency of the CS, $E_{n,t,s}^{\mathrm{b}}$ is the electric energy charged by the EV in the CS during time t in scenario s; g_h is the electrical energy loss parameter. The objective function includes the cost of purchasing electricity from the power grid for the CS, network loss costs, EVs charging costs, and PV power generation costs

To ensure the safe operation of the power grid and CSs, the following constraints need to be met

$$\begin{cases} 0 \leqslant P_{n,t,s}^{\mathrm{bfp}} \leqslant P_{n,t}^{\mathrm{bfp,max}} \\ 0 \leqslant P_{n,t,s}^{\mathrm{stp}} \leqslant P_{n,t}^{\mathrm{stp,max}} \\ 0 \leqslant P_{n,t,s}^{\mathrm{bfg}} \\ 0 < P_{\mathrm{ev},t,s} < P_{\mathrm{ev},t,\max} \\ S_{i,\min}^{\mathrm{SOC}} \leqslant S_i^{\mathrm{SOC}} \leqslant S_{i,\max}^{\mathrm{SOC}} \\ P_{n,t}^{\mathrm{bfg}} + P_{n,t}^{\mathrm{bfp}} + P_{\mathrm{load}} \leqslant P_{\mathrm{m}} \end{cases} \tag{8}$$

where *s* represents the scene number; $P_{n,t}^{\mathrm{bfp,max}}$ is the upper limit for CS *n* to purchase electricity from the platform during time *t*; $P_{n,t}^{\mathrm{stp,max}}$ is the upper limit for CS *n* to sell electricity on the platform during time t; P_{m} is the rated capacity of the transformer

In order to meet the charging demands of conventional loads and EVs, the CS obtains energy from its PV power generation system, trading platform, and power grid. When there is excess PV output, the CS sells the remaining electricity to the trading platform for profit. The power balance constraint of the CS is

$$P_{n,t,s}^{\mathrm{stp}} + P_{n,t,s}^{\mathrm{load}} = P_{n,t,s}^{\mathrm{bfp}} + P_{n,t,s}^{\mathrm{bfg}} + P_{n,t,s}^{\mathrm{pv}} \tag{9}$$

The global constraint for this problem is

$$\sum_{n}^{N_{\mathrm{evcs}}} P_{n,t,s}^{\mathrm{bfp}} = \sum_{n}^{N_{\mathrm{evcs}}} P_{n,t,s}^{\mathrm{stp}} \tag{10}$$

Lagrange multiplier η_t is introduced, and equation (7) is rewritten as

$$F = \max \sum_{s=1}^{N_{\mathrm{pv}}} \pi_s \sum_{t=1}^{T} \sum_{n=1}^{N_{\mathrm{evcs}}} \left\{ \begin{array}{l} \beta_t \left(P_{n,t}^{\mathrm{bfg}}\right)^2 - g_{\mathrm{h}} \left(P_{n,t}^{\mathrm{bfp}}\right)^2 - \\ C_{\mathrm{n}}^{\mathrm{pv}} + c_t E_{n,t}^{\mathrm{b}} / \eta - \eta_t P_{n,t}^{\mathrm{bfp}} + \eta_t P_{n,t}^{\mathrm{stp}} \end{array} \right\} \tag{11}$$

According to the Lagrangian dual decomposition principle, the objective function is decoupled to obtain

$$F = \max \sum_{s=1}^{N_{\mathrm{pv}}} \pi_s \sum_{t=1}^{T} \left\{ \begin{array}{l} -c_t P_{n,t}^{\mathrm{bfg}} - \beta_t \left(P_{n,t}^{\mathrm{bfg}}\right)^2 - g_{\mathrm{h}} \left(P_{n,t}^{\mathrm{bfp}}\right)^2 + \\ c_t E_{n,t}^{\mathrm{b}} / \eta - C_{\mathrm{n}}^{\mathrm{pv}} + \eta_t P_{n,t}^{\mathrm{bfp}} + \eta_t P_{n,t}^{\mathrm{stp}} \end{array} \right\} \tag{12}$$

In order to obtain the optimal solution, it is necessary to solve all sub-problems of the CS, and each sub-problem must meet the constraints in equation (9) during the solving process. In this paper, the Subgradient method [15] is used to solve equation (12). The Lagrange multiplier A is updated with equation (13).

$$\eta_t[\mu+1] = \eta_t[\mu] + \sigma_h \left(\sum_{u=1}^{N_{\mathrm{evcs}}} P_{n,t}^{\mathrm{bfp}}[\mu] - \sum_{u=1}^{N_{\mathrm{evcs}}} P_{n,t}^{\mathrm{stp}}[\mu] \right) \tag{13}$$

where μ is the number of iterations in the solving process; σ_h is a constant step coefficient.

The iteration end condition is

$$\left|\eta_t[\mu+1] - \eta_t[\mu]\right| \leqslant \varepsilon_{\mathrm{h}} \tag{14}$$

where ε_{h} is the iterative convergence criterion.

4.2. EVCS Energy Trading Process

Fig. 4 shows the flow chart of electric energy trading for CSs. The optimization scheduling strategy for CSs considering interactive energy mechanisms proposed in this paper requires information exchange between power and price information to achieve multiple iterations and ultimately achieve system balance.

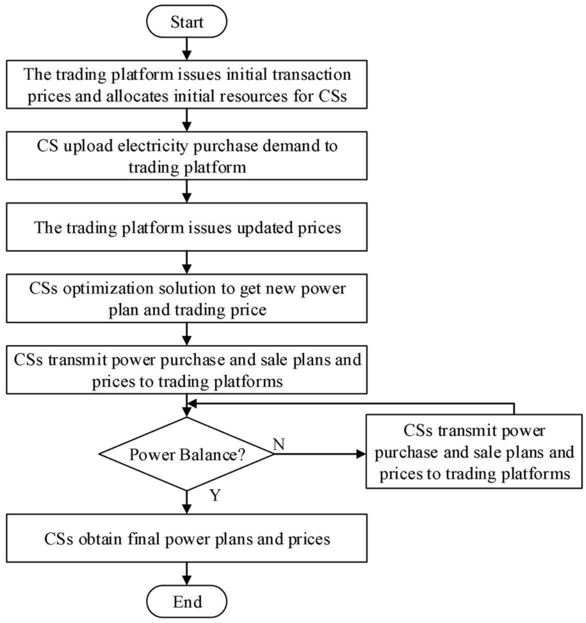

Fig. 4 Flowchart of electric energy transaction of CS

5. Result and Discussion

5.1. Case Analysis

This paper sets a trading cycle of 30 minutes and takes 3 fast charging stations and 2 slow charging stations with PV systems as the research objects. Through simulation analysis, the effectiveness of the proposed optimization scheduling strategy for CSs is verified. Fig. 5 shows the clustering reduction scenarios for each PV output within a day. The parameter settings of the model are shown in Tab.1.

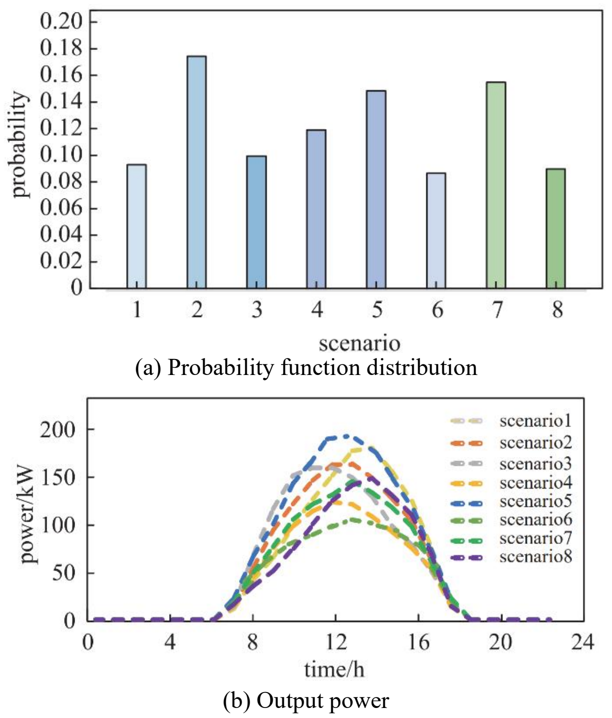

Fig. 5. Situation of each PV station output scenario

Tab. 1 Setting of model parameters

Parameter	Value
$P_{n,t}^{\mathrm{stp,max}}$ /kW	2000
$P_{n,t}^{\mathrm{bfp,max}}$ /kW	2000
P_{m} /kW	10000
β_t	0.001
σ_h	0.0005
ε_{h}	0.000001
$P^{Ev,\max}$ /kW	50

5.2. Transaction situation

Fig. 6 shows the electricity purchase and PV output of each CS from the platform and power grid. CSs 2 and 3 are slow charging stations, while charging stations 4 and 5 are fast charging stations. Due to the relatively high charging power of fast charging stations and the large number of electric vehicle users they serve, the electricity and power purchased from trading platforms and the power grid are higher than those of slow charging stations.

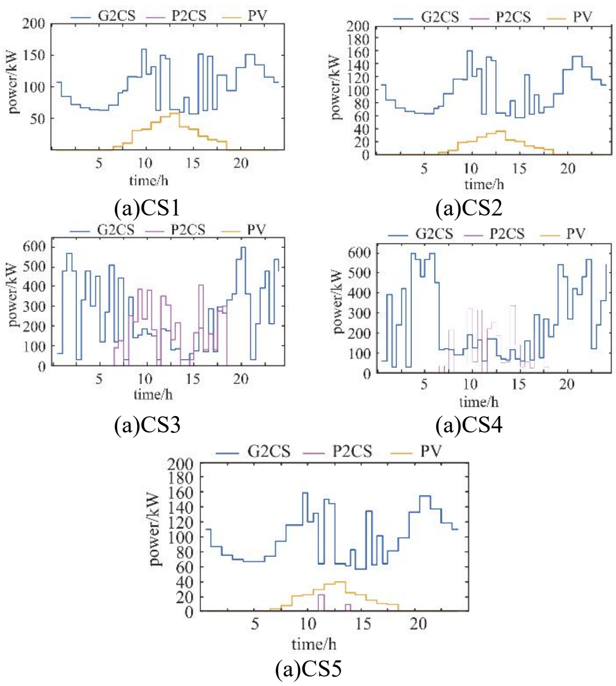

Fig. 6. PV output and electricity purchase situation of CSs

CSs optimize their charging and discharging plans to maximize their interests. Fig. 7 shows the optimization results of different charging stations. Slow charging stations 1, 2, and 3 equipment PV system, and in order to reduce the cost of purchasing electricity, priority is given to using PV output. When the PV output cannot meet the charging needs and basic load of EV users, the CS first purchases electricity from the trading platform, and finally considers the power grid. When the PV output in the CS meets the user's charging demands and there is still a surplus, the remaining electricity can be sold to the trading platform to obtain more profits. Fast charging stations 4 and 5 do not have PV systems and can only purchase electricity from trading platforms and the power grid to meet users' charging demands.

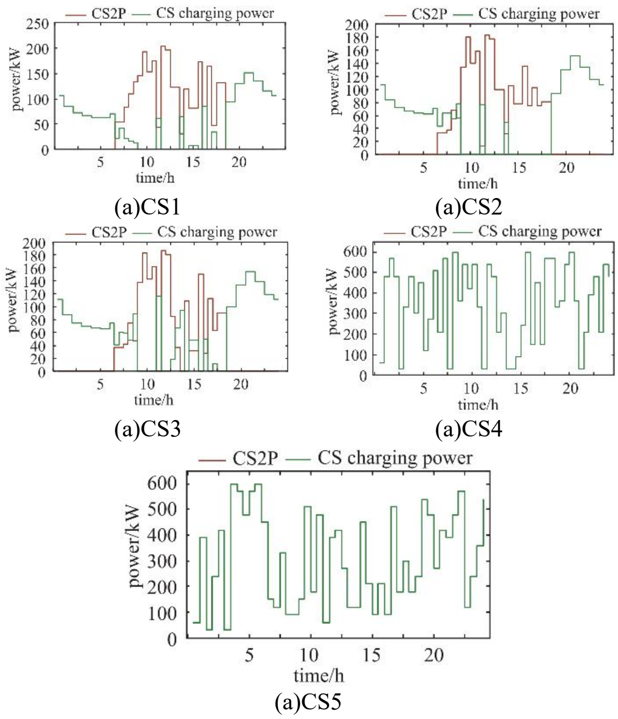

Fig. 7. Charging and discharging power of CSs.

The simulation results show that the proposed optimization scheduling strategy for CSs can improve the utilization rate of renewable energy and increase the operating revenue of CSs. Under the control of this strategy, energy trading is carried out between CSs and platforms, CSs and the power grid in the same area, achieving regional autonomy. Compared with centralized control by the power grid control center, it greatly reduces operating costs and control difficulties and avoids energy loss caused by long-distance transmission of electricity. EVCSs play a market and system-level control role, mobilizing electrical energy to achieve energy balance in the system.

Tab. 2 shows the comparison of benefits between the CS optimization model proposed and the traditional model. From the table, it can be seen that under the charging station transaction model proposed in this paper, the revenue of CSs has significantly increased. The charging station fully utilizes its distributed PV technology, promotes the consumption of renewable resources, and also promotes electricity market transactions, improving economic efficiency.

Tab. 2 Comparison of revenues of each charging station

CS	Revenue/yuan	
	The TE mechanism	The traditional model
1	693.63	517.08
2	657.63	479.76
3	663.77	492.05
4	547.01	365.72
5	616.11	461.69

6. Conclusion

This paper proposes an optimized scheduling strategy for PVCSs that considers interactive energy mechanisms, fully utilizing the "distributed" characteristics of EVCSs to achieve information and energy exchange between the power grid, trading platforms, and CSs. Compared with traditional scheduling models, this strategy can enhance the enthusiasm and flexibility of CSs to participate in the market, increase the utilization rate of renewable energy, and improve the economy of charging stations.

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