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Hierarchical Optimal Dispatching of Electric Vehicles Based on Photovoltaic-Storage Charging Stations

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Abstract: Electric vehicles, known for their eco-friendliness and rechargeable–dischargeable capabilities, can serve as energy storage batteries to support the operation of the microgrid in certain scenarios. Therefore, photovoltaic-storage electric vehicle charging stations have emerged as an important solution to address the challenges posed by energy interconnection networks. However, electric vehicle charging loads exhibit notable randomness, potentially altering load characteristics during certain periods and posing challenges to the stable operation of microgrids. To address this challenge, this paper proposes a hierarchical optimal dispatching strategy based on photovoltaic-storage charging stations. The strategy utilizes a dynamic electricity pricing model and the adaptive particle swarm optimization algorithm to effectively manage electric vehicle charging loads. By decomposing the dispatching task into multiple layers, the strategy effectively solves the problems of the "curse of dimensionality" and slow convergence associated with large numbers of electric vehicles. Simulation results demonstrate that the strategy can effectively achieve peak shaving and valley filling, reducing the load variance of the microgrid by 24.93%, and significantly reduce electric vehicle charging costs and distribution network losses, with a reduction of 92.29% in electric vehicle charging costs and 32.28% in microgrid losses compared to unorganized charging. Additionally, this strategy can meet the travel demands of electric vehicle owners while providing convenient charging services.

Keywords: optimal dispatching; microgrid; photovoltaic-storage charging station; dynamic electricity pricing model; adaptive particle swarm optimization

MSC: 68T07; 90B15; 90C90; 93E20

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1. Introduction

During the United Nations General Assembly in September 2020, President Xi made an international commitment to peak carbon emissions by 2030 and achieve carbon neutrality by 2060 [1–3]. The construction of a green, low-carbon, and clean energy system, primarily based on renewable energy, is not only a strategic choice for China, but also for the global community [4,5]. In recent years, China's energy landscape has been continuously transitioning towards a clean and more diversified structure, with notable growth observed in wind power and photovoltaic (PV) installed capacity. Additionally, electric vehicles

(EVs) have emerged as a research hotspot [6–8] due to their significant environmental and social benefits, including low pollution and high efficiency.

The charging of EVs is characterized by strong randomness, and fluctuating EV load can alter load characteristics, potentially affecting the operation stability of distribution networks. Therefore, it is essential to build proper integrated PV-storage charging stations. These charging stations not only enable the local consumption of PV resources, but also mitigate the impact of charging stations on the distribution network. The integration of EVs and renewable energy sources constitutes an important measure in responding to the Energy Internet Strategy [9,10]. However, with the increasing number of EVs, the large-scale charging of EVs may lead to issues such as decreased power quality in the distribution network and significantly increased peak–valley difference [11,12] due to the uncertainty of user demand and behaviors. To ensure the safe and stable operation of the system, it is necessary to develop optimal dispatching strategies for PV-storage charging stations.

Currently, most countries lack sufficient planning for the charging management of EVs, posing challenges to the safe operation of the power grid with the increasing number of EVs. Therefore, some studies have been conducted on the interaction between EVs and the power grid. In [13], the concept of a virtual power plant, integrating wind power plants, PV power generation, EVs, and traditional power plants, is introduced. Additionally, a stochastic dispatching model considering uncertainty, aiming to decrease the power fluctuation generated by wind and PV power generation, thereby lowering the penalty costs for power shortages, is proposed for virtual power plants. In [14], a collective management strategy considering wind power, PV consumption, and peak shaving is presented for the organized dispatching of EVs in power exchange stations. The authors of [15,16] utilize Vehicle-to-Grid (V2G) technology to control the bidirectional exchange of energy between EVs and the power grid. In [17,18], V2G technology is employed to facilitate charging and discharging EVs based on grid command and the EVs' energy storage requirements. In conclusion, managing the charging and discharging of EVs can effectively accommodate renewable energy generation and reduce the power supply pressure during peak periods, with EVs serving as mobile energy storage resources for the grid.

The current orderly charging and discharging of EVs mainly relies on a centralized control management mode. Refs. [19,20] optimize this by targeting the comprehensive operation cost of microgrids, PV utilization rates, and power fluctuations between microgrids and the main power grid. To shift load demand from peak to valley periods, Ref. [21] proposes a coordinated dispatching method for EV charging based on charging urgency indexes. Refs. [22–24] introduce a new algorithm to optimize the orderly charging and discharging of EVs, effectively enhancing the safety and economic efficiency of the power grid. In [25], a two-stage real-time optimal power dispatching strategy is proposed for residential communities with EV charging loads. This strategy takes into account the uncertainty of EV arrival time, departure time, and charging amount. Ref. [26] presents a distributed robust optimization model for day-ahead dispatching in an NBCSS (Newly Built Communal Smart Substation), considering wind power, PV power, and compliance uncertainty, which effectively reduces the total system costs. Ref. [27] investigates a charging demand prediction method considering multiple sources of information and proposes a multi-objective optimal dispatching strategy for Hybrid EV Charging Stations (HEVCSs). Ref. [28] introduces a park microgrid design incorporating EV charging conformity prediction and a constant power support strategy for the main power grid. This microgrid system enables the economical and stable operation of the microgrid system with EV integration.

In summary, most of the above literature adopts a centralized control method, computing the optimization task intensively. Despite the advantage of simple and straightforward control, the "curse of dimensionality" may occur when a large number of EVs are connected to the power system, resulting in a slow response that may not meet practical demands. To solve this issue, this paper introduces a hierarchical charging and discharging optimization strategy for EVs considering real-time electricity prices. This paper first establishes models and constraints for each internal unit of the microgrid, then develops a dynamic electricity

pricing model for EVs, and finally formulates a hierarchical optimal dispatching strategy for EVs at PV-storage charging stations, along with the corresponding objective functions of each layer. The strategy is optimized through the adaptive particle swarm optimization (APSO) algorithm and verified through simulation.

2. Micro-Grid Source Load Model

2.1. Charge–Discharge Model of EV Unit

EVs are used as energy storage units and play an important role in the power dispatching of microgrid systems. Upon EV arrival at the charging station, microgrid power dispatching can be conducted under constraints on the desired State of Charge (SOC), including the SOC value required by the EV user and charging and discharging time limits.

A model of the operating mechanism of EVs is shown in Figure 1. This figure describes the variation in SOC value during charging or discharging processes. S_{min} and S_{max} represent the minimum and maximum SOC value, respectively, when EVs participate in power dispatching. Tarr and Tdep represent the arrival and departure time of the EV at the microgrid EV charging station, respectively. Sarr is the initial SOC value upon connecting the power system. Sdep is the SOC value required by the user. A, B, and C refer to the maximum boundary values of the SOC when the EV participates in the dispatch, signifying immediate charging upon arrival at the charging station. When the SOC reaches S_{max}, the EV charging is completed, and the remaining time of the SOC remains unchanged. D, E, and F represent the minimum boundary values of the SOC, indicating the immediate discharging of the electric vehicle. When the SOC value drops to the minimum, the EV cannot continue to discharge. If EVs stay at a charging station for a long time, they can remain in a non-charging state. When EVs reach the mandatory charging time, the battery is charged using a fast-charging mode to ensure users' travel needs. EF represents the forced charging process.

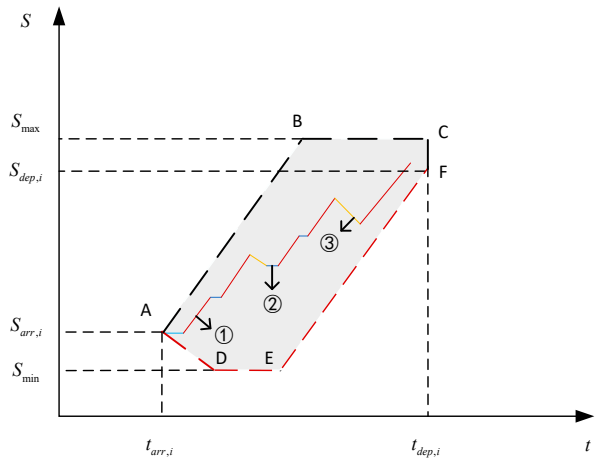


Figure 1. Charging and discharging model of EV unit.

The status of EVs can be described as follows:

$$S_i(t) = S_i(t-1) + \Delta t \frac{\left(\eta_{ch} P_{i,t}^{ch} - P_{i,t}^{disc} / \eta_{disc}\right)}{E_{rated}} \quad (1)$$

where $P_{i,t}^{ch}$ and $P_{i,t}^{disc}$ are the charging and discharging power of the EV, respectively; η_{ch} and η_{disc} are the charging and discharging efficiency of the EV, respectively; and E_{rated} is the rated storage capacity of the EV.

The constraints on the participation of the EV in power dispatching are as follows:

$$\begin{cases} S_{min} \le S_i(t) \le S_{max} \\ t_{arr,i} \le t \le t_{dep,i} \\ S_i(t) + P_{i,t}^{ch}\eta_c(t_{dep,i} - t)/E_{rated} - S_{dep,i} \ge 0 \end{cases} \quad (2)$$

An EV cannot be charged and discharged at the same time. In addition, in order to prevent the peak power consumption of the charging station from exceeding its output capacity, this model sets a constraint on the capacity limit of the charging station. Specifically, when the power demand of a charging station exceeds its output capacity, the charging station will no longer provide charging services to EVs to prevent overloading and ensure the safe and stable operation of the system.

2.2. Charge–Discharge Model of Energy Storage Battery

Given the high cost of energy storage, the impact of time-of-use electricity prices is primarily considered to enhance economic feasibility. Electricity is bought at lower rates and sold during periods of flat or high rates to generate revenue from selling electricity.

The SOC of the energy storage battery is calculated as follows:

$$\begin{cases} SOC(t) = (1-\delta)gSOC(t-1) - \frac{P_b(t)g\Delta tg\eta_c}{E_N\eta_d}, P_b(t) > 0 \\ SOC(t) = (1-\delta)gSOC(t-1) - \frac{P_b(t)g\Delta tg\eta_c}{E_N}, P_b(t) < 0 \end{cases} \quad (3)$$

where $SOC(t)$ and $SOC(t-1)$ represent the SOC of the battery at time t and $t-1$, respectively. $P(t)$ represents the charging/discharging power at time t (positive for discharging, negative for charging). E_N represents the rated capacity of the energy storage battery; η_c and η_d denote the charging and discharging efficiency, respectively. δ represents the self-discharge efficiency. Δt represents the time step.

2.3. Dynamic Electricity Pricing Model for EV Charging and Discharging

In the distribution network system, TOU electricity pricing can effectively reflect the load level across different periods. However, the integration of EVs into microgrids changes the load characteristics, leading to a mismatch between the electricity pricing and the load level, thus affecting the effective guidance for EV charging and discharging. Additionally, the adoption of TOU electricity pricing may induce clustering effects in EVs and new load peaks. Therefore, to ascertain the effective EV consumption of the PV output in the microgrid, a dynamic electricity pricing mechanism based on matching microgrid load, PV output, and EV load is proposed. In this thesis, 24 h is chosen as the time interval to closely follow changes in intraday electricity consumption patterns. This choice allows us to capture intraday electricity demand fluctuations in detail and to model more accurate demand forecasts.

(1) Dynamic updating strategy for incentive-based dispatching prices of EV discharging.

The characteristics of microgrid operation are fully considered in the incentive-based dispatching prices of EV discharging. The price will be updated and formulated according to peak-cutting and valley-filling demands and the charging rate of the EV. The update strategy is as follows:

$$v_t^{comp} = k_t^d v^{bcomp} \quad (4)$$

where v_t^{comp} is the EV discharge incentive dispatching price of the microgrid at time t. v^{bcomp} is the base EV discharge incentive dispatching price, set at 0.35 Yuan/kWh, and k_t^d represents the adjusting coefficient of EV discharge incentive dispatching price, which is positive when the power grid experiences peak demand, and otherwise zero, as illustrated below:

$$\begin{cases} k_t^d = r^d k_t^{dp} k_t^{ds} \\ k_t^{dp} = \begin{cases} 0 \; P_t^{EV} + P_{load,t} < P_{avg} \\ exp\left(\frac{P_t^{EV}+P_{load,t}-P_{avg}}{P_{avg}}\right) P_t^{EV} + P_{load,t} \geq P_{avg} \end{cases} \\ k_t^{ds} = \begin{cases} k_t^{ds1} \; 0 \leq \alpha_t^s < \alpha_t^{ds1} \\ k_t^{ds2} \alpha_t^{ds1} \leq \alpha_t^s < \alpha_t^{ds2} \\ k_t^{ds3} \alpha_t^{ds2} \leq \alpha_t^s < 100\% \end{cases} \\ \alpha_t^s = \frac{N_t}{N^s} \\ P_{avg} = \frac{1}{T} \sum_{t=1}^{T} \left(P_t^{EV} + P_{load}\right) \end{cases} \tag{5}$$

where r^d is the discharge incentive price adjusting coefficient of the microgrid. k_t^{dp} and k_t^{ds} are the peak-cutting coefficient and EV incentive coefficient of the microgrid, respectively. P_{avg} represents the average charging power of EVs. α_t^s represents the utilization rate of EV charging piles. In order to fully stimulate the dispatching potential of Evs, higher incentive subsidies should be offered when the reuse rate is high. Therefore, three discount ranges are set. k_t^{ds1}, k_t^{ds2}, and k_t^{ds3} respectively represent three different incentive levels. α_t^{ds1} and α_t^{ds2} represent the intervals of the utilization rate. N^s is the number of charging piles for microgrid EVs, which is often one-to-one in practice.

(2) Dynamic updating strategy of EV charging price.

The EV charging service fee is formulated and updated by the microgrid, and then dynamically adjusted according to the microgrid operation state, PV output power, and EV charging rate.

$$v_t^{serv} = k_t^c v^{bserv} \tag{6}$$

where v_t^{serv} is the EV charging service fee of the microgrid at time t. v^{bserv} is the basic charging service fee, set at 0.3 CNY/kWh. $k_{i,t}^c$ represents the coefficient for adjusting the charge service fee.

$$\begin{cases} k_t^c = r^c k_t^{cs} k_t^{cp} k_t^{PV} \\ k_{i,t}^{cs} = \begin{cases} k_t^{cs1} \; 0 \leq \alpha_t^s \leq \alpha_t^{cs1} \\ k_t^{cs2} \; 0 \leq \alpha_t^s \leq \alpha_t^{cs2} \\ k_t^{cs3} \; 0 \leq \alpha_t^s \leq 100\% \end{cases} \\ k_t^{cp} = \frac{P_t^{EV}+P_{load,t}}{P_{max}^L - P_{min}^L} \\ k_t^{PV} = \begin{cases} 1 \; P_t^{PV} = 0 \; or \; P_t^{PV} < P_t^{EV} \\ exp\left(\frac{P_t^{EV}}{P_t^{PV}}\right) P_t^{PV} \geq P_t^{EV} \end{cases} \end{cases} \tag{7}$$

where r^c represents the coefficient for adjusting the charging service fee of the microgrid. k_t^{cs} represents the EV adjustment coefficient. To reduce the charging cost of EV users, more discounts should be offered when the utilization rate is high. Three discount ranges are set. k_t^{cs1}, k_t^{cs2}, and k_t^{cs3} represent different discount coefficients in corresponding ranges. α_t^{cs1} and α_t^{cs2} are the ranges of the charging pile utilization rate. k_t^{cp} is the peak-cutting and valley-filling coefficient of the microgrid. P_{max}^{EV} and P_{min}^{EV} are the maximum and minimum values of the EV charging load within the microgrid, respectively; k_t^{PV} is the matching coefficient between the PV output and the EV charging load.

(3) Limitation of electricity price.

$$v_t^{ch} = v_t^e + v_t^{serv} \tag{8}$$

$$v_t^{disc} = v_t^e + v_t^{comp} \tag{9}$$

$$v_t^{ch,min} \leq v_{tt}^{ch} \leq v_t^{ch,max} \tag{10}$$

$$v_t^{disc,min} \le v_t^{ch} \le v_t^{disc,max} \tag{11}$$

where $v_t^{ch,max}$ and $v_t^{ch,min}$ are the upper and lower limits of the EV charging price of the microgrid at time t, respectively. $v_t^{disc,max}$ and $v_t^{disc,min}$ are the upper and lower limits of the EV discharge electricity price of the microgrid at time t.

3. Optimized Architecture and Strategy for PV-Storage Charging Stations

3.1. Optimized Architecture for PV-Storage Charging Stations

Figure 2 illustrates the dispatching framework of a PV-storage charging station comprising a three-layer dispatching system. The lowest layer represents the PV-storage charging station, the middle layer represents the microgrid system, and the upper layer represents the distribution network system. First, the PV-storage charging station will upload the charging and discharging demand of the EV to the microgrid system. The microgrid aims to minimize operation costs, EV dispatching costs, and power fluctuations in the tie-line. During the optimization process, the constraints on the power supply–demand balance, the tie-line power limits, and the constraints on the EV and energy storage power will be considered. Then, the optimized tie-line power is transmitted to the distribution network system for power flow calculations. The flow constraint information will be returned to the microgrid, which reoptimizes if the constraints are violated, until all hierarchical constraints are satisfied. Finally, the EV charging and discharging plans are returned to the PV-storage charging station to achieve the orderly control of EV charging and discharging.

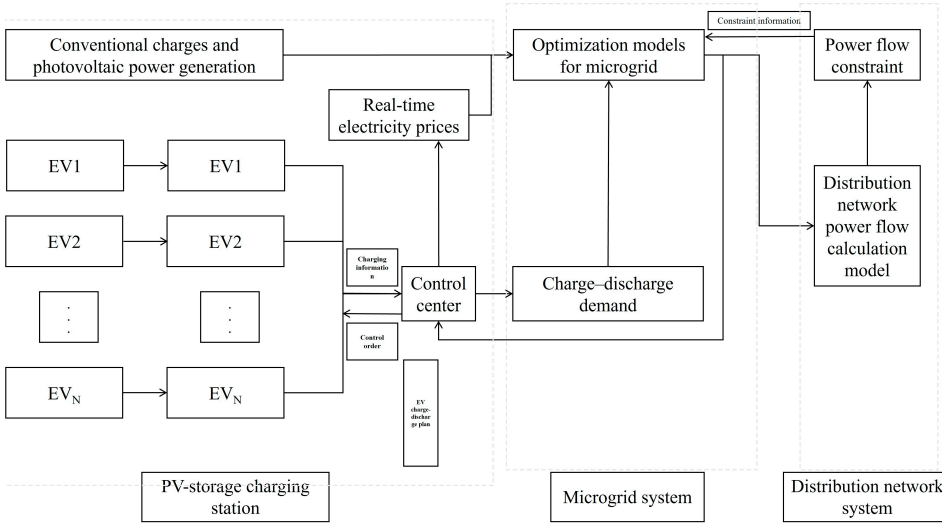


Figure 2. Dispatching framework of PV-storage charging station.

3.2. Underlying EV Dispatching Model

EV dispatching requires the comprehensive consideration of EV SOC, the parking duration, and the driver's preferences. Additionally, the EV SOC should meet the driver's future travel needs at the end of dispatching. If the driver declines dispatching at first, the charging power of the EV remains constant. When the driver accepts dispatching, the participation conditions are evaluated using the following formula:

$$SOC_i^t < SOC_{min} \tag{12}$$

$$T_{stay,i}^t \times P_{ch,max} \le \left(SOC_{dep,i} - SOC_i^t\right) \times E_{rated} \tag{13}$$

where SOC_{min} is the minimum SOC of the EV. $T_{stay,i}^t$ indicates the duration of the EV's stay at the charging station at the current time. $P_{ch,max}$ represents the maximum charging power for the EV. $SOC_{ex,i}$ signifies the desired SOC of the EV.

Equations (12) and (13) are the battery constraint and time constraint of the EV, respectively. If the continuous charging of the EV fails to meet the desired SOC within the limited parking time, the EV should be charged immediately.

When the EV dispatching constraints are met, the dispatchability of the EV is calculated. To prevent the battery from overcharging, the maximum rechargeable power of the EV at time t is calculated as follows:

$$P_{i,t}^{ch} = SOC_{max} - SOC_i^t \times E_{rated}/\Delta t \tag{14}$$

$$P_{ch,i,max}^{t} = \begin{cases} P_{i,t}^{ch}, P_{i.t}^{ch} < P_{ch,max}^{i} \\ P_{ch,max}^{i}, P_{i,t}^{ch} \geq P_{ch,max}^{i} \end{cases} \tag{15}$$

When evaluating the discharge capacity of an EV, it is necessary to ensure that the EV meets the expected battery power level for travel to prevent over-discharge. The maximum discharge power of an EV at time t is calculated as follows:

$$P_{disch}^{t} = \left(SOC_i^t - SOCi_{min}\right)^* E_i/\Delta t \tag{16}$$

$$P_{i,t}^{disc,max} \begin{cases} P_{i,t}^{disc}, P_{i,t}^{disc} < P_i^{disc,max} \\ P_i^{disc,max}, P_{i,t}^{disc} \geq P_i^{disc,max} \end{cases} \tag{17}$$

3.3. Objective Function and Constraints for Microgrid

(1) System operation cost.

The operation cost includes the dispatching costs of the EV and the interaction cost between the microgrid and the distribution network. The operation costs of the microgrid are defined as follows:

$$C = C_{CRID} + C_{EV} \tag{18}$$

where C is the operation cost of the microgrid. C_{GRID} is the interaction cost between the microgrid and the distribution network. C_{EV} is the dispatching cost of the EV.

The interaction cost between the EV and the distribution network can be described as follows:

$$C_{GRID} = \sum_{t=1}^{T} |P_{GRID}(t)|S_t \tag{19}$$

where P_{GRID} is the power transmission between the charging station and the main grid (a positive value indicates the distribution network transmitting power to the charging station, while a negative value indicates the distribution network absorbing power from the charging station). S_t is the electricity price at time t. A positive value indicates buying electricity, while a negative value indicates selling electricity.

The dispatching cost of the EV can be described as follows:

$$C_{EV} = v_{i,t}^{ch} \sum_{i=1}^{N_f} P_{i.f}^{ch}(t) - v_{i,t}^{disc} \sum_{i=1}^{N_{EV}-N_f} P_{i,t}^{disc}(t) \tag{20}$$

where N_f denotes the quantity of EVs being charged and N_{EV} stands for the total number of EVs.

(2) Optimization objectives for microgrid dispatching.

The objective of microgrid energy optimization dispatching is to minimize the tie-line power fluctuation at time t:

$$P = |P_{GRID}(t) - P_{GRID}(t-1)| \tag{21}$$

In summary, the optimization objective function of the microgrid is as follows:

$$\boldsymbol{minF} = \boldsymbol{\omega_1 C} + \boldsymbol{\omega_2 \Delta P} \tag{22}$$

where ω_1 and ω_2 are the weight coefficients of C and $\Delta \boldsymbol{P}$, respectively.

(3) Constraints.

This paper mainly considers the constraints on power supply–demand balance, the transmission capacity between the microgrid and the main grid, and the charging and discharging power of EVs:

① Constraints on power supply–demand balance:

$$\boldsymbol{P_{GRID}} + \boldsymbol{P_{PV}} + \boldsymbol{P_b} = \boldsymbol{P_{load}} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{N_f}} \boldsymbol{P_{i.t}^{ch}(t)} - \sum_{\boldsymbol{i=1}}^{\boldsymbol{N_{EV}-N_f}} \boldsymbol{P_{i,t}^{disc}(t)} \tag{23}$$

② Constraints on transmission power:

To connect the microgrid to the main grid, a power transmission agreement needs to be signed. In addition, the transmission power between the microgrid and the main grid cannot exceed the limit.

$$\boldsymbol{P_{buy}^{min}} \leq \boldsymbol{P_{GRID}} \leq \boldsymbol{P_{buy}^{max}} \tag{24}$$

③ Constraints on energy storage power:

$$\boldsymbol{P_{discharge,max}} \leq \boldsymbol{P_b} \leq \boldsymbol{P_{charge,max}} \tag{25}$$

4. Example Simulation

4.1. Example Parameters

An IEEE33-node system, depicted in Figure 3, is employed with a system base power of 10 MVA and a base voltage of 12.66 kV. The total load is 3.715 MW + j2.30 MVAr and the total active network loss is 0.1998 MW. The microgrid is connected to node 6. The conventional microgrid load, PV output, and time-of-use (TOU) electricity price are illustrated in Figure 4.

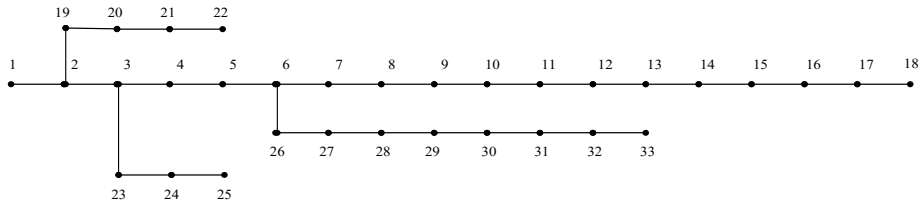


Figure 3. IEEE33-node system.

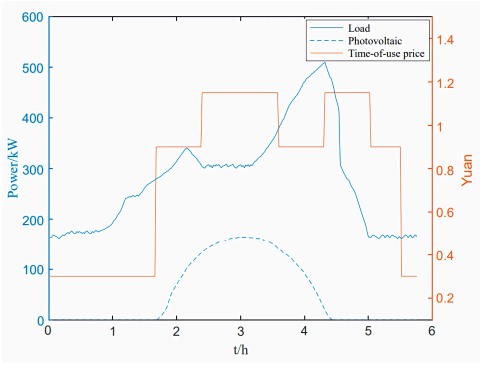


Figure 4. Conventional load, PV output, and TOU electricity price of microgrid.

Based on the actual charging data provided by the Adaptive Charging Network (ACN) laboratory in the United States, data for one randomly selected day are extracted and simulated in a time step of 5 min, with the adaptive particle swarm optimization algorithm employed at the intermediate level for the solution.

4.2. Simulation Analysis

To demonstrate the performance of the hierarchical optimal dispatching scheme for EVs in PV-storage charging stations, two simulation cases are defined here:

Case 1: Simulation of optimal dispatching for EVs in hierarchical PV-storage charging stations;

Case 2: Simulation of hierarchical optimization of PV-storage charging stations based on unordered charging.

(1) Simulation results of Case 1: The charging and discharging power, the energy storage power during charging and discharging, the load curves before and after microgrid dispatching, the voltage and current of the distribution network nodes, the network loss, and the SOC of the EV after dispatching in Case 1 are displayed in Figures 5–12.

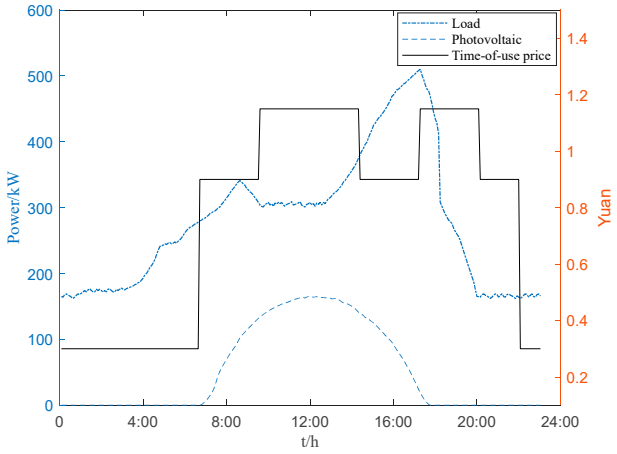


Figure 5. Charging load of EV before and after scheduling.

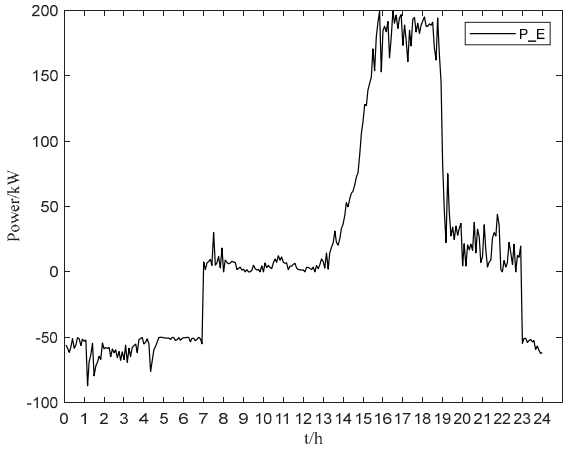


Figure 6. Charging and discharging power of energy storage.

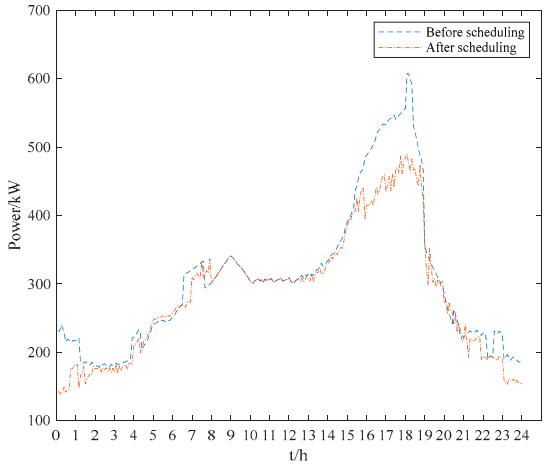


Figure 7. Load of microgrid before and after scheduling.

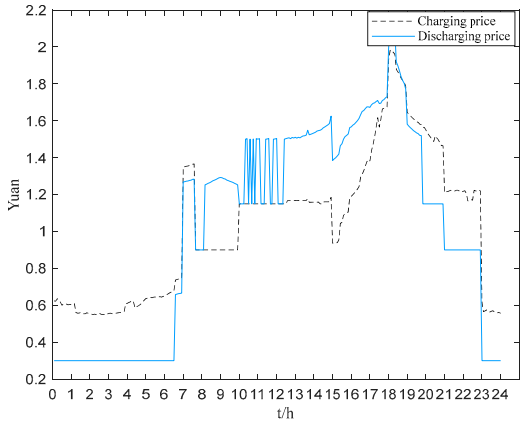


Figure 8. Real-time electricity price.

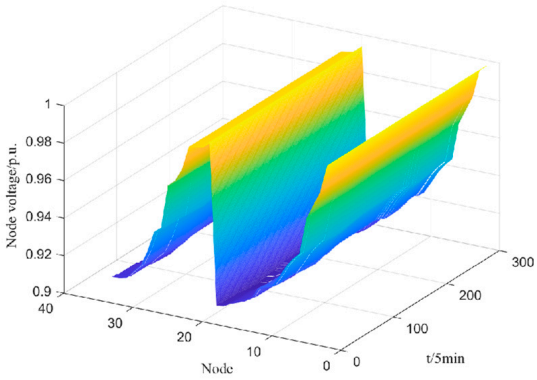


Figure 9. Voltage of distribution network nodes.

As seen from Figures 5 and 7, the peak load of the microgrid is mainly concentrated between 15:00 and 19:00. By controlling the discharge of EVs during this period, the power supply pressure on the microgrid is alleviated, achieving load peak shaving and reducing the load variance of the microgrid by 24.93%. It can be noted in Figure 6 that energy storage is charged during periods of low electricity prices and discharged during periods of flat or high prices, with the majority of discharging occurring between 15:00 and 19:00. This strategy effectively alleviates the power supply pressure on the microgrid and facilitates load peak-shifting. Figure 8 indicates a high dispatching demand for the PV-storage charging station from 13:00 to 20:00, with potential for significant profit from

discharging EVs during this period. Figures 9 and 10 demonstrate that neither the voltage nor the current of the distribution network nodes exceed their limits after optimization. Additionally, Figure 11 indicates that the collaborative optimization between the PV-storage charging station and the distribution network avoids sharp changes in network losses. Figure 12 illustrates that the dispatched EV charging can meet the travel demands of the owner.

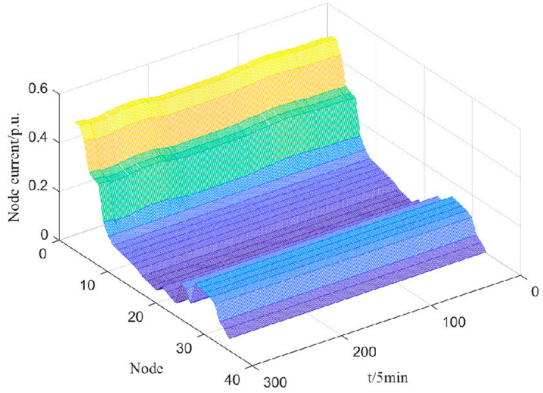


Figure 10. Current of distribution network nodes.

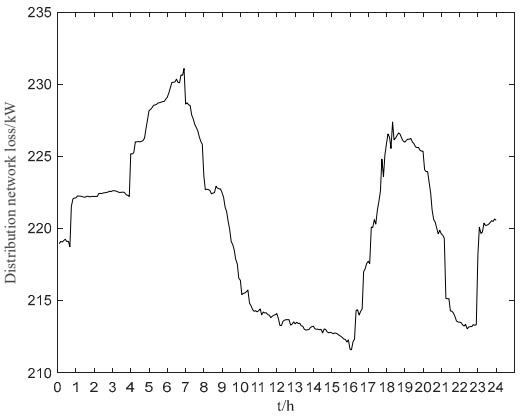


Figure 11. Network loss of distribution network.

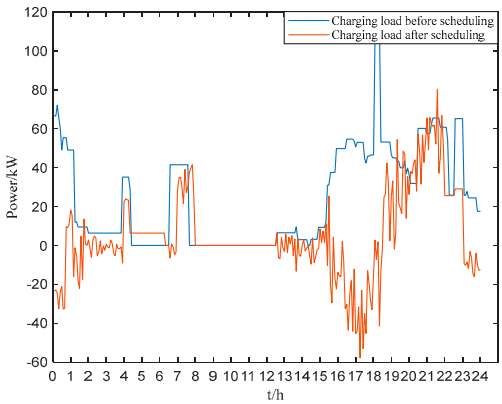


Figure 12. SOC of EV after scheduling.

(2) Simulation results of Case 2: The charging and discharging costs of EVs and the optimization cost of the microgrid are shown in Table 1.

Table 1. EV charging and discharging costs and micro-grid optimization costs.

	Orderly Charging and Discharging of EVs	Unorderly Charging of EVs
Cost of Charging and Discharging (CNY)	55.8842	724.6503
Microgrid Optimization Cost (CNY)	2.9827×10^3	4.4045×10^3

It can be observed from Table 1 that the orderly charging and discharging of EVs can significantly optimize the distribution network loss and reduce the charging cost of EVs and the optimization cost of the microgrid.

5. Conclusions

To address the challenges of the "curse of dimensionality" and slow solutions induced by extensive EV integration, this paper proposed a hierarchical charging and discharging optimization strategy for EVs based on PV-storage charging stations. This approach extends the findings of previous research [29] by incorporating a dynamic electricity pricing model and an adaptive particle swarm optimization algorithm, enabling charging stations to intelligently control and optimize EV charging and discharging based on real-time prices and demand through hierarchical management. The strategy can effectively realize peak shaving and valley filling, and significantly reduce the charging costs and microgrid losses of EVs. The simulation results show that the strategy can reduce microgrid losses by 32.28% and EV charging costs by 92.29% compared to unorganized charging. Additionally, this strategy can meet the travel demands of EV owners by providing convenient charging services. In order to further improve the efficiency of the EV power supply system, it is recommended that power system designers and logisticians consider the following measures: applying hierarchical charging and discharging optimization strategies, establishing EV charging demand forecasting models, and optimizing the layout of EV charging facilities.

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