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Coordinated Market Clearing and Operation for Virtual Power Plants with Multiple Electricity Commodities

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ABSTRACT: Virtual power plants (VPPs) serve as an effective means to aggregate and manage large-scale distributed energy resources (DERs). They can supply multiple electricity commodities—including electric energy, reserve capacity, and carbon allowances—to power systems. This paper proposes a coordinated market clearing and operation (CMCO) method for VPPs involved in trading multiple electricity commodities. First, we establish a bi-level CMCO framework that integrates the energy, reserve, and carbon markets. At the upper level, we build a distribution system decision model designed to minimize the total system costs, which cover wholesale market transactions and trades between VPPs involving various commodities. At the lower level, we construct a VPP operation model to optimize DER operation strategies and multi-commodity trading plans. Transactions between different VPPs follow a peer-to-peer (P2P) structure. This bi-level framework enables coordinated optimization of multi-commodity trading and operational decision-making. To efficiently solve the bi-level model with binary variables while protecting VPP privacy, we develop a distributed algorithm combining the dichotomy method and the alternating direction method of multipliers (ADMM). Numerical simulations on a test system with three VPPs verify that the proposed method reduces operational costs by facilitating multi-commodity trading. The results also show that this approach improves DER utilization and supports the low-carbon transition of power systems.

KEYWORDS: Virtual power plant (VPP); electricity market; coordinated trading and operation; multiple electricity commodities

1 Introduction

The new-generation power system is evolving toward low-carbonization and digitalization, with widespread integration of distributed energy resources (DERs) such as photovoltaics (PV), wind turbines (WT), and energy storage systems (ESS) [1]. The large-scale, decentralized integration of DERs—characterized by the random and intermittent nature of their power output—has raised multiple challenges for the safe and stable operation of power systems, including drastically increased regulatory complexity and operational uncertainty. Virtual power plants (VPPs), which aggregate various types and large quantities of DERs to participate in power system operation and market transactions as a unified entity, serve as an effective solution to these challenges and help unlock the regulatory potential of DERs [2]. Meanwhile, the ongoing deepening of electricity market reforms has led to the gradual establishment and refinement of both energy markets and ancillary service markets. This has laid an essential commercial foundation for VPPs to engage in market trading and realize both economic and environmental value.

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VPPs have emerged as key participants in the electricity market, attracting growing scholarly attention to their operational and trading strategies. Reference [3] develops an optimal dispatch model that accounts for both aggregated consumer satisfaction and VPP benefits, solving it via an improved particle swarm optimization (PSO) algorithm and verifying its effectiveness in DER aggregation and utilization. Reference [4] explores VPP operations and transactions in the medium- and long-term electricity market, establishing a medium- and long-term contract trading model that allocates contracted electricity volumes over specified timeframes. Reference [5] proposes a three-dimensional market framework for VPPs that considers DER aggregation, value creation, and risk management, adopting robust optimization to balance risks and revenues under uncertain conditions. Reference [6] presents an adaptive economic dispatch method tailored to VPP operational status, achieving coordinated optimization of large-scale DERs through a fully distributed algorithm. Reference [7] puts forward an optimal bidding strategy based on a stochastic bi-level framework, which jointly determines electricity market bidding schemes and locational marginal prices. While these studies provide valuable theoretical support and practical guidance for VPPs to improve profitability in the electricity market, they primarily focus on VPPs that only supply electrical energy to the grid. With the rising penetration of renewable energy, the safe and stable operation of power systems is placing higher demands on flexible resources. A sole focus on energy supply can no longer meet the diverse needs of the new-generation power system, making it imperative for VPPs to provide ancillary services.

The uncertain and intermittent power output of renewable energy sources has made power system operation more dynamic and variable, thus requiring greater reserve capacity to maintain real-time power balance and stability [8]. VPPs are capable of providing reserve services such as peak shaving and spinning reserve, thereby effectively enhancing power system flexibility [9,10]. Reference [11] establishes a chance-constrained joint energy and reserve trading model for VPPs, taking into account the decentralized transaction characteristics of DERs. This model provides a quantitative basis for multiple stakeholders to formulate market transaction strategies and offers theoretical references for regulators to improve market inclusiveness. Reference [12] proposes a day-ahead energy and reserve optimization method based on information gap decision theory, which maximizes VPP revenues by optimizing energy and reserve allocation under uncertainty. Reference [13] develops a two-stage stochastic programming model for VPPs participating in day-ahead energy and ancillary service markets, paired with an internal resource scheduling strategy to optimize benefits. Reference [14] builds a systematic framework for VPPs to participate in energy and reserve markets via auction mechanisms over medium- and long-term horizons, considering auction rules, resource complementarity, and market prices. These studies demonstrate that VPPs supplying both electricity and reserve services not only strengthen the risk management capabilities of power systems but also boost the revenues of stakeholders. Therefore, the joint trading of electricity and reserve services incentivizes VPPs to actively participate in system regulation and fully exploit the potential of DERs in supporting grid operation.

Low-carbon transition has become a core trend in the development of new-generation power systems, and the introduction of carbon trading has opened up a new feasible pathway for this transition in energy consumption. Renewable energy resources such as PV and WT are key components of VPPs, providing the economic and technical foundation for VPPs to participate in carbon trading. At present, carbon emission rights trading mechanisms have gradually matured in some countries, laying a viable foundation for flexible transactions in the carbon market [15,16]. Reference [17] develops a low-carbon economic dispatch model for VPPs that integrates carbon trading constraints and green certificate system incentives, achieving the dual goals of economic efficiency and low-carbon operation. Reference [18] presents a multi-objective optimization model incorporating demand response, tiered carbon trading, and hydrogen utilization, which synergistically improves both operational economy and carbon emission reduction performance and offers an innovative, practical scheduling solution for low-carbon transition. Reference [19] explores coordination strategies for linking electricity and carbon markets, providing theoretical support and practical pathways to address market fragmentation. Reference [20] proposes an electricity-carbon interactive optimal dispatch model for VPPs that incorporates integrated demand response, coordinating multiple VPPs under a coupled electricity-carbon market framework to enhance operational flexibility and reduce carbon emissions. However, most existing studies separately address electricity-reserve trading and electricity-carbon coupling, lacking a comprehensive framework that integrates carbon trading into the multi-market participation of VPPs. The synergistic optimization of energy, reserve, and carbon markets remains understudied, which limits VPPs' ability to leverage their full flexibility for cost-effective low-carbon operation.

As power system structures and electricity market mechanisms continue to evolve, individual VPPs face constraints due to their limited adjustable resources [21], which restricts their ability to fully exert their regulatory functions [22,23]. In scenarios where different VPPs belong to distinct stakeholders, peer-to-peer (P2P) trading methods demonstrate high applicability and effectiveness for transactions between VPPs, in light of market fairness considerations [24,25]. Reference [26] investigates distributed P2P trading among multiple VPPs, integrating copula-CVaR theory and trading preferences to develop a risk-controllable practical solution for coordinated energy and carbon trading. Reference [27] proposes a transactive energy framework to coordinate energy trading among multiple stakeholders. Reference [28] designs a distributed solution algorithm based on dual decomposition theory for P2P trading, which achieves market clearing without centralized coordination or the disclosure of private information, thus preserving the autonomy and privacy of individual participants. Reference [29] addresses P2P energy trading between VPPs, adopting a stochastic game approach to construct the trading model. Reference [30] puts forward a coordinated optimization method for bidding, market clearing, and scheduling, which maximizes revenues and balances risks while providing decision support for hydro-wind-PV alliances to adapt efficiently to the electricity spot market. In summary, the P2P trading architecture offers significant advantages for the collaborative operation of multiple VPPs by ensuring market fairness and protecting commercial privacy, thus holding broad application prospects in future electricity markets. Distributed optimization algorithms are critical to fully leveraging the privacy protection benefits of the P2P architecture, as they enable VPPs to achieve global optimization through minimal information exchange without disclosing internal operational parameters to central authorities. Therefore, developing efficient distributed algorithms is essential to promote the application of VPPs in multi-commodity electricity trading.

A review of existing literature reveals that with the continuous evolution of VPP transaction mechanisms in electricity markets, the range of commodities traded by VPPs has become increasingly diversified, covering electrical energy, reserve capacity, and carbon allowances. Given the close coupling between VPP trading activities and operational processes, it is essential to develop a coordinated approach that integrates multi-commodity market trading with operational scheduling. Against this backdrop, this paper proposes a coordinated trading and operation method for VPPs engaging in multi-commodity electricity transactions. The main research contributions are summarized as follows:

(1) The coordinated market clearing and operation framework with multiple electricity commodities: A comprehensive framework coordinating market clearing and operational scheduling with multiple electricity commodities is established, which incorporates a P2P architecture enabling direct transactions among VPPs. This framework provides a systematic approach for VPPs to participate in diversified electricity markets while ensuring distributed decision-making.
(2) The bi-level coordinated clearing and operation model with multiple electricity commodities: A bi-level optimization model explicitly incorporating electricity energy, reserve, and carbon allowance is established. In the upper-level, the distribution system decision model is established to minimize the

total costs including the wholesale market and VPPs' trading with consideration of multiple electricity commodities. In the lower-level, the VPPs' operation model with energy trading decisions and DERs operation decisions are determined. This structure achieves coordinated optimization between the trading and operational stages.

(3) An efficient distributed solution algorithm: A two-stage distributed algorithm is developed by integrating the dichotomy method and alternating direction method of multipliers (ADMM). The dichotomy method efficiently addresses the computational challenges posed by binary variables in the bi-level model, and ADMM enables distributed solution implementation that preserves the operational privacy and commercial confidentiality of all participating VPPs.

2 The Coordinated Market Clearing and Operation Framework for VPPs with Multiple Electricity Commodities

The VPP aggregates various types of DERs with diverse operation characteristics and different response time scales, thus it can provide multiple electricity commodities as power energy, reserve and carbon trading to the power system. In the fair electricity market transactions, each VPP can trade with the distribution system (DS) and other VPPs freely. In this paper, the coordinated market clearing and operation framework for VPPs with multiple electricity commodities is established as shown in Fig. 1.

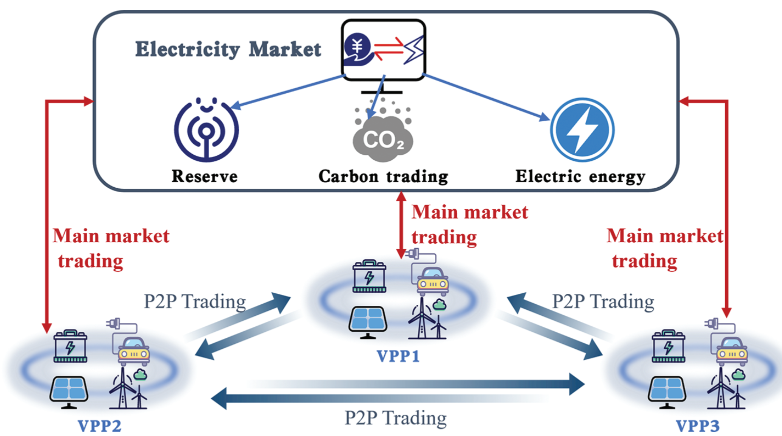


Figure 1: The coordinated market clearing and operation framework for VPPs.

The proposed coordinated framework is formulated in a bi-level structure with coupling of the energy market, reserve market and carbon trading market. In the upper-level, the DS participates in the wholesale market and trades with the multiple VPPs simultaneously, to determine the price of multiple electricity commodities based on its operation status and collecting the trading requirements from the VPPs. Thus, the multiple electricity markets clearing is conducted coordinately and the optimal trading decisions and operation boundary are obtained. In the lower-level, the multiple VPPs receive the price signals from the upper-level, and then optimize the trading volume of multiple electricity commodities and operation strategies of aggregated DERs meanwhile. Moreover, as the operation status of different VPP is always different which leads to the energy surplus or shortage status is also different. Then, the energy trading between different VPPs is implemented in a P2P structure. To be specific, the VPP that has power surplus can sell electricity or carbon emission to other VPPs or the DS while the VPP faces energy shortage can trade with other VPPs or the DS. Ultimately, the trading and operation for multiple VPPs and the DS can be achieved coordinately through bidirectional information exchange and closed-loop feedback between the upper and lower levels with the established framework.

3 Bi-Level Market Clearing and Operation Model Considering Multiple Electricity Commodities

The DS has the authority to determine the prices of multiple electricity commodities in trading with multiple VPPs. Meanwhile, the unreasonable pricing will bring negative influence as reducing transaction volume, which also reduces the total revenue. Therefore, with the aim of maximizing the total revenue for the DS and multiple VPPs, a bi-level market clearing and operation model is built based on the established bi-level framework.

3.1 Upper-Level: Distribution System Decision Model

In the upper-level, the DS sets the price signals based on its operation status and the trading requirements from multiple VPPs, while the VPP responds to the price signals by adjusting the multiple electricity commodities volumes in the lower-level. Through multiple iterations, the market equilibrium solution that maximizes the total benefits can be achieved. Then, in the upper-level, the DS aims to minimize its costs which include the multiple electricity commodities transaction costs in the wholesale market and with VPPs. In this paper, the costs are the actual costs minus the revenue. As for both the wholesale market and trading with VPPs, the cost of DS includes the electricity energy trading costs, reserve trading costs and carbon trading costs.

(1) Electricity Energy Trading Costs of DS in Wholesale Market

The electricity energy trading costs of DS in the wholesale market is established as below:

$$C_t^{EDSO} = \lambda_t^{EWMB} P_t^{EWMB} - \lambda_t^{EWMS} P_t^{EWMS} \tag{1}$$

where C_t^{EDSO} shows the total electricity energy trading costs in the wholesale market at time t, λ_t^{EWMB} and P_t^{EWMB} reflects the price and volume of DS purchase electricity in the wholesale market, λ_t^{EWMS} and P_t^{EWMS} shows the prices and amount of DS sell electricity in the wholesale market.

(2) Reserve Revenue of DS in Wholesale Market

The reserve revenue of DSO participating in the wholesale market is shown as below:

$$R_t^{RDSO} = \lambda_t^{RWM} R_t^{RWM} \tag{2}$$

where R_t^{RDSO} shows the revenue of DS selling reserve in the wholesale market, λ_t^{RWM} and R_t^{RWM} reflects the price and amount for reserve.

(3) Carbon Trading Costs of DS in Wholesale Market

The carbon trading cost of DS participating in wholesale market is shown as below:

$$C_t^{CDSO} = \lambda_t^{CWMB} E_t^{CWMB} - \lambda_t^{CWMS} E_t^{CWMS} \tag{3}$$

where C_t^{CDSO} shows the total carbon trading cost of DS in wholesale market, λ_t^{CWMB} and λ_t^{CWMS} shows the carbon emission purchase and sales price while E_t^{CWMB} and E_t^{CWMS} reflects the carbon emission purchase and sales amount.

(4) Electricity Energy Trading Revenue of DS with VPPs

The DS also trades electricity energy with the VPPs, and the corresponding revenue is shown as below:

$$R_t^{EDSO} = \lambda_t^{EVPPS} P_t^{EVPPS} - \lambda_t^{EVPPB} P_t^{EVPPB} \tag{4}$$

where R_t^{EDSO} shows the electricity energy revenue of DSO trading with VPP, λ_t^{EVPPS} and λ_t^{EVPPB} reflects the electricity energy sales and purchase prices while P_t^{EVPPS} and P_t^{EVPPB} shows the volume of electricity energy sale and purchase.

(5) Reserve Trading Cost of DS with VPPs

As for the reserve trading, the cost of DS purchase from VPP is established as below:

$$C_t^{RDSO} = \lambda_t^{RVB} R_t^{RVB} - \lambda_t^{RVS} R_t^{RVS} \tag{5}$$

where C_t^{RDSO} shows the cost of DS purchasing reserve from VPPs, λ_t^{RVB} and λ_t^{RVS} represents the reserve price for DS purchasing and selling with VPP while R_t^{RVB} and R_t^{RVS} reflect the corresponding volume for reserve for DSO trading with VPPs.

(6) Carbon Trading Cost of DS with VPPs

The carbon trading cost of DS with VPPs is shown as below:

$$C_t^{CDSV} = \lambda_t^{CVB} E_t^{CVB} - \lambda_t^{CVS} E_t^{CVS} \tag{6}$$

where C_t^{CDSV}shows the carbon trading cost of DS with VPPs, λ_t^{CVB} and λ_t^{CVS} shows the carbon purchase and sales price for DSO with VPP while E_t^{CVB} and E_t^{CVS} reflects the corresponding carbon purchase and sales volume.

Based on above analysis, the objective function of DS decision is shown as below:

$$\min C^{DSO} = \sum_{t=1}^{T} \left(C_t^{EDSO} + C_t^{RDSO} + C_t^{CDSO} + C_t^{CDSV} - R_t^{EDSO} - R_t^{RDSO} \right) \tag{7}$$

In the bi-level multiple electricity commodities trading, the DS can get revenues with the prices margin. Then, the price of multiple electricity commodities for DS with VPP can be set as below:

$$\lambda_t^{e,r,VPP,\min} \le \lambda_t^{e,r,VPP} \le \lambda_t^{e,r,VPP,\max} \tag{8}$$

$$\lambda_t^{e,buy,VPP} \le \lambda_t^{e,sell,VPP} \tag{9}$$

where $\lambda_t^{e,r,VPP}$ shows the multiple electricity commodities for DS trading with VPP where e represents the types of electricity commodities including electricity energy, reserve and carbon trading, r represents the role of DS as the buyer or seller. $\lambda_t^{e,r,VPP,\min}$ and $\lambda_t^{e,r,VPP,\max}$ represents the maximum or minimum value of the price. $\lambda_t^{e,buy,VPP}$ and $\lambda_t^{e,sell,VPP}$ represent the prices of DS purchase and sell electricity commodity with the VPP, respectively.

Moreover, the energy balance should also be satisfied as below:

$$\sum_{i \in N^{VPP}} P_t^{EVPPB} + P_t^{EWMB} + P_t^{G} = P_t^{D} + P_t^{EWMS} + \sum_{i \in N^{VPP}} P_t^{EVPPS} \tag{10}$$

$$R_t^{RWM} = \sum_{i \in N^{VPP}} R_{i.t}^{RVPP} \tag{11}$$

where N^{VPP} represent the set of VPPs and i shows the index of VPP, P_t^{G} shows the total power generation for DS such as the WT and PV, P_t^{D} represents the total load demand.

3.2 Lower-Level: VPP's Operation Model with Multiple Electricity Commodities Trading

In the lower-level, the VPP receive the price signals from the DS based on upper-level optimization, then the VPP optimize its multiple electricity commodities trading decisions and DERs scheduling decisions simultaneously with the aim of minimizing its costs.

3.2.1 Objective Function

During the market clearing, the objective function is to minimize the total cost of all the market participants. As for each VPP, the cost includes the electricity energy trading costs, reserve trading cost, carbon trading costs and devices dispatch costs such as ESS. Then, the objective function is established as follows:

$$\min C_{i,t}^{VPP} = C_{i,t}^{TRDS} + C_{i,t}^{TRVPP} + C_{i,t}^{C} + C_{i,t}^{R} + C_{i,t}^{ESS} \tag{12}$$

$$C_{i,t}^{TRDS} = \lambda_t^{EVPPB} P_{i,t}^{EVPPB} - \lambda_t^{EVPPS} P_{i,t}^{EVPPS} \tag{13}$$

$$C_{i,t}^{TRVPP} = \lambda_t^{EVPPBV} P_{i,t}^{EVPPBV} - \lambda_t^{EVPPSV} P_{i,t}^{EVPPSV} \tag{14}$$

$$C_{i,t}^{R} = \lambda_t^{RVPPB} R_{i,t}^{RVPPB} - \lambda_t^{RVPPS} R_{i,t}^{RVPPS} \tag{15}$$

$$C_{i,t}^{C} = \lambda_t^{CVPPB} E_{i,t}^{CVPPB} - \lambda_t^{CVPPS} E_{i,t}^{CVPPS} \tag{16}$$

$$C_{i,t}^{ESS} = c^{ESS} \left(P_{i,t}^{CHA} \cdot \eta + P_{i,t}^{DIS} / \eta \right) \tag{17}$$

where $C_{i,t}^{VPP}$ shows the total cost of VPP i at time t, $C_{i,t}^{TRDS}$ represents the electricity energy trading costs for VPP with DS, $C_{i,t}^{TRVPP}$ represents the electricity energy trading costs for VPP with other VPPs, $C_{i,t}^{R}$ shows the reserve trading costs, $C_{i,t}^{C}$ shows the carbon trading cost, $C_{i,t}^{ESS}$ represents the ESS operation costs. λ_t^{EVPPB} and λ_t^{EVPPS} shows the electricity energy prices for VPP purchase and sales with the DS, $P_{i,t}^{EVPPB}$ and $P_{i,t}^{EVPPS}$ shows the electricity volume for VPP buying and selling with the DS, λ_t^{EVPPBV} and λ_t^{EVPPSV} shows the electricity energy prices for VPP i purchase and sale with other VPPs, $P_{i,t}^{EVPPBV}$ and $P_{i,t}^{EVPPSV}$ represent the electricity energy amount for VPP i purchase and sale with other VPPs. λ_t^{RVPPB} and λ_t^{RVPPS} represent the reserve purchase and sale prices for VPP with DS, $R_{i,t}^{RVPPB}$ and $R_{i,t}^{RVPPS}$ represent the corresponding reserve purchase and sale volume. $\lambda_{i,t}^{CVPPB}$ and λ_t^{CVPPS} shows the carbon emission purchase and sales price for VPP in the carbon market while E_t^{CVPPB} and E_t^{CVPPS} represents the corresponding carbon allowances for VPP i at time t. $P_{i,t}^{CHA}$ and $P_{i,t}^{DIS}$ represent the sets of charging and discharging power of the ESS within the VPP over the dispatch cycle, respectively, c^{ESS} shows the cost of ESS and η shows efficiency.

3.2.2 Reserve Capacity Balance Constraint

The reserve capacity provided by ESS and load curtailment must meet the reserve capacity requirement of the VPP. Simultaneously, the reserve capacity provided by VPP is limited within the trading scope, then the specific constraints are as follows:

$$R_{i,t}^{RVPPB} - R_{i,t}^{RVPPS} + R_{i,t}^{ESS} + R_{i,t}^{DC} \geq R_{i,t}^{VPP,req} \tag{18}$$

$$R_{i,t}^{ESS} \leq E_{i,t} - P_{i,t}^{DIS} / \eta + P_i^{CHA} \cdot \eta \tag{19}$$

$$R_{i,t}^{VPP,req} = \varpi P_{i,t}^{VPP,D} \tag{20}$$

where $R_{i,t}^{ESS}$ shows the reserve capacity that can be provided by ESS at time t, $R_{i,t}^{DC}$ represents the reserve capacity from flexible load curtailment, $R_{i,t}^{VPP,req}$ is the reserve requirement of VPP i, $E_{i,t}$ is the current electricity amount of ESS at time t, ϖ represents the reserve demand coefficient.

3.2.3 Carbon Quota Balance Constraint

Analyzing from the contribution of carbon emission for VPP, it primarily generates from two pathways: (1) the direct carbon emissions generated by the devises such as micro turbines aggregated in the VPP; (2) the indirect carbon emission associated with the electricity purchase from the DS, attributable to the generation side (e.g., coal-fired and gas-fired generation). In this paper, only the PV, WT, ESS and flexible loads are aggregated in the VPP, then only the carbon emission for VPP trading with DS is considered. Consequently, the carbon allowance transactions conducted by the VPP in the carbon market should satisfy the following carbon emission-related constraints:

$$E_{i,t}^{CVPPB} - E_{i,t}^{CVPPS} + C_{i,t}^{VPP,\max} \geq C_{i,t}^{VPP,WS} \tag{21}$$

$$C_{i,t}^{WS} = \rho P_{i,t}^{EVPPB} \tag{22}$$

$$C_{i,t}^{\max} = \sigma P_{i,t}^{VPP,D} \tag{23}$$

where $C_{i,t}^{VPP,\max}$ represents the carbon emission quota limitation for VPP i, $C_{i,t}^{VPP,WS}$ is the carbon emission amount for VPP i at time t, ρ represents the carbon emission factor for purchased electricity is the unit carbon quota coefficient for load, $P_{i,t}^{VPP,D}$ shows the load demand for VPP i at time t.

3.2.4 Power Balance Constraint

As for the VPP, the power balance constraint including power generation, consumption and multiple electricity commodities trading, then the power balance constraint requires to be satisfied. The power balance is shown as below:

$$P_{i,t}^{WT} + P_{i,t}^{PV} + P_{i,t}^{DIS}/\eta + P_{i,t}^{EVPPB} + P_{i,t}^{EVPPBV} + P_{i,t}^{DC} = P_{i,t}^{VPP,D} + P_{i,t}^{CHA}\eta + P_{i,t}^{EVPPSV} + P_{i,t}^{EVPPS} \tag{24}$$

where $P_{i,t}^{WT}$ and $P_{i,t}^{PV}$ represents the active power supplied by WT and PV, respectively, $P_{i,t}^{DC}$ shows the load curtailment.

3.2.5 Devices Operation Constraints

The ESS is core devices aggregated in the VPP, then the operation constraints are shown as below:

$$\begin{cases} 0 \leq P_{i,t}^{CHA} \leq S_{i,t}^{CHA} \cdot P_i^{CHA\max} \\ 0 \leq P_{i,t}^{DIS} \leq S_{i,t}^{DIS} \cdot P_i^{DIS\max} \\ 0 \leq S_{i,t}^{CHA} + S_{i,t}^{DIS} \leq 1 \\ E_{i,t}^{ESS\min} \leq E_{i,t}^{e} + P_{i,t}^{CHA} \cdot \eta - P_{i,t}^{DIS}/\eta \leq E_{i,t}^{ESS\max} \\ E_{i,t}^{e} = E_{i,t-1}^{e} + \eta P_{i,t}^{CHA} - P_{i,t}^{DIS}/\eta \\ E_{i,1}^{e} = E_{i,24}^{e} \end{cases} \tag{25}$$

where $S_{i,t}^{CHA}$ and $S_{i,t}^{DIS}$ are the binary variables corresponding to the ESS charge and discharge, $E_{i,t}^{ESS\min}$ and $E_{i,t}^{ESS\max}$ show the lower and upper limitations for ESS capacity, $E_{i,t}^{e}$ is the ESS capacity at time t.

When load demand suddenly increases, partial load curtailment can be implemented to ensure the power supply-demand balance of the VPP. The load curtailment constraint is as follows:

$$0 \leq P_{i,t}^{DC} \leq \theta \cdot P_{i,t}^{VPP,D} \tag{26}$$

where θ represents the load curtailment coefficient.

4 Solution Algorithm

The established coordinated trading and operation model is formulated in a bi-level structure, and the DS send price signals to the VPPs from the upper-level while the VPP determines its operation and trading decision in the lower-level. Moreover, multiple VPPs trade with each other in the lower-level with a P2P framework. With the aim of solving the model effectively and protecting the operation privacy, the distributed solution method which integrates the dichotomy and alternating direction method of multipliers (ADMM) is proposed.

4.1 Bi-Level Trading and Operation Solution Strategy Based on Dichotomy

The established coordinated market clearing and operation model is a bi-level model with binary variables. Generally, the bi-level model can be solved via the Karush-Kuhn-Tucker (KKT) condition to transfer the bi-level problem into signal level problem. As for the KKT condition, it is restricted in solving problem with binary variables. Meanwhile, it requires the operation and trading information of all the market participants including the DS and VPPs, which cannot protect the information privacy. Then, a distributed solution strategy based on dichotomy is utilized in this paper. During the trading procedure, the upper-level DS formulates decisions to minimize the costs and generate price signals based on the VPP's trading requirement, while the lower-level VPP respond to the price signals and optimize its trading and operation decisions. The information communication between these two levels are conducted as the DS send price signals to the VPPs and the VPPs report the multiple electricity commodities trading amount to the DS, and after several rounds of interactive iteration, the model can be solved.

The dichotomy is an iterative solving method that dynamically determines variable search boundaries by analyzing the difference between the results of upper-level and lower-level, then gradually narrowing the feasible region of the optimal solution, and finally achieving the optimal solution. The detailed solving flowchart of the dichotomy method can be referred to in Fig. 2.

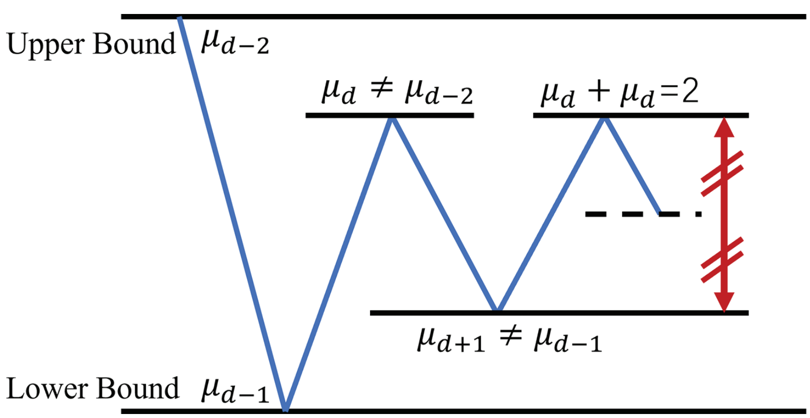


Figure 2: Schematic diagram of the dichotomy.

As shown in Fig. 2, the detailed solution procedure is shown as below:

(1) Parameters Initialization:

Set the algorithm convergence tolerance ε^d, and input the multiple electricity commodities trading prices as $\lambda_t^{e,r,VPP,k-1}$ and $\lambda_t^{e,r,VPP,k-2}$ between DS and VPP at the $(k-1)$-th and $(k-2)$-th iterations, respectively. Input the multiple electricity commodities trading volumes. Set the lower and upper limits of VPP trading with DS as $\lambda_t^{e,r,VPP,\min}$ and $\lambda_t^{e,r,VPP,\max}$.

(2) Multiple Electricity Commodities Prices Update:

Based on the multiple electricity commodities trading volume reported via the VPP in (k − 1)-th iteration, the upper-level model as Eqs. (1)–(11) is solved to renew the k-th iteration trading price $\lambda_t^{e,r,VPP,k}$.

(3) Multiple Electricity Commodities Volume Update:

Based on the k-th iteration multiple electricity commodities trading price $\lambda_t^{e,r,VPP,k}$, the lower-level model as Eqs. (12)–(25) is solved to renew the k-th iteration trading volume between DS and VPPs. Moreover, with consideration of P2P trading between different VPPs, the ADMM is utilized in this step.

(4) Add Constraints:

If $\lambda_t^{e,r,VPP,k} = \lambda_t^{e,r,VPP,k-2}$, then set $\lambda_t^{e,r,VPP,k} = \left(\lambda_t^{e,r,VPP,k-1} + \lambda_t^{e,r,VPP,k-1}\right)/2$; otherwise, compare the trading prices between the k-th and (k − 1)-th iterations, and set the smaller upper bound as the upper bound in next iteration and set the bigger lower bound as the lower bound in next iteration.

(5) Convergence Check:

If it satisfies $\left(\lambda_t^{e,r,VPP,k} - \lambda_t^{e,r,VPP,k-1}\right)/\lambda_t^{e,r,VPP,k} \le \varepsilon^d$, stop the iteration. Otherwise, update the iteration index $k = k + 1$ and return to step (1) until the convergence conditions are met.

It should be noted that, during the solution procedure of multiple electricity commodities volume update, the multiple VPPs' operation model is solved in distributed pattern via the ADMM. And the detailed solution procedure is illustrated in next section.

4.2 The Distributed Solution Strategy for the Lower-Level Model

At the lower-level, the VPP engage in transaction with the DS and with other VPPs in a P2P scheme, then only the trading prices and volume are the globally coupled constraints. The other constraints such as DERs operation constraints or energy balance constraints are mutually independent. The traditional centralized solution algorithm has limitations as its slow solution procedure or the privacy protection, the ADMM is utilized to solve the lower-level model. The augmented Lagrangian function is established as below:

$$\min L_{i,t}\left(\boldsymbol{x}_{i,t}, \boldsymbol{u}_{i,t}, \boldsymbol{\lambda}_{i,t}\right) = \min \sum_{i=1}^{T}\left[C_{i,t}^{VPP}\left(\boldsymbol{x}_{i,t}\right) + \sum_{j\in\Omega_{VPP}\setminus i}\left\{\boldsymbol{\lambda}_{i,t}^{T}\left(\boldsymbol{x}_{ij,t} - \boldsymbol{u}_{ij,t}\right) + \frac{\rho}{2}\left\|\boldsymbol{x}_{ij,t} - \boldsymbol{u}_{ij,t}\right\|_2^2\right\}\right] \tag{27}$$

where $\boldsymbol{x}_{i,t}$ is the decision variables in the lower-level VPP operation model, $\boldsymbol{u}_{i,t}$ is the auxiliary variables including P2P trading prices and amount, $\boldsymbol{\lambda}_{i,t}$ is the dual variables represents the shadow electricity price, ρ is the penalty parameter. Then, the solution procedure can be illustrated as follows.

(1) Parameter Initialization:

Initialize the iteration count $k = 1$, set the auxiliary and dual variables, the penalty parameter and the algorithm convergence tolerance.

(2) Decision Variable Update:

Based on the parameters from step (1), the decision variables can be updated as follows:

$$\boldsymbol{x}_{i,t} = \arg\min L_{i,t}\left(\boldsymbol{x}_{i,t}, \boldsymbol{u}_{i,t}^{k-1}, \boldsymbol{\lambda}_{i,t}^{k-1}\right) \tag{28}$$

(3) Auxiliary Variable Update:

Then update the auxiliary variable based on the following equation:

$$\boldsymbol{u}_{i,t}^{k} = \frac{\boldsymbol{x}_{ij,t}^{k} - \boldsymbol{x}_{ji,t}^{k}}{2} + \frac{\boldsymbol{\lambda}_{i,t}^{k-1} - \boldsymbol{\lambda}_{i,t}^{k-1}}{2\rho_t} \tag{29}$$

where $\boldsymbol{x}_{ij,t}^{k}$ and $\boldsymbol{x}_{ji,t}^{k}$ are the boundary condition variables.

(4) Dual Variable Update:

$$\boldsymbol{\lambda}_{i,t}^{k} = \boldsymbol{\lambda}_{i,t}^{k-1} + \rho\left(\boldsymbol{x}_{ij,t}^{k} - \boldsymbol{u}_{i,t}^{k}\right) \tag{30}$$

(5) Convergence Check:

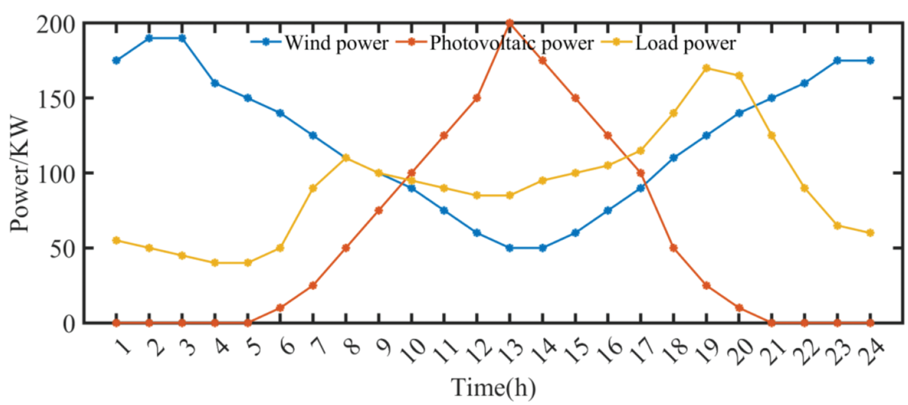
If both the primal residual and the dual residual are smaller than the termination tolerance, then the iteration is terminated; otherwise, update the iteration index and return to step (2) until the convergence conditions are met.

5 Case Study

To verify the effectiveness of the proposed coordinated market clearing and operation method for VPPs dealing with multiple electricity commodities, numerical simulations were conducted using MATLAB 2023. The problem was modeled using YALMIP and solved with the GUROBI 10.0 solver. All calculations were performed on a computer equipped with an Intel Core i7-12700H processor and 32 GB of memory.

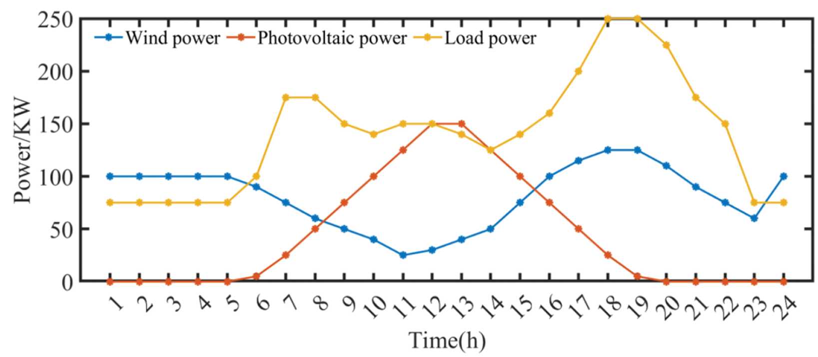
5.1 Test System Description

A test system containing three VPPs is constructed, and a series of simulation scenarios are designed. The simulation spans a 24-h scheduling horizon with an hourly time resolution. This section presents the key input data and system parameters used in the simulations. All parameters are configured based on typical daily operational profiles and publicly available market data to ensure the reproducibility and validity of the results. The predicted active power of WT, PV and load demand of the three VPPs are shown in Fig. 3 while specific values are listed in Table 1. These curves illustrate the temporal distribution and volatility characteristics of DERs throughout the day, providing a foundation for evaluating VPP trading and operation strategies. The simulation incorporates time-series price signals from three distinct markets as electricity energy, reserve and carbon trading. The carbon price is generated based on the trading prices of Chinese certified emission reductions. The operation and trading parameters are set in Table 2. These parameters constrain the scheduling capabilities and market behaviors of VPPs.

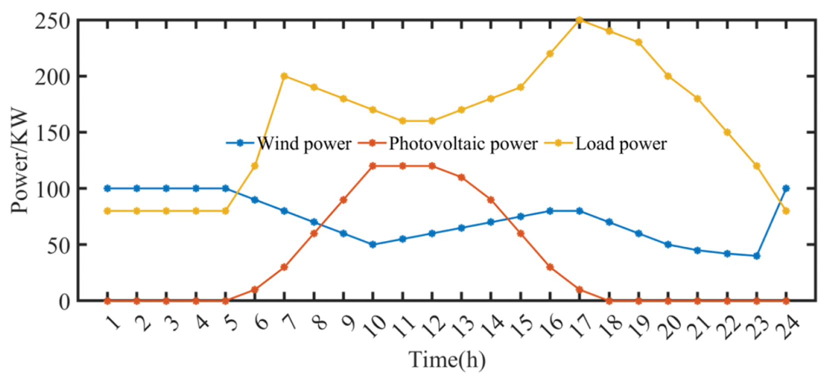


(**a**) VPP1

Figure 3: (Continued)



(**b**) VPP2



(**c**) VPP3

Figure 3: The predicted active power of WT, PV and load demand of the three VPPs.

Table 1: Installed capacity of WT, PV and maximum load within each VPP.

VPP	Wind Power Installed Capacity (kw)	Photovoltaic Installed Capacity (kw)	Maximum Electrical Load (kw)
VPP1	100	150	250
VPP2	110	112	128
VPP3	121	104	84

Table 2: Operation and trading parameters for VPPs.

Category	Parameter	Value
Energy Storage System (ESS)	Rated Capacity (kWh)	500
	Maximum Charging/Discharging Power (kW)	200
	Charging/Discharging Efficiency (%)	0.95
	Operating Cost Coefficient (CNY/kWh)	0.1
	SOC Operating Lower/Upper Limit (%)	10%, 90%
	SOC Operating Lower/Upper Limit(kW)	10%, 90%
Network and Trading Constraints	Maximum Trading Power with DS (kW)	200
	Maximum P2P Trading Power Among VPPs (kW)	100

(Continued)

Table 2 (continued)

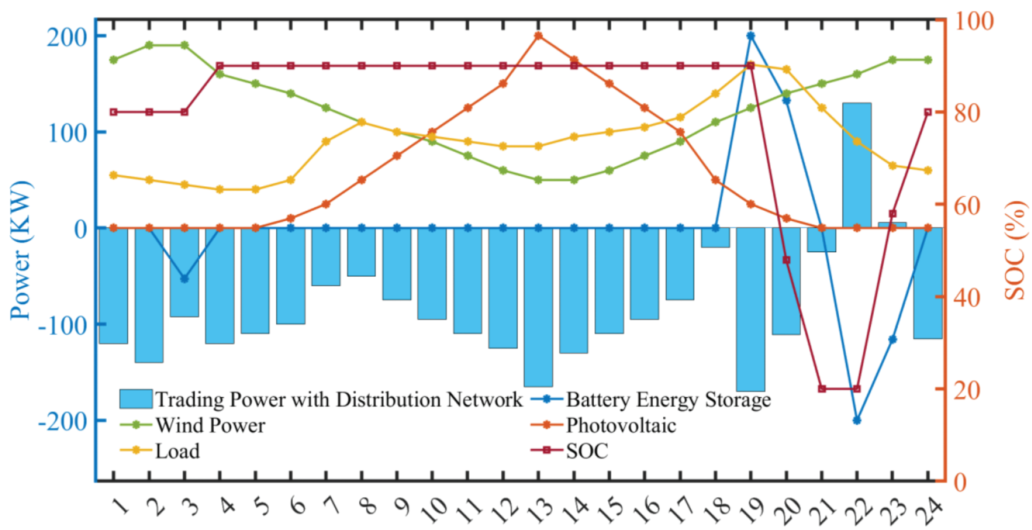
Category	Parameter	Value
Carbon Market Related	Carbon Emission Coefficient (Power Purchase) (kg/kWh)	0.5
	Initial Carbon Quota Ratio Coefficient	0.3
Load and Reserve	Unit Penalty Cost for Load Curtailment (CNY/kWh)	100
	Upper Limit of Load Curtailment Coefficient (%)	20
	Reserve Demand Coefficient (%)	10

5.2 Single Electricity Energy Trading Scenario

(1) Scenario EETI: Electricity Energy Trading in Independent Mode

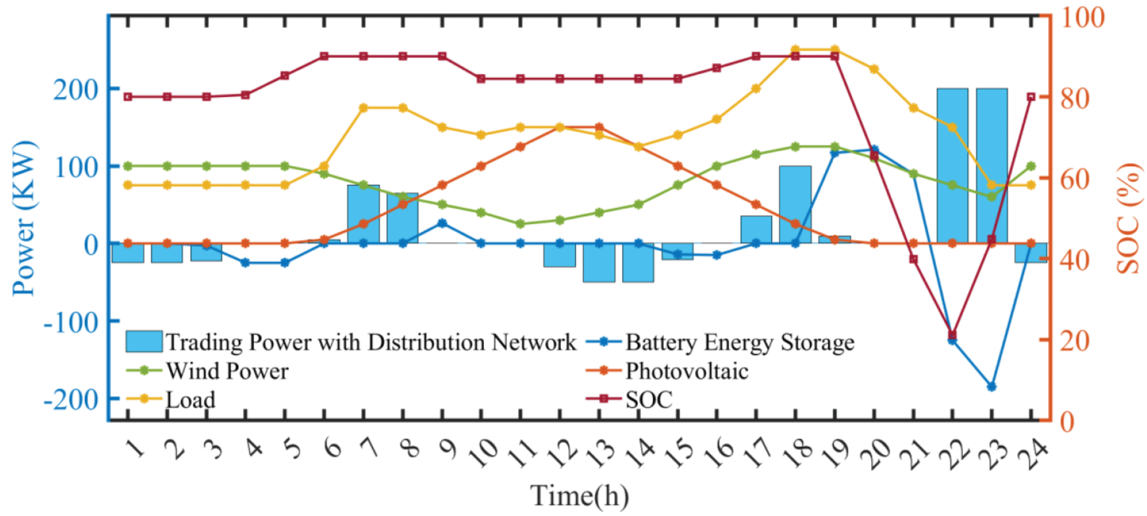
In this scenario, the VPPs operate independently and only participate in the electricity energy trading with the DS. This scenario aims to establish an analysis benchmark and reveal the operation characteristics of uncoordinated, single-commodity trading. The ESS is limited to local power smoothing and arbitrage. With the model solution, the energy trading and operation decisions are shown in Fig. 4.

As shown in Fig. 4, VPP1 maintains an overall "energy surplus" state, with renewable energy output consistently exceeding load demand in both day and night. Its primary strategy involves selling electricity to the DS during most periods and utilizing the ESS to store excess generation. Electricity purchases are minimal, occurring only briefly during specific evening intervals. As for VPP2 which is load dominant, it exhibits a typical double-peak load profile that aligns poorly with the renewable generation. While VPP2 sells a small amount of electricity during the midday PV peak, it relies heavily on purchasing electricity from the DS to meet demand during morning and evening peaks. Its ESS is primarily utilized for peak shaving and valley filling. The VPP3 has the lowest load level and provides significant WT active power at night, resulting in substantial surplus generation during off-peak hours. While its scheduling behavior mirrors VPP1, VPP3 exhibits a larger energy surplus amplitude, more concentrated electricity sales, and more frequent ESS arbitrage activities. Corresponding with the operation strategies, the cost of VPPs are shown in Table 3.

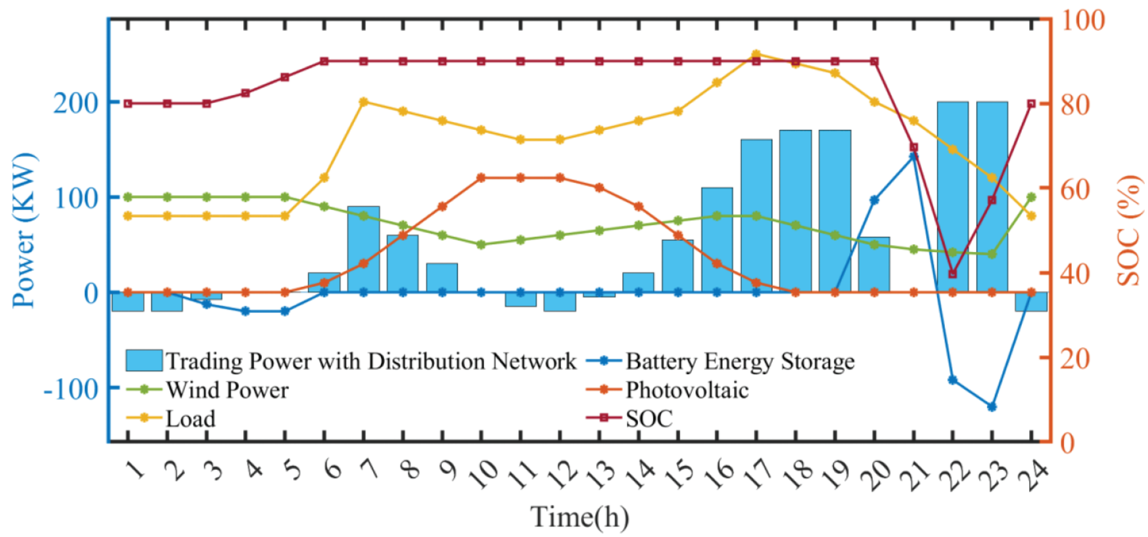


(a) VPP1

Figure 4: (Contiuned)



(**b**) VPP2



(**c**) VPP3

Figure 4: Trading and operation strategies for VPPs under EETI scenario.

Table 3: Cost analysis of VPPs under the EETI scenario (CNY).

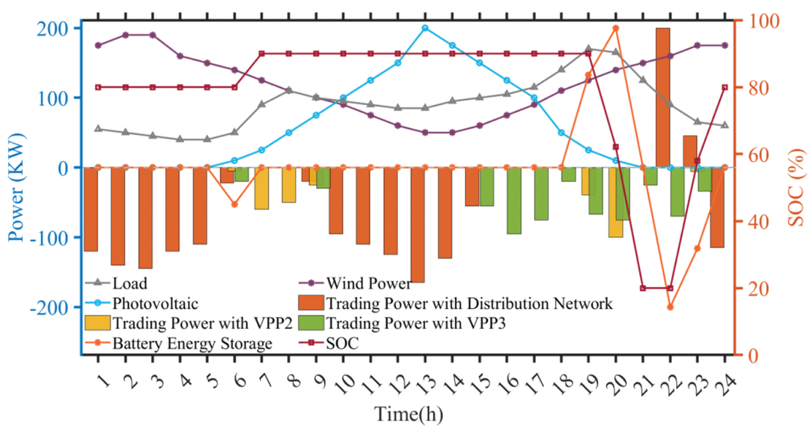
VPP	Energy Storage Cost	Electricity Cost with DS	Total Cost
VPP1	70.09	−1031.60	−961.54
VPP2	74.53	216.42	290.96
VPP3	50.34	888.30	938.65

It can be seen in Table 3, the sign of the transaction cost with the DS indicates the VPP's net market position: a negative value represents seller, while a positive value represents buyer. Leveraging significant renewable surpluses, both VPP1 and VPP3 generate electricity sales revenue that fully offsets their ESS operating costs, resulting in a profit. VPP1's profit is derived primarily from its continuous electricity sales. Conversely, VPP2 operates as a buyer, whose primary cost driver is electricity procurement from the grid, leading to a positive total cost. Under the independent operation mode, each VPP manages local renewable consumption through internal optimization. As for each VPP, the market performance and economic viability are highly dependent on the internal alignment between its resources and load profiles, leading to severe disparities in profitability across the VPPs. Due to the lack of cross-VPP complementarity channels, all energy surpluses and deficits must be balanced through the DS. This subjects the VPPs to the price spread between buying and selling, causing potential value loss and limiting the flexibility of the system.

(2) Scenario EETP: Electricity Energy Trading in P2P Mode

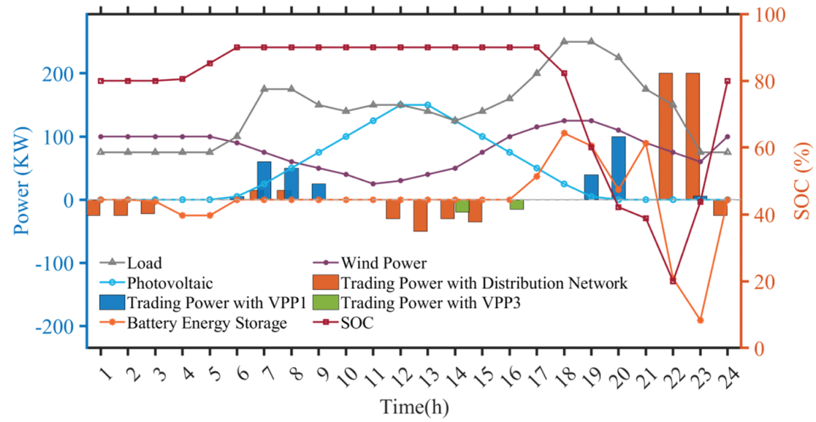
On the basis of the benchmark Scenario *EETI*, this scenario introduces an electricity P2P trading mechanism among VPPs. The P2P trading price fluctuates within the range of DS buy-sell electricity prices, thereby creating economic incentives for direct transactions among VPPs. Each VPP prioritizes matching power surpluses and deficits through the P2P network, and then settles the remaining unbalanced power with the DS. via solving the established model with proposed algorithm, the energy trading and operation decisions of VPPs are shown as in Fig. 5.

As shown in Fig. 5, the transaction power between each VPP and the DS is reduced, compared with Scenario EETI in Fig. 4. This indicates that the energy imbalance between different VPPs has been eliminated via the P2P coordination. To be specific, during the time period of new energy high supply, the VPP1 sells the surplus energy to other VPPs in priority and then trade with the DS. Moreover, the cost of P2P trading under this scenario is shown in Table 4. The total cost of all VPPs is negative, which means all the VPPs gain profits. The total trading cost of the VPPs with DS is negative, and the total electricity sales income increases compared with Scenario EETI. More importantly, the internal electricity replacement achieved through P2P reduces the dependence on the DS as the sole counterparty, enhancing market vitality and resiliency.

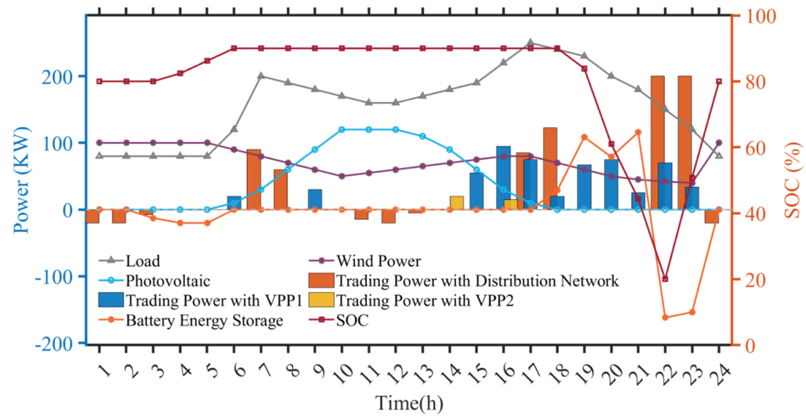


(**a**) VPP1

Figure 5: (Continued)



(**b**) VPP2



(**c**) VPP3

Figure 5: Trading and operation strategies for VPPs under EETP scenario.

Table 4: Cost analysis of VPPs under scenario EETP (CNY).

VPP	ESS Cost	Electricity Cost with DS	Electricity Cost with VPPs	Total Cost
VPP1	70.09	−569.42	498.07	−997.40
VPP2	70.09	47.74	−172.20	290.02
VPP3	70.09	347.25	−434.24	851.58

As shown in Table 4, the total cost of all the VPPs is 144.20 while the total cost of all VPPs under the scenario EETI is 268.07, shown as in Table 3. Then, with importing the P2P structure, the total cost of all VPPs is reduced as 123.87, which reflects the effectiveness of established bi-level CMCO framework.

5.3 Electricity-Carbon Joint Trading Scenario

(1) Scenario ECJTI: Electricity-Carbon Joint Trading in Independent Mode

This scenario expands the VPP transaction categories by introducing carbon emission allowance trading on the basis of the electricity transaction, quantitatively analyzing the improvement in economic benefits for VPPs brought by carbon trading. To maintain compliance, VPPs actively trade quotas in the carbon market to balance their accounts. The temporal dynamics between actual carbon emissions and initial quotas are depicted in Fig. 6. With employing the proposed method to solve the established electricity-carbon joint trading model, the trading and operation decisions are shown in Fig. 7. The cost analysis of VPPs under this scenario is illustrated in Table 5.

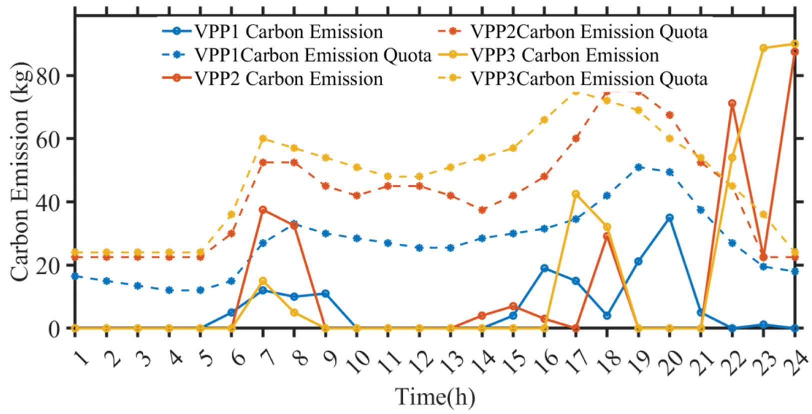
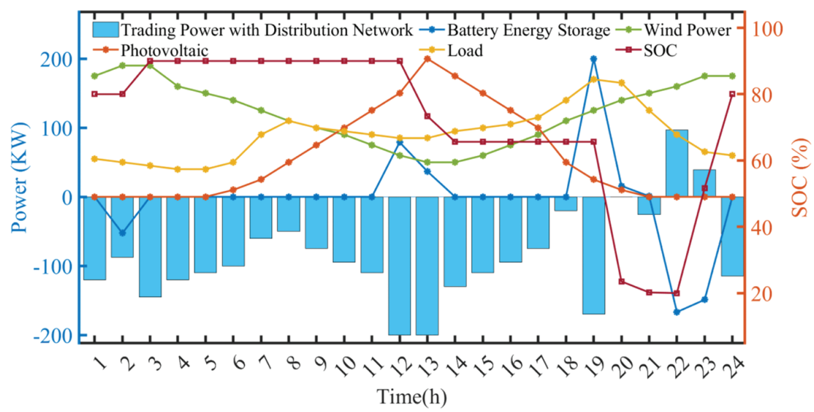
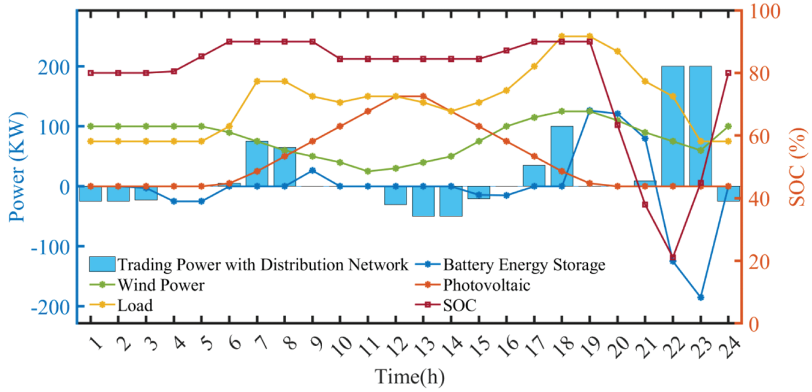


Figure 6: Carbon emissions and quotas of VPPs with electricity-carbon joint trading.

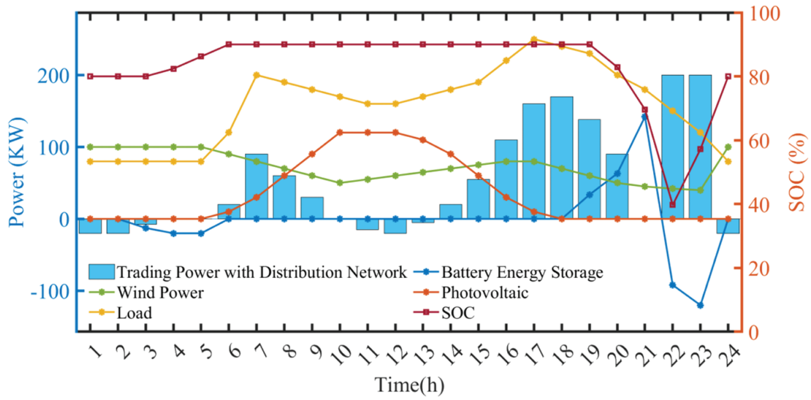


(**a**) VPP1

Figure 7: (Continued)



(**b**) VPP2



(**c**) VPP3

Figure 7: Trading and operation decisions of VPPs under ECJTI scenario.

Table 5: Cost analysis of VPPs under ECJTI scenario (CNY).

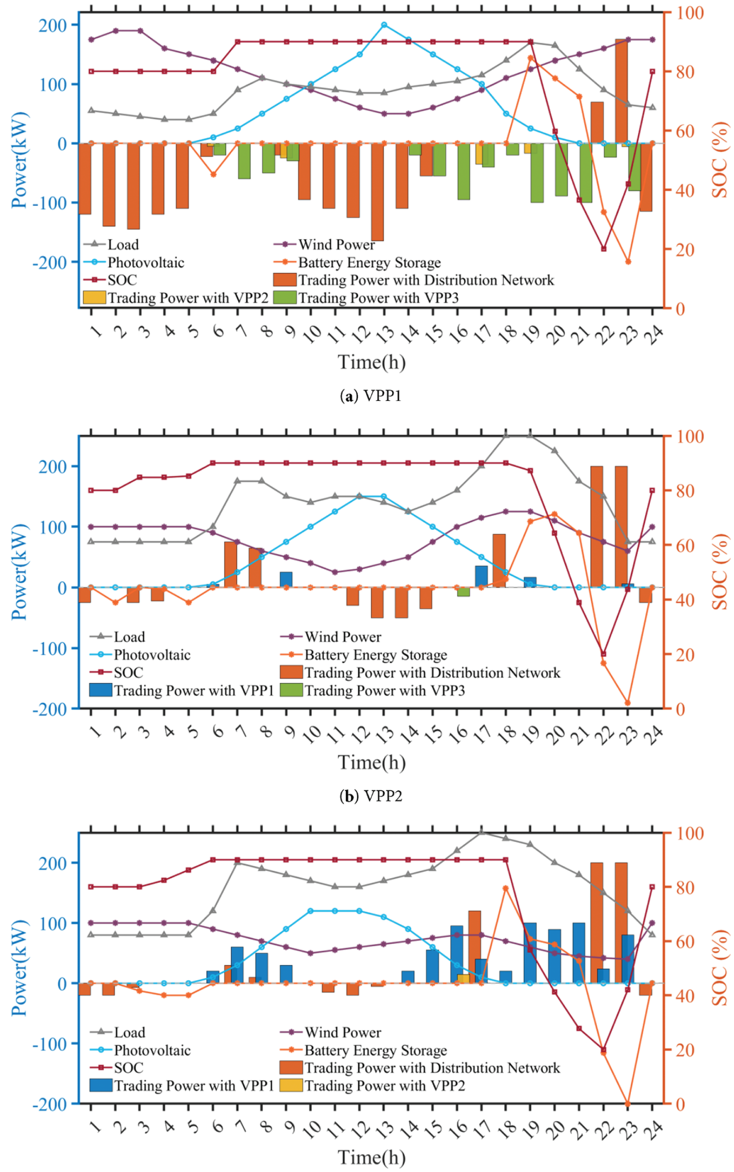
VPP	ESS Cost	Electricity Cost with DS	Carbon Cost with DS	Total Cost
VPP1	68.25	1031.6	−28.86	−992.25
VPP2	72.57	216.42	−32.14	256.85
VPP3	49.02	888.30	−21.90	915.42

As shown in Fig. 7, the VPP2 secures the most carbon revenue. Regarding electricity costs, VPP1 and VPP3 remain stable, whereas VPP2 sees a reduction in electricity purchase. This decrease suggests that carbon cost constraints have incentivized VPP2 to further optimize its operation strategy. Consequently, the total costs for all three VPPs are improved. Compared to the electricity trading only scenario as in Table 4, the carbon emission cost for all VPPs are negative, which indicates that each VPP generates revenue by selling carbon quotas. To be specific, the profit of VPP1 and VPP3 has been increased while the cost of VPP2 has been reduced.

Following the introduction of the carbon trading mechanism, the VPPs exhibit distinct operational characteristics. Carbon costs are internalized as an important factor, prompting VPPs to adjust their electricity purchasing and energy storage schedules. Specifically, VPPs proactively reduce external electricity purchases during high-carbon periods, marking a transformation from electricity trading to a coordinated economic-carbon trading strategy. Simultaneously, the carbon market creates a new value stream independent of electricity trading. For VPP2 in particular, revenue from carbon emission effectively offsets the financial burden of its electricity purchases, significantly improving its economic performance.

(2) Scenario ECJTP: Electricity-Carbon Joint Trading in P2P Mode

On the basis of the independent Electricity-Carbon Joint *Scenario ECJTI*, this scenario further introduces P2P trading of electricity and carbon among VPPs. This allows VPPs to not only coordinate energy but also synergistically manage carbon assets, realizing the optimal operation of all VPPs. The corresponding trading and operation decisions are shown in Fig. 8 while the cost analysis is illustrated in Table 6.



(a) VPP1

(b) VPP2

(c) VPP3

Figure 8: Trading and operation decisions of VPPs under ECJTP scenario.

Table 6: Cost analysis of VPPs under ECJTP scenario (CNY).

VPP	ESS Cost	Electricity Cost with DS	Electricity Cost with Other VPPs	Carbon Cost with DS	Carbon Cost with Other VPPs	Total Cost
VPP1	70.09	−558.62	−510.07	−5.32	−22.17	−1026.09
VPP2	70.09	155.85	55.69	−29.62	−5.07	246.95
VPP3	70.09	228.34	562.75	−56.92	27.24	831.49

As shown in Fig. 8, with the P2P carbon transaction between different VPPs, the trading and operation decisions are more flexible. Carbon costs are internalized as a decision-making factor, prompting VPPs to adjust their electricity procurement and energy storage scheduling strategies. The VPPs actively reduce external electricity purchases during periods of high carbon emissions, shifting from a purely economic optimization approach to a coordinated economic–low-carbon optimization. VPPs with high carbon costs (such as VPP2) are more motivated to purchase electricity from low-carbon intensity P2P partners or buy surplus carbon to comply with regulations, thereby achieving resource complementarity in a broader dimension. The carbon market creates an additional revenue stream for VPPs, independent of electricity trading. This is particularly evident for VPP2, where income from carbon quotas effectively offsets the cost pressure from its net electricity purchases, significantly improving its economic performance.

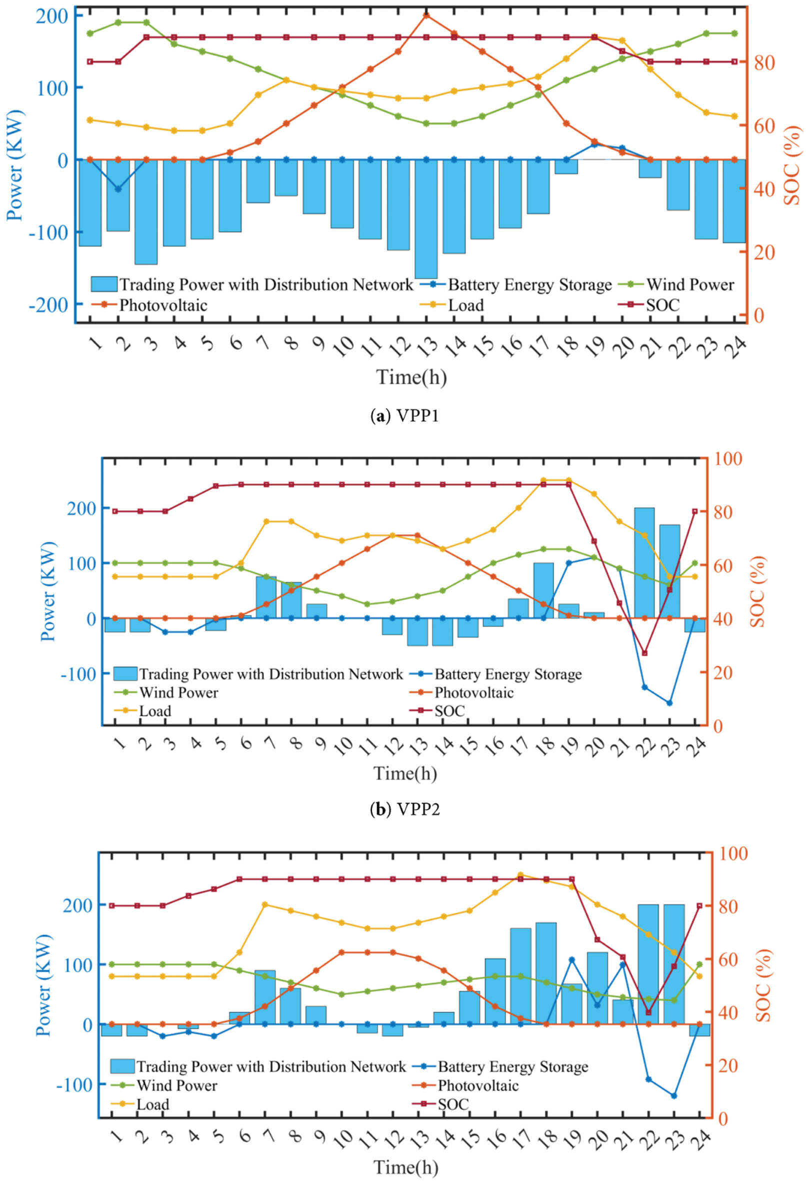
As shown in Table 6, the total cost of all VPPs is reduced by 22.1% compared with scenario EETP, and the improvement is more significant compared with the scenario ECJTI. As the "carbon cost with DS" of all VPPs are negative, which indicates that the VPPs get profit via the carbon trading. Data for VPP2 shows that it sold amount carbon allowance through carbon transactions with the DS and VPP3, obtaining significant carbon income. While maintaining 100% local consumption of renewable energy, the carbon trading mechanism drives a reduction in overall system carbon emissions and optimizes total operating costs. This initially validates the effectiveness and efficiency of intruding the electricity commodity as carbon trading.

5.4 Electricity-Carbon-Reserve Joint Trading Scenario

(1) Scenario ECRJTI: Electricity-Carbon-Reserve Joint Trading in Independent Mode

In this scenario, the multiple electricity commodities as electricity energy, reserve capacity and carbon are traded coordinately. With the aim of minimizing the total trading and operation cost, the established model is solved via the proposed algorithm. Then, the trading and operation decisions of all VPPs are shown in Fig. 9 while the reserve capacity provided by the DERs within each VPP are shown in Fig. 10. The cost analysis is illustrated in Table 7.

As shown in Figs. 9 and 10, it reserves service trading imposes higher requirements on VPP resource dispatch. VPPs need to rationally allocate DERs such as ESS and flexible load to provide reserve capacity while ensuring electrical energy supply and carbon emission compliance. Reserve services can bring additional revenue but also increase resource allocation costs. Therefore, VPPs need to dynamically balance between reserve capacity investment and revenue.

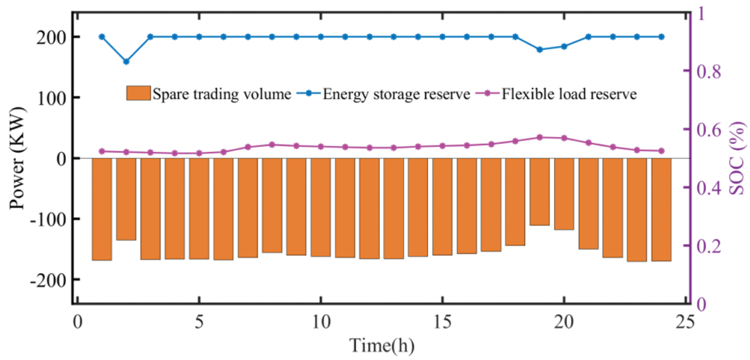


(**a**) VPP1

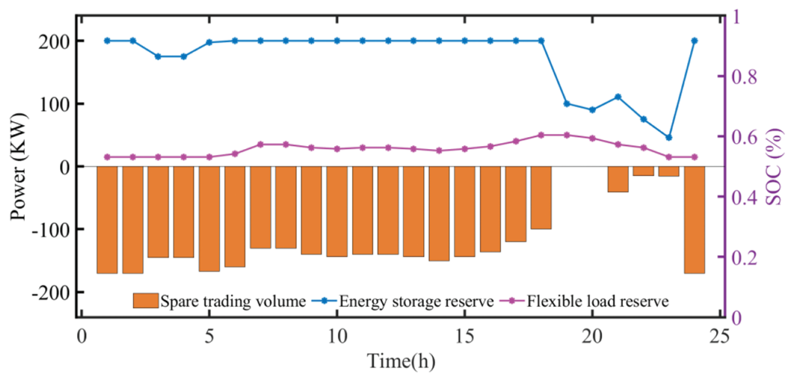
(**b**) VPP2

(**c**) VPP3

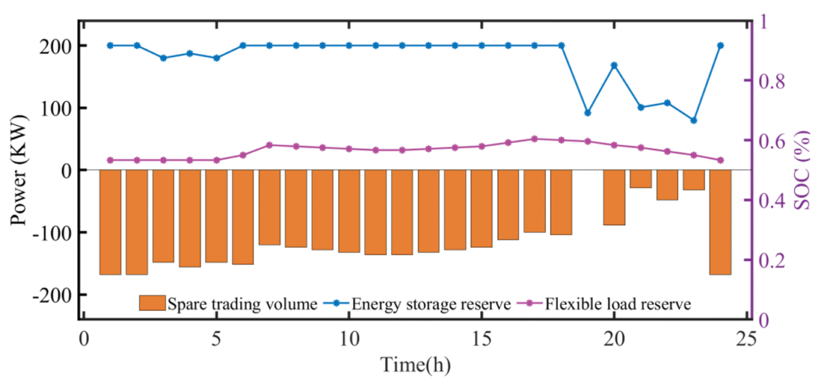
Figure 9: Trading and operation decision of VPPs under scenario ECRJTI.



(**a**) VPP1



(**b**) VPP2



(**c**) VPP3

Figure 10: Reserve trading and DERs operation decision under scenario ECRJTI.

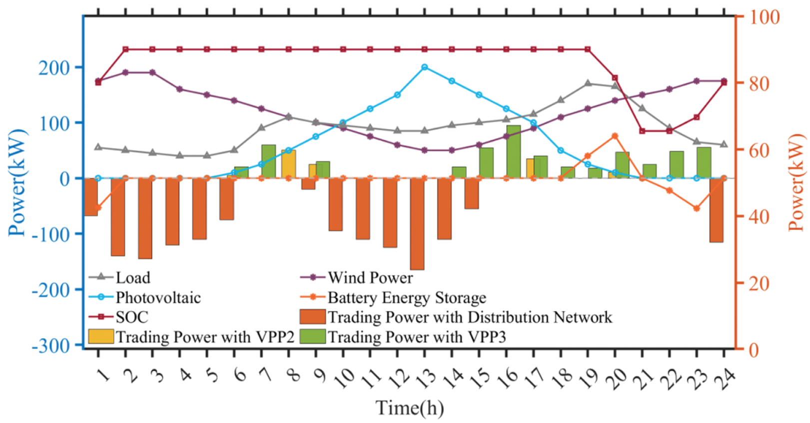
Table 7: Cost analysis of VPPs under scenario ECRJTI (CNY).

VPP	ESS Cost	Electricity Cost	Carbon Cost	Reserve Cost	Total Cost
VPP1	7.56	−936.06	−32.47	−433.21	−1394.2
VPP2	61.47	238.14	−31.78	−309.14	−41.31
VPP3	49.02	888.30	−21.90	−307.68	607.74

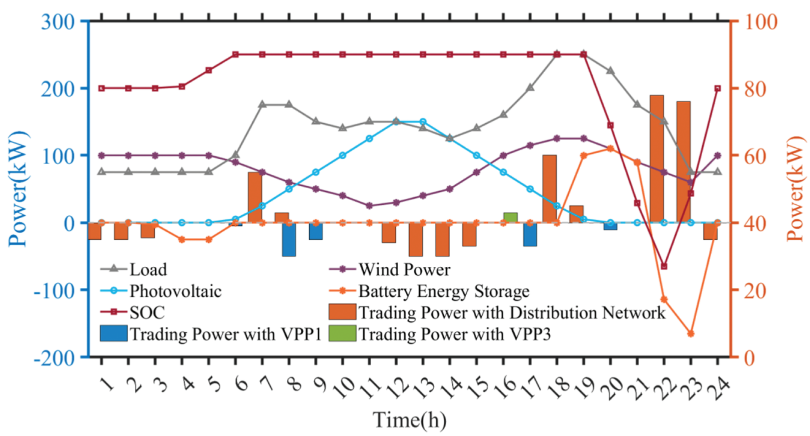
Table 5 shows the detailed cost structure under electricity-carbon-reserve joint trading scenario. Compared with last scenario as Table 4, the costs of VPPs have been reduced or the profits of VPPs have been increased. Moreover, the ESS operation costs for all the VPPs have decreased substantially. This is because based on the reserve trading, the frequency of ESS charge-discharge is optimized, thereby reducing costs. Specifically, for VPP2 and VPP3, reserve market transactions have become a primary component of the revenue and expenditure profiles. While electricity and carbon costs remain relatively stable, the reserve market significantly enhances the overall economy of each VPP. This is most prominent for VPP2, which transforms from an expenditure state to a profit state.

(2) Scenario ECRJTP: Electricity-Carbon-Reserve Joint Trading in P2P Mode

In this scenario, the VPPs participate in the multiple electricity commodities trading as electricity energy, reserve capacity and carbon with utilization of the P2P structure. The operation decisions of VPPs are shown in Fig. 11, and the cost of VPPs under this scenario is shown in Table 8.

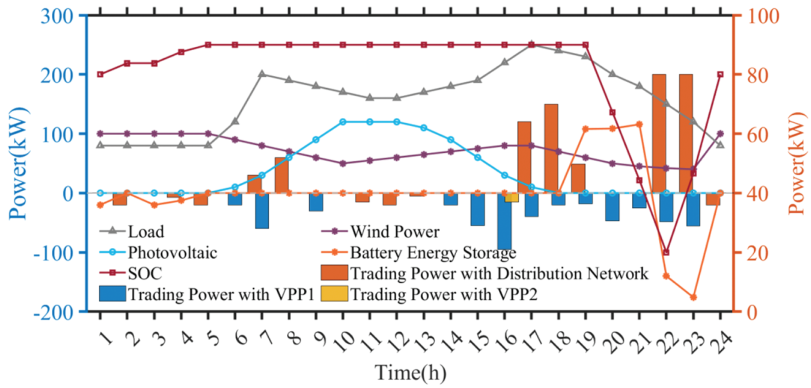


(**a**) VPP1



(**b**) VPP2

Figure 11: (Continued)



(**c**) VPP3

Figure 11: Trading and operation decision of VPPs under scenario ECRJTP.

Table 8: Cost analysis of VPPs under scenario ECRJTP (CNY).

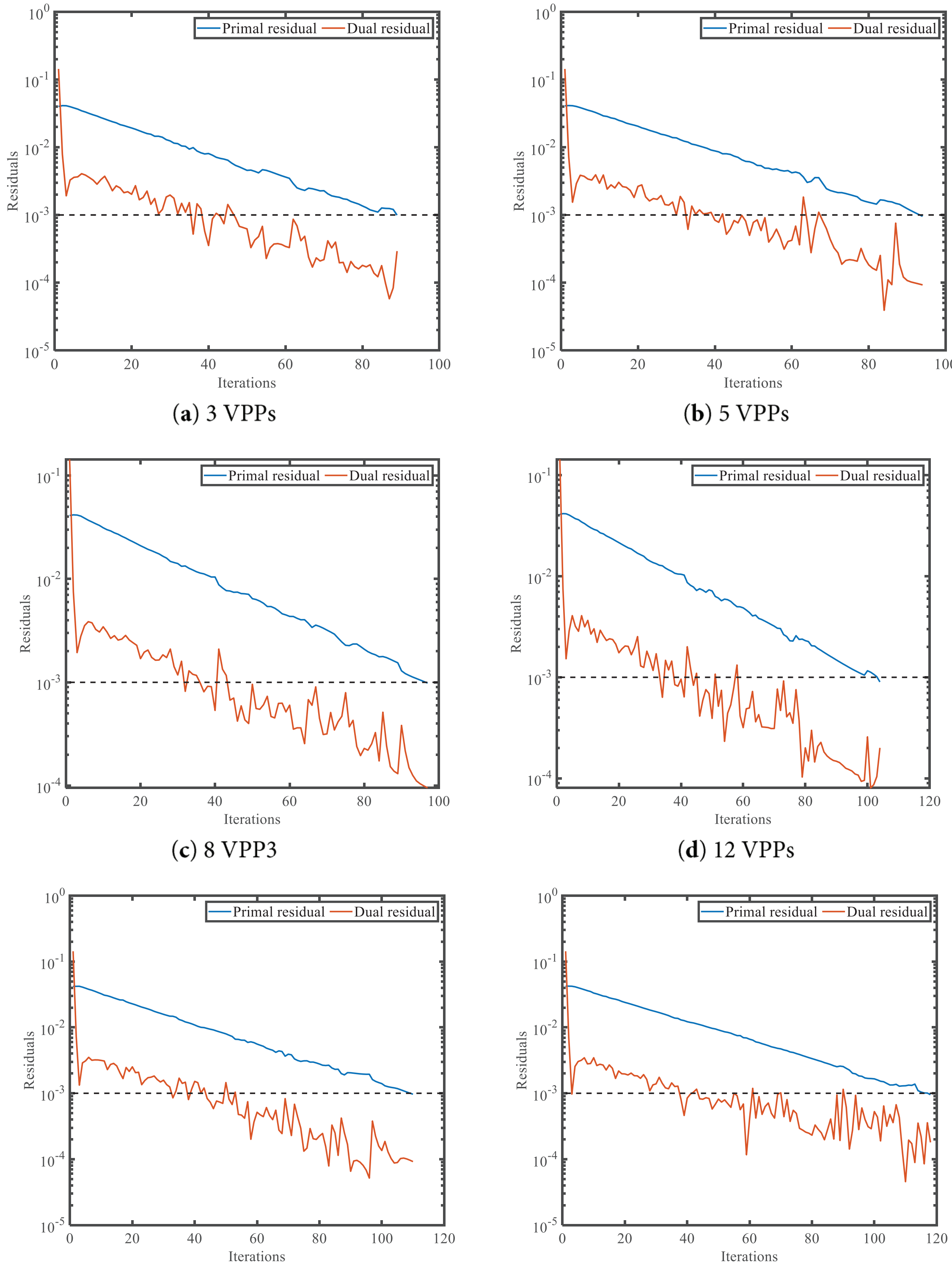
VPP	ESS Cost	Electricity Cost with DS	Electricity Cost with Other VPPs	Reserve Cost with DS	Reserve Cost with Other VPPs	Carbon Cost with DS	Carbon Cost with Other VPPs	Total Cost
VPP1	24.51	−654.31	−419.02	−179.96	−114.76	−6.85	−10.24	−1360.63
VPP2	63.13	161.57	49.65	−289.43	−110	−30.14	−12.52	−167.74
VPP3	70.09	429.95	292.11	−267.34	−104.05	−64.4	22.76	379.12

As shown in Table 8, all VPPs achieve substantial profits, significantly exceeding the profits recorded in any previous scenario. The total system cost reaches −1149.25 CNY, representing an absolute economic improvement of 1149.25 CNY. Furthermore, compared to Scenario ECRJTI (multi-commodity without P2P), profitability increases by 38.837%. These results underscore the immense economic potential of the proposed method. The income streams for each VPP are highly diversified. For example, VPP1 generates revenue through electricity sales, reserve service and carbon trading with both DS and other VPPs.

5.5 Compreheomsive Analysis

(1) Analysis on Scalability of Distributed Algorithm

With the aim of analyzing the scalability of the distributed algorithm, the test with increasing number of VPPs in the lower-level is conducted. The convergency tolerance of ADMM is set 10^{-3} and the penalty parameter of ADMM is set as 0.5. According to there are many VPPs, then the primal residual and dual residuals are calculated by selecting the maximum value of the residuals vector referring to [31]. Then, the iteration procedures of all the scenarios with different amount of VPPs are shown in Fig. 12.



(**a**) 3 VPPs (**b**) 5 VPPs

(**c**) 8 VPP3 (**d**) 12 VPPs

(**e**) 18 VPPs (**f**) 25 VPPs

Figure 12: Iteration procedures with different VPPs.

As shown in Fig. 12, it requires 89 iterations for the residuals go under 10^{-3} under the ECRJTP scenario, and the algorithm converges, which shows the high efficiency of the proposed method. To analyze the scalability of the proposed distributed algorithm, the iteration times and computation time are utilized as the key indicators. As the amount of VPP increasing from 3 to 25 gradually, the iteration times and computation time also increased slowly. When there are 3 VPPs, the iteration times is 89 while the computation time is 47.133245 s. As for the scenario with 5, 8, 13, and 20 VPPs, the iteration times is 94, 97, 104 and 110, respectively while the computation time is 51.393662, 51.393662, 55.883824 and 58.585263 s, respectively. At the beginning of VPP amount increasement as from 3 to 5, the computation time increased from 47.133245 to 51.393662 s, which is relatively large compared with the following increasement as to 8, 13 and 20. And with the amount of VPPs increasing much, the increasement speed of computation time getting slowly. Therefore, although the iteration times and computation times are increased with the model scale increasing, the overall trend is relatively gentle. The parallel and advanced computation technology can be leveraged in practical application, thus the solution efficiency can meet the requirement of day-ahead multiple electricity commodities trading.

(2) Analysis on Economic Performance

To comprehensively evaluate the proposed method, Table 9 summarizes the key performance indicators of all six scenarios. Based on the comparative analysis, the following core conclusions are drawn:

Table 9: Comparison and summary of key performance indicators for all scenarios.

Scenario	Trading Mode	Total System Cost (CNY)
EETI	Independent, Electricity-Only	268.07
ECJTI	Independent, Electricity + Carbon	180.02
ECRTJI	Independent, Full Commodities	−827.77
EETP	Coordinated (P2P), Electricity-Only	144.20
ECJTP	Coordinated (P2P), Electricity + Carbon	52.35
ECRTJP	Coordinated (P2P), Full Commodities	−1149.25

1. Effectiveness of P2P Coordination: Comparisons (EETI vs. EETP, ECJTI vs. ECJTP, ECRTJI vs. ECRTJP) clearly show that under the exact same commodity combination, introducing P2P trading can always lead to a significant reduction in total system cost. This stems from P2P trading eliminating the buy-sell spread loss generated through DS transactions, realizing the optimal direct matching of resources among VPPs, and improving market efficiency.
2. Effectiveness of Multiple Electricity Commodities: Vertical comparisons indicate that each additional dimension of trading commodities such as carbon or reserve improves the economy for each VPP. Carbon trading guides low-carbon operation, reserve trading taps into flexible value, and both generate synergistic effects with electricity trading, making the total benefit greater than the simple sum of single-commodity benefits.
3. Superiority of the Proposed Method: In the last scenario ECRTJP, the VPPs achieve the best performance among all scenarios. It not only validates the accuracy and effectiveness of established model and proposed algorithm, but also reveals that the multiple electricity commodities with P2P structure can improve the VPPs' profit. By reshaping the interaction logic between VPP and DS, this framework is beneficial for constructing an efficient, low-carbon market mechanism for the power system.

6 Conclusion

Considering the ability of virtual power plants (VPPs) to supply electrical energy, reserve capacity, and carbon emission allowances, this paper proposes a coordinated trading and operation method for VPPs. A coordinated trading and operation framework is established for VPPs, incorporating multiple electricity commodities—namely electrical energy, reserve capacity, and carbon allowances. A bi-level trading model is then constructed: the upper layer enables the distribution system to determine prices for multiple electricity commodities, while the lower layer optimizes VPP operations to identify optimal trading volumes. This structure achieves coordinated optimization of VPP trading activities and operational processes. Finally, an efficient two-stage distributed algorithm integrating the dichotomy method and the alternating direction method of multipliers (ADMM) is proposed, which efficiently solves the bi-level model with binary variables in a distributed manner while preserving VPP privacy. Ultimately, by participating simultaneously in the energy, reserve, and carbon markets, VPPs realize substantial reductions in total operating costs and enhanced carbon emission reduction benefits. These outcomes verify that the proposed method effectively improves the economic and environmental performance of VPPs.

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Nomenclature

Abbreviations

ADMM	Alternating Direction Method of Multipliers
CMCO	Coordinated Market Clearing and Operation
DER	Distributed Energy Resource
DS	Distribution System
ECJTI	Electricity-Carbon Joint Trading in Independent Mode
ECJTP	Electricity-Carbon Joint Trading in P2P Mode
ECRJTI	Electricity-Carbon-Reserve Joint Trading in Independent Mode
ECRJTP	Electricity-Carbon-Reserve Joint Trading in P2P Mode
EETI	Electricity Energy Trading in Independent Mode
EETP	Electricity Energy Trading in P2P Mode
ESS	Energy Storage System
FL	Flexible Load
FWCI	Field-Weighted Citation Impact
GUROBI	Gurobi Optimizer

KKT	Karush–Kuhn–Tucker Conditions
MVPP	Multiple Virtual Power Plants
P2P	Peer-to-Peer
PV	Photovoltaic
VPP	Virtual Power Plant
WT	Wind Turbine
YALMIP	Yet Another LMI Parser

Indices

t	Index of dispatch periods
T	Total number of periods
i,j	Index of VPPs
k	Index of iterations
e	Index of electricity commodity types
r	Index of trading roles: buyer or seller

Parameters

λ_t^{EWMB}	Wholesale electricity purchase price
λ_t^{EWMS}	Wholesale electricity sell price
λ_t^{RWM}	Wholesale reserve price
λ_t^{CWMB}	Wholesale carbon purchase price
λ_t^{CWMS}	Wholesale carbon sell price
λ_t^{EVPPS}	DSO-VPP electricity sell price
λ_t^{EVPPB}	DSO-VPP electricity purchase price
λ_t^{RVB}	DSO-VPP reserve purchase price
λ_t^{RVS}	DSO-VPP reserve sell price
λ_t^{CVB}	DSO-VPP carbon purchase price
λ_t^{CVS}	DSO-VPP carbon sell price
$\lambda_t^{e,r,VPP,\max}$	Maximum price of DSO-VPP commodity trade
$\lambda_t^{e,r,VPP,\min}$	Minimum price of DSO-VPP commodity trade
P_t^G	VPP total power generation
P_t^D	VPP total load demand
N^{VPP}	Set of VPPs
c^{ESS}	ESS operation cost coefficient
η	ESS efficiency
ρ	Carbon emission factor for purchased electricity
σ	Unit carbon quota coefficient for load
ϖ	Reserve demand coefficient
θ	Load curtailment coefficient
$E_{i,t}^{ESS\min}$	Minimum ESS capacity of VPP i
$E_{i,t}^{ESS\max}$	Maximum ESS capacity of VPP i
ε	Algorithm convergence tolerance
ρ_i	Penalty parameter (ADMM)

Variables

C_t^{EDSO}	DSO wholesale electricity trading cost
P_t^{EWMB}	DSO wholesale electricity purchase quantity
P_t^{EWMS}	DSO wholesale electricity sell quantity
R_t^{RDSO}	DSO wholesale reserve revenue
R_t^{RWM}	DSO wholesale reserve trade quantity
C_t^{CDSO}	DSO wholesale carbon trading cost

E_t^{CWMB}	DSO wholesale carbon purchase quantity
E_t^{CWMS}	DSO wholesale carbon sell quantity
R_t^{EDSO}	DSO-VPP electricity trading revenue
P_t^{EVPPS}	DSO-VPP electricity sell quantity
P_t^{EVPPB}	DSO-VPP electricity purchase quantity
C_t^{RDSO}	DSO-VPP reserve trading cost
R_t^{RVB}	DSO-VPP reserve purchase quantity
R_t^{RVS}	DSO-VPP reserve sell quantity
C_t^{CDSV}	DSO-VPP carbon trading cost
E_t^{CVB}	DSO-VPP carbon purchase quantity
E_t^{CVS}	DSO-VPP carbon sell quantity
$\lambda_t^{com,r,VPP}$	DSO-VPP commodity trade price
C^{DSO}	DSO total operation cost
$C_{i,t}^{VPP}$	VPP *i* total operation cost
$P_{i,t}^{EVPPB}$	VPP *i* purchase electricity from DS
$P_{i,t}^{EVPPS}$	VPP *i* sell electricity to DS
$C_{i,t}^{TRVPP}$	VPP *i*-VPP electricity trading cost
$P_{i,t}^{EVPPBV}$	VPP *i* purchase electricity from other VPPs
$P_{i,t}^{EVPPSV}$	VPP *i* sell electricity to other VPPs
$C_{i,t}^{C}$	VPP *i* carbon trading cost
$E_{i,t}^{CVPPB}$	VPP *i* carbon purchase quantity
$E_{i,t}^{CVPPS}$	VPP *i* carbon sell quantity
$C_{i,t}^{R}$	VPP *i* reserve trading revenue
$R_{i,t}^{RVPPB}$	VPP *i* reserve purchase quantity
$R_{i,t}^{RVPPS}$	VPP *i* reserve sell quantity
$C_{i,t}^{ESS}$	VPP *i* ESS operation cost
$P_{i,t}^{CHA}$	VPP *i* ESS charging power
$P_{i,t}^{DIS}$	VPP *i* ESS discharging power
$C_{i,t}^{VPP,\max}$	VPP *i* carbon emission quota limitation
$C_{i,t}^{VPP,WS}$	VPP *i* carbon emission amount
$P_{i,t}^{VPP,D}$	VPP *i* load demand
$R_{i,t}^{VPP,req}$	VPP *i* reserve capacity requirement
$R_{i,t}^{ESS}$	VPP *i* ESS reserve capacity
$R_{i,t}^{DC}$	VPP *i* load curtailment reserve capacity
$P_{i,t}^{WT}$	VPP *i* WT active power output
$P_{i,t}^{PV}$	VPP *i* PV active power output
$P_{i,t}^{DC}$	VPP *i* load curtailment quantity
$S_{i,t}^{CHA}$	VPP *i* ESS charging binary variable
$S_{i,t}^{DIS}$	VPP *i* ESS discharging binary variable
$E_{i,t}^{e}$	VPP *i* ESS capacity at time t
$\boldsymbol{x}_{i,t}$	VPP *i* decision variables
$\boldsymbol{u}_{i,t}$	Auxiliary variables (P2P trade)
$\boldsymbol{\lambda}_{i,t}$	Dual variables (shadow price)

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