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Coordinated DSO-VPP Operation Framework with Energy and Reserve Integrated from Shared Energy Storage: A Mixed Game Method

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ABSTRACT

Virtual power plants (VPPs) contribute to the flexibility and economy of distributed system by leveraging integrated distributed renewable resources, optimizing energy production and consumption patterns, and facilitating dynamic grid management. However, challenges arise when multi-VPPs coordinated operate, including complex spatial and temporal correlation characteristics and conflicting interests in multi-agent decision-making. Shared energy storage (SES), as a product of the sharing economy, can be more flexible to help VPPs consume power generation from distributed renewable resources. Hence, focusing on the complementary problems and conflicts of interest between VPPs and improving the utilization of distributed renewable resources, this paper proposes an energy-reserve coordinated optimization model led by the distribution system operator (DSO) and involves the participation of both multi-VPPs and SES. Firstly, a Stackelberg-cooperative mixed game (SC-mixed game) framework is proposed for the DSO-VPP system, which leverages the DSO as the leader. The transactional electricity price between DSO and VPPs is optimized via the Stackelberg game, and the operation strategies for multi-VPPs can be calculated by the Cooperative game. Besides, an energy-reserve model is proposed for SES, which considers six reserve modes for further exploring the reserve potential of SES and guarantee the reserve provision ability. Additionally, a tailored alternating direction method of multipliers (ADMM), integrating a bisection method, is proposed to solve the SC-mixed game model efficiently. Finally, several case studies are conducted to validate the effectiveness of the proposed model.

KEY WORDS

Virtual power plant; Shared energy storage; Reserve capacity; Optimal operation; Game theory; Pricing scheme

1. Introduction

The virtual power plant (VPP) concept entails the aggregation of various distributed energy resources (DERs) [1], which encompass a spectrum of components, including renewable energy sources [2,3], energy storage systems (ESS) [4,5], controllable loads [6], among others. The operating economy of the VPP or distribution system can be significantly

improved through reasonably optimized regulation [7,8]. The operation of a single VPP primarily focuses on minimizing its operation cost [9,10]. However, it tends to overlook the global optimization of the electricity distribution system, potentially jeopardizing the safe and stable operation of the electrical grid. When multi-VPPs are integrated into the electricity distribution system, the operational mechanism between VPPs and the distribution system operator (DSO) remains nascent [11]. Hence, further research is needed into the co-optimization of multi-VPPs and DSO.

Nomenclature		β_k	Cost coefficient of treating pollutant k
Abbreviations		$\beta_{i,t}^{buy}$	VPP i 's state of power purchase
		$\beta_{i,t}^{sell}$	VPP i 's state of power sell
	AC	ε	Maximum allowable proportion of electric load
	ADMM	$\mu_i^{rec,\kappa}$	Recovery cost coefficient of DG κ
	DER	$\mu_t^{ser,dis}$	Cost coefficient of discharging
	DG	$\mu_t^{ser,ch}$	Cost coefficient of charging
	DR	μ_i^κ	Power cost coefficient of DG κ
	DSO	η^{ch}	Power transmission efficiency of charging
	ESS	η^{dis}	Power transmission efficiency of discharging
	EV	ρ_{ij}	Penalty term

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GA	Genetic algorithm	ρ_t^{dn}	Down reserve power cost coefficient
GB	Gas boiler	ρ_t^{up}	Up reserve power cost coefficient
GT	Gas turbine	ϕ	Proportion of the total electric load
ISO	Independent system operators	$\omega_{i,k}^k$	Emission coefficient of pollutants k
PSO	Particle swarm optimization	ξ	Convergence precision
PV	Photovoltaic	$\lambda_{ij,t}$	Lagrange multiplier
SC	Stackelberg game and cooperative game	τ	Residual convergence set point
SES	Shared energy storage	Δt	Unit period of operation time
VPP	Virtual power plant		
WT	Wind turbine		
Indices		Variables	
i	Index of VPPs	E_t^{SES}	State of energy of SES at time t
k	Index of pollution	E_{t+1}^{SES}	State of energy of SES at time $t + 1$
l	Index of iterations	L_t^e	Electrical load of VPP i
t	Index of time slots in operation horizon	$L_{i,t}^{e,f}$	Flexible load of VPP i
t_1	Beginning of continuous up/down reserve	$L_{i,t}^{e,f*}$	Flexible load after adjusted
κ	Index of DGs	$L_{i,t}^{e,r}$	Rigid load of VPP i
Parameters		$P_{i,t}^{AC}$	Output power of AC
$E^{SES,max}$	Maximum allowable capacity of SES	$P_{i,t}^{buy}$	Purchase power of VPP i
$E^{SES,min}$	Minimum allowable capacity of SES	$P_{i,t}^{ch}$	Charging power of SES to VPP i
l^{max}	Maximum number of iterations	$P_{i,t}^{DG}$	Output power of DG
N^{vpp}	The number of VPPs	$P_{i,t}^{dis}$	Discharging power of SES to VPP i
p^{buy}	Up limit of electricity purchase	$P_{i,t}^{ex}$	Exchange power with other VPPs
$p^{ch,max}$	Up limit charging power of SES in the same time	$P_{i,t}^{EV}$	Output power of EV
$p_i^{ch,max}$	Up limit power in state of charge of VPP i	$P_t^{grid,b}$	Purchase power of upper grid
$p^{dis,max}$	Up limit discharging power of SES in the same time	$P_t^{grid,s}$	Sell power of upper grid
$p_i^{dis,max}$	Up limit power in state of discharge of VPP i	$P_{i,t}^{PV}$	Output power of PV
p^{line}	Up limit of line transmission power	$P_{i,t}^{sell}$	Sell power of VPP i
p^{sell}	Up limit of electricity sale	$P_{i,t}^{WT}$	Output power of WT
$p_i^{\kappa,max}$	Up limit of output power for different units	$r_{i,t}^d$	Real down reserve power of VPP i
T	Time in a typical day	$r_{i,t}^{dn}$	Down reserve capacity of VPP i
u	Self-discharge rate of the energy storage	$r_{i,t}^u$	Real up reserve power of VPP i
$\alpha_t^{ave,b}$	Average value of the electricity price purchased	$r_{i,t}^{up}$	Up reserve capacity of VPP i
$\alpha_t^{ave,s}$	Average value of the electricity price sold	R_t^{dn}	Upper bound of continuous down reserve
α_t^{cd}	Transmission cost coefficient of SES	R_t^{up}	Upper bound of continuous up reserve
α_t^{down}	Cost coefficient of down reserve capacity	$u_{i,t}^{ch}$	State of charge of VPP i
$\alpha_t^{grid,b}$	Feed-in tariff of grid	$u_{i,t}^{dis}$	State of discharge VPP i
$\alpha_t^{grid,s}$	Tariff of grid	$\alpha_t^{real,b}$	Electricity purchase price
α_t^{up}	Cost coefficient of up reserve capacity	$\alpha_t^{real,s}$	Electricity sale price
		$\beta_{i,t}^{buy}$	State of electricity buy
		$\beta_{i,t}^{sell}$	State of electricity sell

Recently, several attempts have been engaged in VPP operation. At the early stage, the primary focus of research lies in developing individual operational strategies for a single VPP [12–16]. Reference [12] formulates a technical VPP operational model to optimize the dispatch strategy of heterogeneous DERs within the day-ahead energy market while concurrently considering constraints inherent to grid management. Reference [13] proposed an improved operational strategy for a VPP utilizing an aggregation model of inverter air conditioners. Reference [14] proposed a two-level optimization model designed for VPPs, which leverages source-load interactions to efficiently tackle the challenges of power output variability, intermittency, and stochasticity. Reference [15] proposed a windfall profit-aware stochastic scheduling model for an industrial VPP based on risk preference. However, an individual VPP is generally limited in size and cannot aggregate enough DERs to meet the needs of distributed system's operation.

Later, the research on the coordinated scheduling of DSO and VPPs is also advancing in references [17–24]. Reference [17] proposed a novel

multi-stage adaptive stochastic-robust optimization approach to solve multi-energy microgrids operation problems. A two-level based VPP operation model was proposed in reference [19], which considers the competition and cooperation relationship between VPP and distribution network companies. Reference [20] proposed an optimal dispatch model based on potential game theory, realizes the internal coordination and optimization of multi-VPPs to improve the economic benefits and stability of the entire power system. Reference [21] proposed an optimal operation strategy for VPPs, which emphasizes utilizing low-cost resources while accounting for temporal coupling and leveraging the complementary attributes of heterogeneous resources. Based on market information asymmetry, reference [22] proposed a cooperative game coordinated operation method for VPP-P2H system considering the interests of each participant. References [23,24] proposed a Stackelberg game strategy for operator and multi-VPPs considering a ladder-type carbon price mechanism and a dual-compensated demand response (DR). However, if the Stackelberg game is used solely as a model of the DSO-VPPs system, it

may adversely affect the followers' interests due to the subjects' unequal status. Suppose the cooperative game is used solely, even though followers' interests are reasonably and evenly considered, there is no leader to coordinate them, which could adversely affect the overall system's interests. Therefore, the paper proposes the Stackelberg-cooperative-mixed Game (SC-mixed Game), a mixed approach integrating Stackelberg and Cooperative game frameworks. This model leverages the leader's function for macro-control while incorporating cooperative strategies to address the collective interests of the followers.

Moreover, the coordination of multi-VPPs can incorporate shared energy storage (SES) to enhance the operational efficiency of the DSO-VPPs system. SES can provide both energy and reserve services for multi-VPPs. In order to fully utilize the advantages of energy storage, reference [25] introduced SES station within building user groups. Additionally, flexible load participation in DR is also considered to provide system incentives. Reference [26] proposed a collaborative design method for community energy systems and shared energy storage, and established a shared pricing mechanism for energy storage based on bounded rationality theory. Simultaneously, energy-reserve joint consideration can further enhance resource utilization as well as energy dispatch flexibility. Reference [27] proposed a novel electricity-gas energy sharing model of micro-energy grid based on Nash bargain game. Reference [28] proposed a peer to peer energy trading model combined with SES, and studied the cooperative residual allocation mechanism based on asymmetric Nash

bargaining theory. It solved the intermittent characteristics of distributed power supply and the difficulty of mutual coupling of various energy types. Reference [29] proposed a two-level dynamic game optimization considering SES. The profit potential of SES is fully exploited by analysing the demands of multi-agents involved in grid auxiliary services. Therefore, SES needs to urgently consider the reserve capacity involved in the coordinated optimization of multi-VPPs.

Additionally, to safeguard the internal privacy of VPPs, distributed algorithms are commonly employed for coordinated strategy resolution [30–32]. Reference [30] used alternating direction method of multipliers (ADMM) and the fitted Q iteration algorithm, combined with distributed optimization and reinforcement learning, to optimize the power exchange between the grid and the microgrid at the residential user level. Reference [31] explored a distributed optimization approach founded on the consensus-based ADMM. Reference [32] proposed a fully distributed load dispatching scheme employing ADMM. However, while ADMM ensures privacy, traditional approaches encounter issues such as uneven update speeds and anomalous convergence when dealing with interactions among multiple variables. Therefore, customized enhancements tailored to the specific model are required.

Table 1 compares the main contents of previous research and this paper. The gaps in the previous studies are mainly reflected in:

Table 1 A comparative summary of this paper and previous researches.

Literature	DSO	Individual VPP	Multi-VPPs	SES	Game theory	Energy & Reserve market
[9],	✓	✓	×	×	None	None
[10], [11], [12], [13], [15],	×	✓	×	×	None	Energy Market
[14], [21],	✓	✓	✓	×	None	Energy Market
[19]	×	✓	✓	×	None	Energy Market
[20], [22]	×	✓	✓	×	Stackelberg	Energy Market
[23],	×	✓	✓	×	Cooperative	Energy Market
[25]	✓	✓	✓	×	Stackelberg	Energy Market
[29]	×	×	×	✓	None	Energy Market
[33]	×	✓	×	✓	Cooperative	Both
[34]	✓	✓	×	✓	None	Both
[35]	×	×	×	×	None	Both
[36]	×	×	✓	×	None	Both
This paper	✓	✓	✓	✓	Mixed	Both

In summary, the DSO can formulate transaction price between DSO and VPPs, and provide enough power for the economical operation of VPPs. VPPs can also fully dispatch DERs and contribute to the operational flexibility of distributed system. As an auxiliary to VPPs, SES can reduce the impact of the volatility of DERs and help VPPs operate more flexibly. This paper introduces a DSO-VPPs coordinated system considering SES, which devises an SC-mixed game model based on the coordinated operation of multi-VPPs led by a DSO, along with cooperative engagement of SES. This model meets the needs of each entity (DSO, VPPs, SES) involved in the operation and can optimize the overall economy. The primary contributions of this paper are outlined as follows:

1) An SC-mixed game model is formulated and solved for the determination of the optimal operation strategy of DSO, VPPs and SES

over a 24-hour scheduling horizon. The upper-level DSO acts as a leader to formulate electricity prices under the energy market to maximize profits, while the lower-level multi-VPPs and SES act as followers to formulate corresponding dispatch strategies. Specially, SES not only participate in the energy trading among VPPs and DSO, but also set the reserve capacity to provide the reserve service to VPPs and get more benefits. The overall framework involves the Stackelberg game between the upper and lower levels, which solves the problem of the rationality of DSO's electricity price setting. A cooperative game is formulated between the VPPs and SES. Also, the distribution of interests between VPPs and SES is realized by obtaining the Nash equilibrium solution. Ultimately, this approach improves the performance of the DSO-VPP-SES system under the both energy and reserve market.

2) A tailored ADMM algorithm is proposed. This paper first uses the bisection method to solve the electricity price signal transmitted between the upper level and the lower level. The bisection method is used to quickly solve the iterative problem of electricity price optimization. Then the ADMM algorithm is used to solve the interactive power problem between the lower-level VPPs and SES. The tailored ADMM algorithm ensures the effectiveness of solving the optimization problems of electricity price and energy separately.

3) The paper proposed an SES considering multi-reserve modes and reserve capacity. The SES model represents six different reserve states. The six different states include: increasing discharge power, decreasing discharge power, increasing charge power, decreasing charge power, transitioning from charging to discharging state, and transitioning from discharging to charging state. Multi-reserve states enable SES to play a greater role in participating in the reserve market. In addition, SES's continuous reserve capability can provide reserves for several hours in the reserve market, ensuring the effectiveness of reserves. To the best of the

authors' knowledge, it is the first paper where a SES is considered to act in the reserve market and provide reserve power to VPPs. This is highly beneficial since it allows the coordinated DSO-VPPs operate with energy and reserve integrated from SES to take advantage of its benefit.

The remainder of this paper is structured as follows. Section 2 introduces the system operation modes and the power reserve model of SES. Section 3 presents the mathematical formulations of DSO, VPPs and SES. Section 4 presents the mixed game model and the solving method. Section 5 provides case studies, and Section 6 concludes this paper.

2. Multi-Agent Operation Framework and Model of SES Considering Reserve Capacity

2.1 The operation framework of the DSO-VPP system

The DSO-VPP system's operation framework is constructed in this paper.

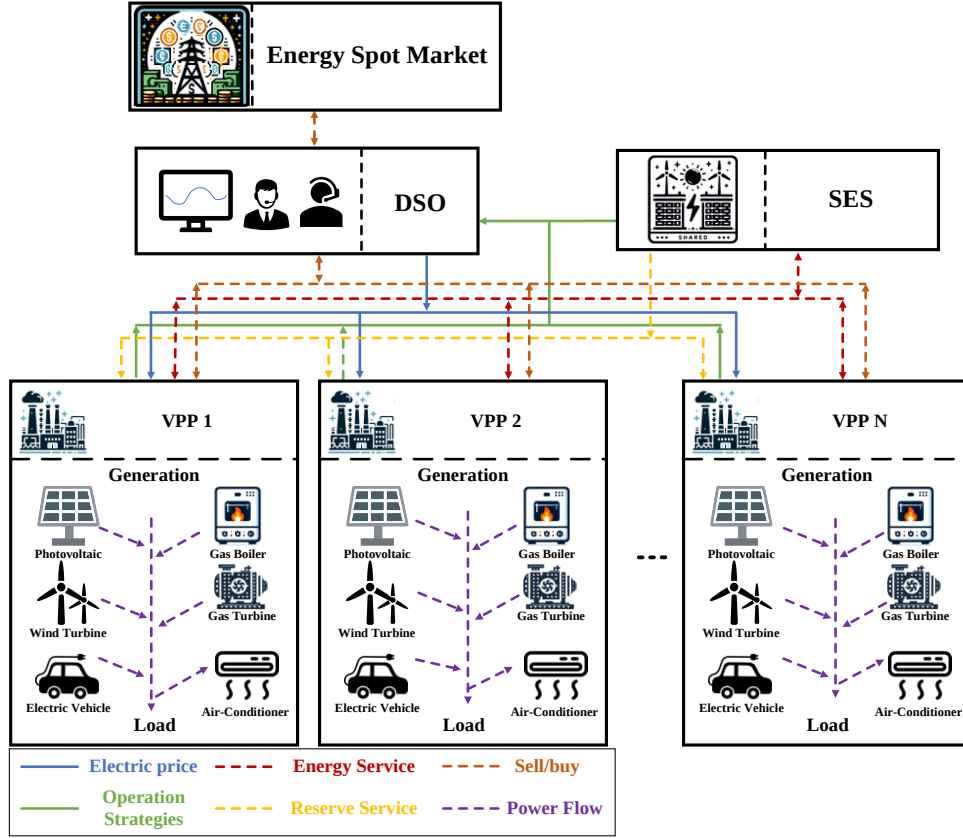


Fig. 1 Operation framework of DSO-VPP system.

As shown in Fig.1, the model constructed in the paper consists of multi-agents, including DSO, VPPs and SES. As the leader, DSO will manage and control VPP and SES to participate in energy spot market and reserve service market for energy trading and reserve capacity trading. In addition, the transaction is subject to relevant policy documents and operators to ensure the fairness of multi-agent market transactions. In the optimization dispatch, DSO is mainly responsible for re-setting the day-ahead electricity price based on the tiered electricity price, and at the same time helping VPPs and SES to trade electricity power with the best price signal when

participating in market transactions. In the process of setting electricity prices and trading with VPP, DSO also maximizes its own profit. SES can provide energy storage services and reserve services for VPPs during the entire dispatching process. Due to the volatility and uncertainty of renewable energy, SES can help VPPs store some energy when the generators' output power is higher to reduce the waste of electricity. During the dispatching process, SES will set up reserve capacity to prevent some extreme situations from happening. The set reserve capacity can provide operation support for VPP and DSO to ensure the safety of system operation.

For VPPs, the existence of SES can help VPPs reduce the economic losses caused to VPP by DSO changing the electricity price. The objective of SES is also to maximize its revenue (energy trading profit and reserve service profit). The VPPs re-optimize the scheduling strategy of every DG based on the price set by the DSO and the help of the SES to minimize their own operating costs. Fig.1 depicts the DSO, VPPs and SES's operation framework in the paper, which are assumed to be geographically adjacent and connected with one line through the electric power line. Each VPP can provide electricity power for load demand. They can also interact with other VPPs or DSO or SES through information exchange. The information data that interact between the DSO, VPPs and SES include power flow, electric price, energy/reserve service information, sell/buy information and operation strategies. The energy spot market is set as infinite energy system to ensure energy balance.

During the operation, the DSO needs to formulate initial electricity prices based on the electricity prices set in the energy market to supply VPPs and SES for reference. The VPPs and SES develop an initial operating strategy and SES's reserve capacity based on the electricity price and send it to the DSO. The DSO will optimize the electricity price according to the SC-mixed game model constructed in the paper and the received lower level's operation strategy. After many rounds of games, the trading electricity price for intraday operation is finally formulated to achieve a balance of interests among DSO, VPPs, and SES. Since the SES can effectively integrate DERs and balance load fluctuations, it plays a vital role in system operation. Therefore, the paper will first model SES.

2.2 Power reserve model of SES

When SES is in the charging state, it can provide up reserve by decreasing the charging power or switch from charging to discharging. The down reserve can be realized by increasing charging power. Accordingly, when SES is in the discharge state, the method to realize the up reserve is increasing the discharge power. While the down reserve involves decreasing the discharge power or switching from the discharging to charging. Therefore, the reserve capacity of SES must fully consider its characteristics in the charging or discharging state. The up and down limits of reserve capacity can be expressed as follows:

$$r_{i,t}^{up} \leq \max \left\{ \begin{aligned} &(1 - u_{i,t}^{dis})(P_i^{dis,max} + P_{i,t}^{ch}), \\ &(1 - u_{i,t}^{ch})(P_i^{dis,max} - P_{i,t}^{dis}) \end{aligned} \right\} \quad (1)$$

$$r_{i,t}^{dn} \leq \max \left\{ \begin{aligned} &(1 - u_{i,t}^{dis})(P_i^{ch,max} - P_{i,t}^{ch}), \\ &(1 - u_{i,t}^{ch})(P_i^{ch,max} + P_{i,t}^{dis}) \end{aligned} \right\} \quad (2)$$

$$0 \leq r_{i,t}^u \leq r_{i,t}^{up} \quad (3)$$

$$0 \leq r_{i,t}^d \leq r_{i,t}^{dn} \quad (4)$$

where i is the index of VPPs, $i \in \{1, 2, \dots, N^{vpp}\}$. N^{vpp} is the number of VPPs. t is the index of time slots in operation horizon. $r_{i,t}^{up}/r_{i,t}^{dn}$ is the up/down reserve capacity set by SES for VPP i . $P_i^{ch,max}$ and $P_i^{dis,max}$ are the upper and lower limits of charging and discharging power of the i^{th} VPP when using the SES for charging and discharging behavior. $u_{i,t}^{ch}$ and $u_{i,t}^{dis}$ are Boolean variables, which represent the charging and discharging status of the i^{th} VPP in the period t . When $u_{i,t}^{ch} = 1, u_{i,t}^{dis} = 0$, it indicates a charging state. And when $u_{i,t}^{ch} = 0, u_{i,t}^{dis} = 1$, it indicates a discharging state. $P_i^{ch,max}$ and $P_i^{dis,max}$ are the maximum charging and discharging power per unit time of SES. When VPPs use the SES simultaneously, they are not allowed to exceed the upper limit. $r_{i,t}^u$ and $r_{i,t}^d$ are the up and down reserve power that can be delivered to VPP i in time t .

According to the different operation states of the SES: charging, discharging, and stationary, six types of constraints of the reserve capacity can be obtained from it. The six different states include 1) increasing discharge power, 2) decreasing discharge power, 3) increasing charge power, 4) decreasing charge power, 5) transitioning from charging to discharging state, and 6) transitioning from discharging to charging state.

SES's reserve types can be divided into two types, which shown in Fig. 2:

Type 1: Increasing discharge power: When SES is in the discharge state, $u_{i,t}^{dis} = 1, u_{i,t}^{ch} = 0$. At this time, if SES increases the discharge power, it can provide up reserve capacity service. The boundary of the up reserve capacity can be calculated by $r_{i,t}^{up} \leq P_i^{dis,max} - P_{i,t}^{dis}$.

Type 2: Decreasing charge power: When SES is in the charging state, $u_{i,t}^{dis} = 0, u_{i,t}^{ch} = 1$. At this time, if SES decreases the charging power, it can provide up reserve capacity service. The boundary of the up reserve capacity can be calculated by $r_{i,t}^{up} \leq P_i^{dis,max} + P_{i,t}^{ch}$.

Type 3: Transitioning from charge to discharge: When SES switches from the charging state to the discharging state $\{u_{i,t}^{dis} = 0, u_{i,t}^{ch} = 1\} \rightarrow \{u_{i,t}^{dis} = 1, u_{i,t}^{ch} = 0\}$, it will provide up reserve capacity service. The boundary of the up reserve capacity can be calculated by $r_{i,t}^{up} \leq P_i^{dis,max} + P_{i,t}^{ch}$.

Type 4: Decreasing discharge power: When SES is in the discharging state $u_{i,t}^{dis} = 1, u_{i,t}^{ch} = 0$, if SES decreases the discharge power, it can provide down reserve capacity service. The boundary of the down reserve capacity can be calculated by $r_{i,t}^{dn} \leq P_i^{ch,max} + P_{i,t}^{dis}$.

Type 5: Increasing charge power: When SES is in the charging state, $u_{i,t}^{dis} = 0, u_{i,t}^{ch} = 1$. At this time, if SES increases the charging power, it can provide down reserve capacity service. The boundary of the down reserve capacity can be calculated by $r_{i,t}^{dn} \leq P_i^{ch,max} - P_{i,t}^{ch}$.

Type 6: Transitioning from discharge to charge: When SES switches from the discharging state to the charging state $\{u_{i,t}^{dis} = 1, u_{i,t}^{ch} = 0\} \rightarrow \{u_{i,t}^{dis} = 0, u_{i,t}^{ch} = 1\}$, it will provide down reserve capacity service. The boundary of the down reserve capacity can be calculated by $r_{i,t}^{dn} \leq P_i^{ch,max} + P_{i,t}^{dis}$.

Energy storage is different from traditional generator units. It receives the limit of its own capacity and does not have unlimited reserve delivery ability. Energy storage needs to respond to the market access rules and improve the responsibility to the market mechanism (increase the power reserve capacity) under the premise of considering the upper and lower constraints of the energy storage capacity. According to the available data, most of the existing independent system operators (ISO) in the United States require the operation time of an energy storage system to participate in the market at least 4 hours. SES needs to ensure that the reserve capacity does not exceed the upper and lower limits of the entire energy storage capacity when using reserve capacity within a continuous period. When the reserve capacity of the SES is dispatched for long continuous hours, it may occur that the energy power and reserve power cannot be provided for the subsequent time. This is to ensure that the energy storage system can continue to provide reserve power for the following operation of the system.

Therefore, according to most ISO regulations [37,38] the reserve capacity of SES set in this paper should have the delivery ability under the limit, down or up, for four consecutive hours.

$$R_{i,t}^{up} \geq \sum_{t_1=0}^3 r_{i,t+t_1}^{up} \Delta t \quad (5)$$

$$R_{i,t}^{dn} \geq \sum_{t_1=0}^3 r_{i,t+t_1}^{dn} \Delta t \quad (6)$$

$$E_t^{SES} + \sum_{i=1}^{N^{VPP}} R_{i,t}^{up} \leq E^{SES,max} \quad (7)$$

$$E_t^{SES} - \sum_{i=1}^{N^{VPP}} R_{i,t}^{dn} \geq E^{SES,min} \quad (8)$$

where $R_{i,t}^{up}$ and $R_{i,t}^{dn}$ are the upper bound when up reserve capacity and down reserve capacity are invoked for VPP i , respectively. t_1 is the beginning of continuous up or down reserve. E_t^{SES} and E_{t+1}^{SES} are the SES's capacity of SES in periods t and $t+1$, respectively. $E^{SES,max}$ and $E^{SES,min}$ are the maximum and minimum allowable capacity of the SES, respectively.

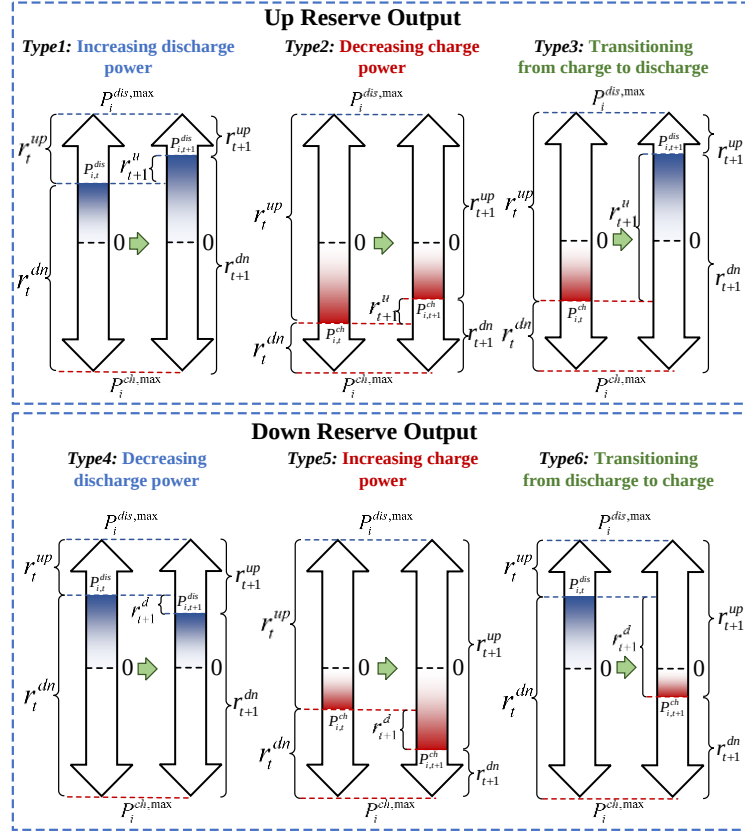


Fig. 2 The operating illustration of SES considering reserve capacity.

3. The SC-Mixed Game Model of DSO-VPP System

3.1 Bi-level interactive framework

An SC-mixed game bi-level model is constructed in the paper for DSO-VPP system. By finding the equilibrium point between the SC-mixed game, the interests of agents are considered.

The model divides the system operation into two levels [39]:

- DSO is the leader at the upper level. It aims to maximize its revenue and optimize the electricity price for the lower level. At the same time,

it generates interactive power with VPPs and formulates their scheduling strategies.

- At the lower level, SES and VPPs cooperate to reduce costs. According to the electricity price transmitted by the upper level, VPPs change strategies of generation units and energy trading. The operation strategies are sent to the upper level as the initial strategy.

The bi-level model is shown in Fig. 3. The upper level is the DSO's operation problem, and the lower level is the VPPs-SES's scheduling problem.

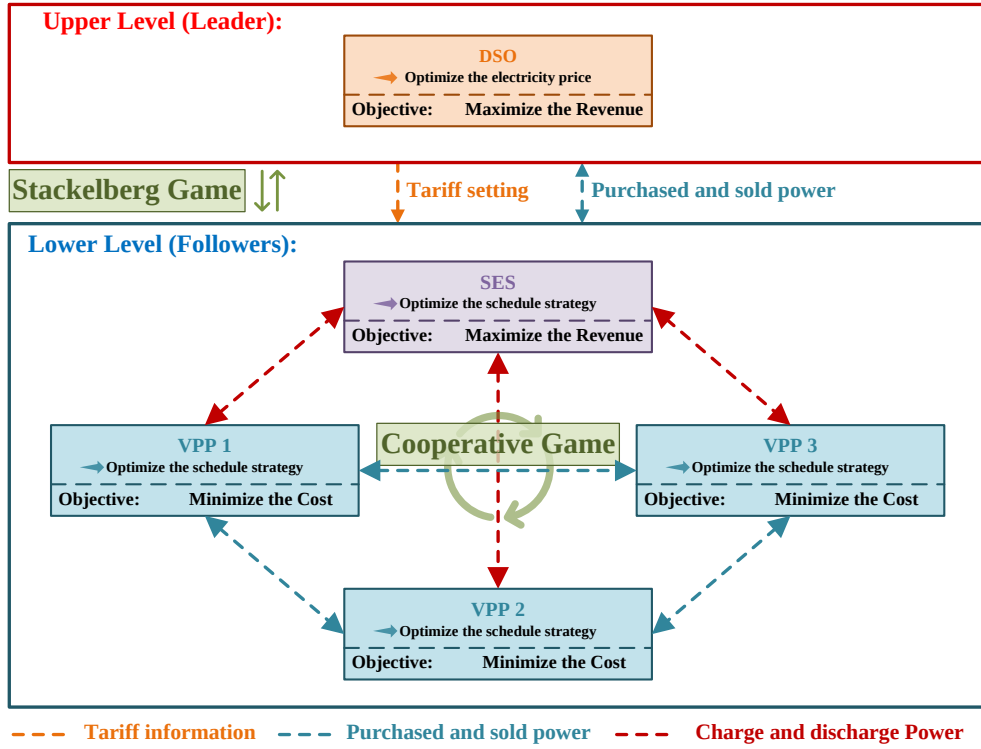


Fig. 3 The bi-level framework of the SC-mixed game.

3.2 Model of upper level for DSO

1) Objective

The upper level aims to maximize the total profit of DSO as follows:

$$\max F^{DSO} = R^{sell} - C^{buy} + C^{SES,res} \quad (9)$$

$$R^{sell} = \sum_{t=1}^T \sum_{i=1}^{N^{vpp}} (\alpha_t^{real,s} p_{i,t}^{sell}) \Delta t + \sum_{t=1}^T (\alpha_t^{grid,b} p_t^{grid,b}) \Delta t \quad (10)$$

$$C^{buy} = \sum_{t=1}^T \sum_{i=1}^{N^{vpp}} (\alpha_t^{real,b} p_{i,t}^{buy}) \Delta t + \sum_{t=1}^T (\alpha_t^{grid,s} p_t^{grid,s}) \Delta t \quad (11)$$

$$C^{SES,res} = \sum_{i=1}^{N^{vpp}} \sum_{t=1}^T (\alpha_t^{up} r_{i,t}^{up} + \alpha_t^{down} r_{i,t}^{dn}) \quad (12)$$

where R^{sell} is the revenue of DSO by selling electricity to VPPs during the intra-day operation phase. C^{buy} is the cost of DSO to purchase surplus power from VPPs during the intra-day operation phase. $C^{SES,res}$ is the reserve capacity cost of SES, which is the revenue of DSO here. T is the time in a typical day. Δt is the unit period of operation time. $p_{i,t}^{buy}$ and $p_{i,t}^{sell}$ are the brought and sell power of DSO to VPP i . $\alpha_t^{real,s}$ and $\alpha_t^{real,b}$ are the sell and buy electricity price designed by DSO respectively. $\alpha_t^{grid,s}$ is the tariff in time t . $p_t^{grid,b}$ and $p_t^{grid,s}$ are the power brought and sell power of upper grid to DSO.

2) Upper and lower limit constraints of power price formulation:

$$\alpha_t^{grid,b} \leq \alpha_t^{real,b} \leq \alpha_t^{real,s} \quad (13)$$

$$\alpha_t^{grid,b} \leq \alpha_t^{real,s} \leq \alpha_t^{grid,s} \quad (14)$$

where $\alpha_t^{grid,b}$ is the feed-in tariff in time t .

3) Line transmission capacity constraints:

$$0 \leq \sum_{i=1}^{N^{vpp}} (p_{i,t}^{buy} + p_{i,t}^{sell}) \leq P^{line} \quad (15)$$

$$0 \leq p_{i,t}^{buy} \leq \beta_{i,t}^{buy} p^{buy} \quad (16)$$

$$0 \leq p_{i,t}^{sell} \leq \beta_{i,t}^{sell} p^{sell} \quad (17)$$

$$0 \leq \beta_{i,t}^{buy} + \beta_{i,t}^{sell} \leq 1 \quad (18)$$

$$\beta_{i,t}^{buy}, \beta_{i,t}^{sell} \in \{0,1\} \quad (19)$$

where P^{line} is the upper limit of distribution grid line transmission power. $\beta_{i,t}^{buy}$ and $\beta_{i,t}^{sell}$ are the VPP i 's state of power purchase and sale in time t . $\beta_{i,t}^{buy}$ and $\beta_{i,t}^{sell}$ are Boolean variables. p^{buy} and p^{sell} are the upper limit of power purchase and sale.

4) Average price constraint of electricity purchase and sale

In order to avoid DSO maximizing its own revenue, which leads to the highest electricity sale price of DSO to the VPPs, the average price constraint of the electricity buy and sell price of the DSO is added [40]. The average price is due to the time-of-use in table 4.

$$\frac{\sum_{t=1}^T \alpha_t^{real,b}}{24} \leq \alpha_t^{ave,b} \quad (20)$$

$$\frac{\sum_{t=1}^T \alpha_t^{real,s}}{24} \geq \alpha_t^{ave,s} \quad (21)$$

where $\alpha_t^{ave,b}$ and $\alpha_t^{ave,s}$ are the average value of the electricity price purchased and sold by the DSO to VPPs.

5) Power balance constraint of DSO's trading

$$\sum_{i=1}^T \left[\sum_{i=1}^{N^{vpp}} (p_{i,t}^{buy} - p_{i,t}^{sell}) + (p_t^{grid,s} - p_t^{grid,b}) \right] = 0 \quad (22)$$

3.3 Model of single VPP agent

1) Objective

A single VPP acts as both a consumer and a producer in the system. And it aims to minimize the total cost as in (23)-(29). The objective functions include units' operation cost, units' maintenance cost, reserve

power dispatching cost, environmental remediation cost, electricity buy and sell cost, and SES service cost in turn.

$$\min F_i^{VPP} = C_i^{ope} + C_i^{rec} + C_i^{res} + C_i^{env} - C_i^{buy} + R_i^{sell} + R_i^{ser} \quad (23)$$

where C_i^{ope} is the operation cost of VPP i . C_i^{rec} is the recovery cost of VPP i . C_i^{res} is the reserve cost of VPP i pay for SES. R_i^{sell}/C_i^{buy} is DSO's revenue of selling power/cost of buying power with VPP i , which is the cost/revenue of VPP i here. C_i^{env} is the environmental remediation cost that VPP i needs to pay for the pollution caused to the environment when the system.

$$C_i^{ope} = \sum_{\kappa} \sum_{t=1}^T (\mu_i^{\kappa} P_{i,t}^{\kappa}) \Delta t, \quad \kappa \in \{GB, GT, EV, PV, WT\} \quad (24)$$

$$C_i^{rec} = \sum_{\kappa} \sum_{t=1}^T (\mu_i^{rec, \kappa} P_{i,t}^{\kappa}) \Delta t \quad (25)$$

$$C_i^{res} = \sum_{t=1}^T (\rho_t^{up} r_{i,t}^u + \rho_t^{dn} r_{i,t}^d) \quad (26)$$

$$C_i^{env} = \sum_{k=1}^K 10^{-3} \beta_k \left(\sum_{t=1}^T \sum_{\kappa} \omega_{i,k}^{\kappa} P_{i,t}^{\kappa} \right) \Delta t \quad (27)$$

$$C_i^{buy} = \alpha_t^{real, b} P_{i,t}^{buy} \quad (28)$$

$$R_i^{sell} = \alpha_t^{real, s} P_{i,t}^{sell} \quad (29)$$

where μ_i^{κ} is the power cost coefficient of DERs, including Gas Boiler (GB), Gas Turbine (GT), Electric Vehicle (EV), Photovoltaic (PV) and Wind Turbine (WT). $P_{i,t}^{\kappa}$ is the output power of DGs in VPP i at time t . $\mu_i^{rec, \kappa}$ is the recovery cost coefficient of DG κ . ρ_t^{up} and ρ_t^{dn} are the reserve cost coefficient when VPP i uses the SES's up or down reserve capacity in time t . k is the type number of pollutants discharged during the operation of the unit. $\omega_{i,k}^{\kappa}$ is the emission coefficient of pollutants k for unit κ in VPP i . β_k is the cost of treating pollutant k .

2) Power balance constraint

$$P_{i,t}^{DG} + P_{i,t}^{PV} + P_{i,t}^{WT} + P_{i,t}^{EV} + P_{i,t}^{dis} + P_{i,t}^{sell} + P_{i,t}^{ex} = P_{i,t}^{ch} + P_{i,t}^{buy} + P_{i,t}^{AC} + L_{i,t}^e \quad (30)$$

where $P_{i,t}^{PV}$ and $P_{i,t}^{WT}$ are the output power of PV unit and WT in VPP i at time t . $P_{i,t}^{EV}$ is the output power of EV. $P_{i,t}^{ex}$ is the exchange power for VPP i to other VPPs. $P_{i,t}^{AC}$ is the consumption power of air-conditioner (AC). $L_{i,t}^e$ is the load of VPP i at time t .

3) Unit operation constraint

$$0 \leq P_{i,t}^{\kappa} \leq P_{i,t}^{\kappa, max} \quad (31)$$

where $P_{i,t}^{\kappa, max}$ is the upper limit power of DG κ .

4) Load constraints

$$L_{i,t}^e = L_{i,t}^{e, f} + L_{i,t}^{e, r} \quad (32)$$

where $L_{i,t}^{e, f}$ and $L_{i,t}^{e, r}$ are the flexible load and rigid load of VPP i at time t respectively [35].

In order to describe the VPP's DR ability more uniformly, the automatic DR ability of all VPPs' flexible electric load is measured by the adjustable proportion ε per period and the total proportion of electricity adjustment φ . The flexible electric load adjustment of user aggregators is constrained as follows:

$$\frac{|L_{i,t}^{e, f*} - L_{i,t}^{e, f}|}{L_{i,t}^e} \leq \varepsilon \quad (33)$$

$$\sum_{t=1}^T |L_{i,t}^{e, f*} - L_{i,t}^{e, f}| \leq \varphi \sum_{t=1}^T L_{i,t}^e \quad (34)$$

$$\sum_{t=1}^T L_{i,t}^{e, f*} = \sum_{t=1}^T L_{i,t}^{e, f} \quad (35)$$

where $|L_{i,t}^{e, f*} - L_{i,t}^{e, f}|$ is the electric load adjustment of VPP i at time t . $L_{i,t}^{e, f*}$ is the flexible electric load adjusted by VPP i at time t . ε is the maximum allowable proportion of electric load adjustment at time t . φ is the proportion of the total electric load adjustment in VPP i in a day. The larger ε and φ are, the more flexible VPP is to adjust the electricity load, and the greater VPPs' DR capability is.

3.4 Model of SES

1) Objective

The objective function of SES is to maximize revenue, including the charging and discharging revenue charged to VPPs, the energy storage charging-discharging cost, the reserve capacity setting cost and the reserve power revenue charged to VPP.

$$\max F^{SES} = R^{ser} - C^{cd} - C^{SES, res} + \sum_{i=1}^{N^{VPP}} C_i^{res} \quad (36)$$

$$R^{ser} = \sum_{i=1}^{N^{VPP}} \sum_{t=1}^T (\mu_t^{ser, dis} P_{i,t}^{dis} - \mu_t^{ser, ch} P_{i,t}^{ch}) \quad (37)$$

$$C^{cd} = \sum_{i=1}^{N^{VPP}} \sum_{t=1}^T \alpha_t^{cd} (P_{i,t}^{ch} + P_{i,t}^{dis}) \quad (38)$$

where F^{SES} is the objective function of SES, which denotes the cost of SES. R^{ser} is the service revenue. C^{cd} is the charge-discharge cost of SES. $C^{SES, res}$ is the cost of reserve capacity that SES needs to pay to DSO. C_i^{res} is the reserve cost of VPP i pay for SES as in (26), which is the revenue here. $P_{i,t}^{ch}$ and $P_{i,t}^{dis}$ are the charging and discharging power of the i^{th} VPP user using the SES for charging and discharging behaviors in period t . $\mu_t^{ser, dis}$ and $\mu_t^{ser, ch}$ are the cost coefficient of unit charge and discharge of SES. N^{VPP} is the number of VPPs. T is the final time of a typical day operation. α_t^{cd} is the unit transmission cost of energy storage during charging and discharging. α_t^{up} and α_t^{down} are the unit costs coefficient of the up reserve capacity and down reserve capacity. $r_{i,t}^{up}$ and $r_{i,t}^{dn}$ are the up reserve capacity and down reserve capacity of VPP i to SES, respectively.

2) Constraints

The conventional model of SES is detailed in (A.1)-(A.9) in the Appendix A. The spare capacity constraints are shown in (1)-(8).

In summary, the DSO model contains 624 decision variables, 1 equality constraint and 387 inequality constraints; the single VPP model contains 216 decision variables, 25 equality constraints and 265 inequality constraints; the SES model contains 408 decision variables, 24 equality constraint and 960 inequality constraints.

4. Model Solving

4.1 Model equivalent conversion

In the paper, an SC-mixed game is constructed, which is dominated by DSO and followed by VPPs-SES, taking into account the respective interests of each agent.

The game model contains three elements: players, strategies and revenue, which are expressed as follows:

$$G = \{N_p, \rho^{DSO}, \{\delta^{SES}, \delta^{VPPi}\}, I^{DSO}, \{I^{SES}, I^{VPPi}\}\} \quad (39)$$

where N_p is the set of participants including DSO, SES and VPPs. $\rho^{DSO} = \{\alpha_t^{real, b}, \alpha_t^{real, s}\}$ is the pricing strategy of DSO. $\delta^{SES} =$

$\{P_{i,t}^{ch}, P_{i,t}^{dis}, r_t^u, r_t^d, r_t^{up}, r_t^{down}\}$ is the strategy of SES. $\delta^{VPPi} = \{P_{i,t}^K, P_{i,t}^{buy}, P_{i,t}^{sell}, L_{i,t}^{ef}\}$ is the strategy of VPP i .

The VPPs-SES in the lower level of the system feedback the energy price is transmitted downward by the upper DSO through cooperation. And the association minimize the cost in the process of cooperation [41,42]. The Nash criterion model can define the Pareto equilibrium solution for solving multi-agent cooperation as follows:

$$\begin{cases} \min \prod_{i=1}^N (C_i - C_i^0) \\ s. t. C_i - C_i^0 \geq 0 \end{cases} \quad (40)$$

where C_i is the cost of VPPs and SES participating in the negotiation respectively; C_i^0 is the cost obtained by the VPPs and SES not participating in the negotiation, which is the negotiation breakdown point. Since the model is non-convex and nonlinear, it is difficult to solve it directly. It needs to be converted into two sub-problems (multi-agent cooperation cost minimization problem and cost allocation problem) to be solved in turn [43].

Sub-problem 1: multi-agent cooperation revenue maximization problem.

$$\begin{cases} \min F^{sys} = \left(F^{DSO} - \sum_{i=1}^{N^{VPP}} F_i^{VPP} + F^{SES} \right) \\ s. t. (1) - (8), (12) - (21), (29) - (34), (A.1) - (A.9) \end{cases} \quad (41)$$

where F^{sys} is the total cost of the system.

Sub-problem 2: cost allocation problem.

$$\begin{cases} \min \sum_{t=1}^T \ln \left[\sum_{i=1, j \neq i}^{N^{VPP}} (\alpha_{i-j,t}^{ex} P_{i-j,t}^* + F^{sys*} - C_i^0) \right] \\ s. t. \sum_{t=1}^T \left[\sum_{i=1, j \neq i}^{N^{VPP}} (\alpha_{i-j,t}^{ex} P_{i-j,t}^* + F^{sys*}) \right] \geq C_i^0 \\ \alpha_t^{real,b} \leq \alpha_{i-j,t}^{ex} \leq \alpha_t^{real,s} \end{cases} \quad (42)$$

where $\alpha_{i-j,t}^{ex}$ is the electricity price of exchange power between VPP i and VPP j . $P_{i-j,t}^*$ is the optimal solution for the amount of electricity traded between VPP i and j obtained from sub-problem 1. F^{sys*} is the minimum value of cooperation cost obtained by sub-problem 1.

4.2 The tailored ADMM algorithm

This paper uses the ADMM algorithm to solve the transaction problem of different stakeholders, which can protect the privacy of each agent.

1) First construct the augmented Lagrangian.

The paper builds the augmented Lagrangian L_i for VPP i .

$$\begin{aligned} L_i(P_{i-j,t}^*, P_{j-i,t}^*, \lambda_{ij,t}, \rho_{ij}) = & \min F_i^{VPP} + \sum_{j \neq i} \sum_{t \in T} \lambda_{ij,t} (P_{i-j,t}^* + P_{j-i,t}^*) \\ & + \sum_{j \neq i} \sum_{t \in T} \frac{\rho_{ij}}{2} \|P_{i-j,t}^* + P_{j-i,t}^*\|_2^2 \end{aligned} \quad (43)$$

where $\lambda_{ij,t}$ is the Lagrange multiplier. ρ_{ij} is the penalty term.

2) Iterative initialization.

The paper sets the initial value of the number of iterations $l = 1$. l^{max} is the maximum number of iterations. The electricity traded between VPPs $P_{i-j,t}^* = P_{j-i,t}^* = 0$. Lagrange multiplier $\lambda_{ij,t} = 0$.

3) Iterative calculation steps.

$$\begin{cases} P_{i-j,t}^{*,l+1} = \arg \min L_i(P_{i-j,t}^*, P_{j-i,t}^*, \lambda_{ij,t}^l, \rho_{ij}^l) \\ P_{j-i,t}^{*,l+1} = \arg \min L_j(P_{j-i,t}^*, P_{i-j,t}^*, \lambda_{ij,t}^l, \rho_{ij}^l) \\ \lambda_{ij,t}^{l+1} = \lambda_{ij,t}^l + \rho_{ij}^l (P_{i-j,t}^{*,l+1} + P_{j-i,t}^{*,l+1}) \end{cases} \quad (44)$$

where $P_{i-j,t}^{*,l+1}$ is the $(l+1)^{th}$ electricity traded.

4) Determine algorithm convergence

$$\sum_{j \neq i} \sum_{t \in T} \|P_{i-j,t}^{*,l+1} - P_{j-i,t}^*\|_2 \leq \tau \quad (45)$$

where τ is the residual convergence set point.

Firstly, the parameters are initialized and the initial load of VPPs and the initial tariff set by DSO are imported into the system. After one round of optimization of the scheduling strategy by VPPs-SES, it will be fed back to DSO, which will optimize and adjust the tariff according to the strategy and transmit it to VPPs-SES. After one round of iteration, a criterion is made by (45) to determine whether the convergence condition is reached or not. If it reaches, it skips the iteration to output the resultant tariff and scheduling strategy, and if it does not reach, the tariff is changed by using the dichotomy method. Re-enter the iteration loop.

The solution flow chart is shown in Fig. 4. d is the number of iterations of the bisection method.

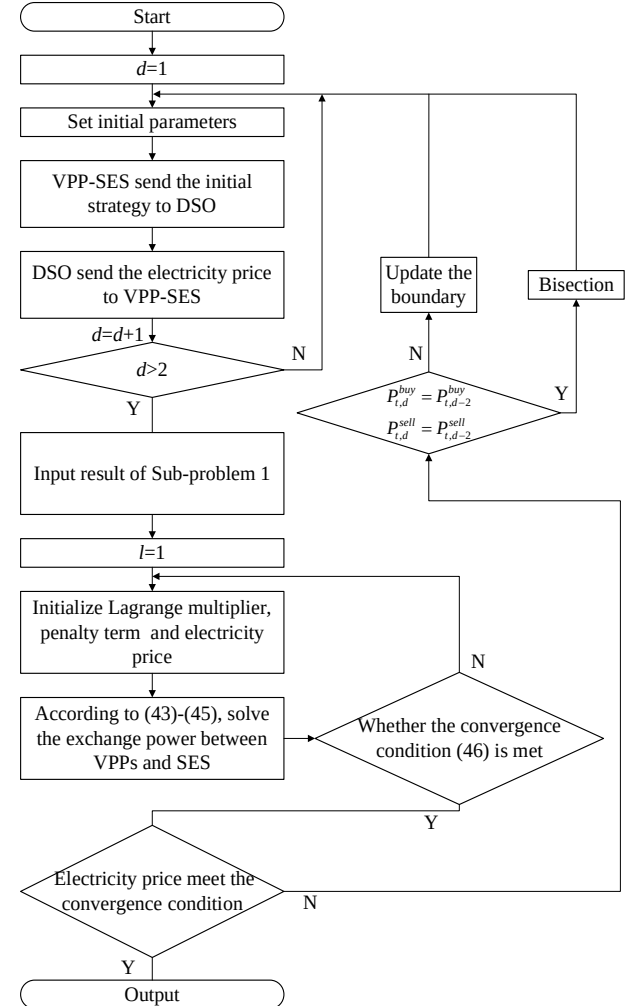


Fig. 4 Flow chart of the SC-mixed game solving.

The convergence criterion for rapidly shrinking the boundary in each

iteration is as follows:

$$\frac{\alpha_{t,d+1}^{real,\psi} - \alpha_{t,d}^{real,\psi}}{\alpha_{t,d}^{real,\psi}} \leq \xi \quad \psi \in \{s, b\} \quad (46)$$

where $\alpha_{t,d}^{real,b}$ and $\alpha_{t,d}^{real,s}$ are the electricity purchase and sale price set by the DSO at the d^{th} iteration. ξ is the convergence precision. The electricity price obtained after the iteration results satisfies the convergence condition and is used as the electricity price set by DSO which is the initial parameter of the lower level.

5. Results and Discussion

5.1 Parameters setting

In this paper, the effectiveness of the above design model is verified through simulation experiments. All simulations are implemented using the YALMIP toolbox in the MATLAB R2023a environment. The optimization problem is solved using GUROBI Optimizer version 10.0.3 on a laptop with Apple M2 CPU and 16GB memory. This paper selects 24 hours on a typical day as the total operating time, and the time interval is 1 hour. Some of the parameter settings in this paper are shown in Table 2, and the pollutant emission coefficients of different types of generating units and the treatment costs of different types of pollutants are shown in Table 3. The feed-in tariffs and selling prices of the external distribution grid are shown in Table 4 [44]. When quoting parameters, appropriate modifications are made to the scale of the model.

Table 2 A part of the parameters of the model

Agents	Parameters	Value
SES	$E^{SES,max}$	1500kWh
	$E^{SES,min}$	100kWh
	η^{ch}	0.95
	η^{dis}	0.95
	$p^{ch,max}$	120kW
	$p^{dis,max}$	120kW
	$p_i^{ch,max}$	50kW
	$p_i^{dis,max}$	50kW
	SOC_0	0.4
	u	0.98
VPP	μ_i^{GB}	0.45 CNY/kW
	μ_i^{GT}	0.45 CNY/kW
	μ_i^{EV}	0.128 CNY/kW
	μ_i^{PV}	0.02 CNY/kW
	μ_i^{WT}	0.02 CNY/kW

Table 3 Pollutant treatment costs and discharge coefficients

Type	Costs of pollution control(CNY/kg)	Pollutant emission factor($g/(kW \cdot h)$)				
		GT	GB	EV	AC	Grid
CO_2	0.210	698.53	389.64	0.001	408.2	889
SO_2	14.842	0.000928	0.0076	0.0012	0.002	1.8
NO_x	62.964	0.068	0.3263	0	0.356	1.6
CO	10.49	0.047	0.1348	0	0.412	0.081

Table 4 Time-of-use tariffs of the market

Time	Feed-in tariff (CNY/kWh)	Tariff(CNY/kWh)
7:00--10:00,14:00--18:00	0.36	0.82
10:00--14:00,18:00--23:00	0.36	1.35
23:00--7:00	0.36	0.38

In this paper, we compare and analyse the scheduling of DSO and VPPs on a typical day by setting up different scenarios. To distinguish the scheduling schemes under different VPPs' models, this paper sets up different units for different VPPs as follows:

- VPP A: PV, WT, GT, GB, EV;
- VPP B: PV, WT, GT, GB;
- VPP C: PV, GT, GB.

Besides, Fig.5 shows the load before considering demand response of the three VPPs. From load information, the load of VPP A and VPP B is relatively low at 6:00-17:00, both of which are residential VPPs. The VPP C has a high load during this period and belongs to the factory VPP. At

night, the load of VPP A and VPP B has increased to varying degrees. The load of VPP C at night is lower than that at daytime.

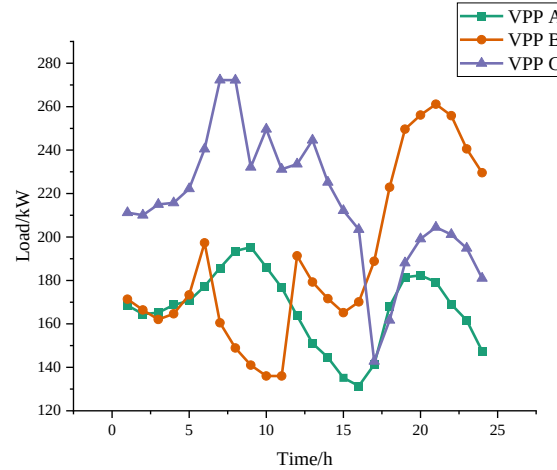


Fig. 5 The load information of VPPs before DR.

To prove that the SES considering the reserve capacity proposed in the paper can optimize the operation of the whole system by participating in the optimal scheduling of VPPs, the case study sets up several control schemes for comparison. The specific operation schemes are shown in Table 5.

Table 5 The factors considered by the system operating under different schemes

Scheme	Factors			
	Reserve Capacity	SES	DSO	VPPs
1	✓	✓	✓	✓
2	×	✓	✓	✓
3	✓	✓	×	✓
4	×	×	✓	✓
5	×	×	×	✓

5.2 Electricity price analysis

In the paper, after receiving the pre-scheduling plan provided by VPPs, DSO re-formulates the purchase and sale price of VPPs participating in the market transaction according to the electricity price of the electricity market. In the two-stage mixed game model established above, the electricity price is remade through VPPs operation strategies after the game. Finally, the intraday purchase and sale price is obtained as shown in Fig.6.

From the diagram, the 'Buy low, Sell high' strategy after optimization for DSO keeps the electricity price in a more reasonable range. When the price of electricity sold in the electricity market is high, the functions of DSO are used to appropriately reduce the price of electricity sold and increase the willingness of VPPs to purchase electricity from the operator to meet the scheduling needs of VPPs. At the same time, when VPPs are filled with electricity, the feed-in tariff should be appropriately increased to

form DSO's own profit situation. For VPPs, the excess electricity can be sold at a higher selling price; when the load demand cannot be met, the power generation vacancy can also be filled with a lower purchase price to meet the load demand.

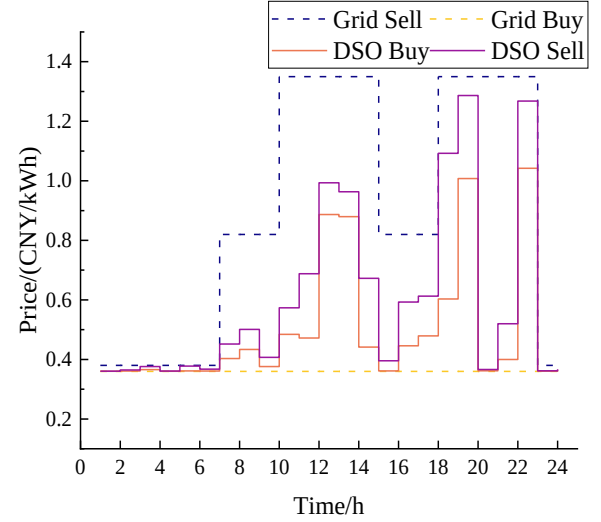


Fig. 6 Electricity price strategy diagram of DSO under the scheme 1.

5.3 Comparative analysis of different system schemes

The results of different schemes are shown in Table 6 as follows:

Table 6 The results of the operation under different schemes

Scheme	Profit of DSO/CNY	VPP	Cost of VPPs/CNY	Revenue between VPPs trading/CNY	Total cost of VPPs/CNY	Profit of SES/CNY	Total cost of lower level/CNY
1	1808.92	A	16.57	961.97	4666.89	385.74	4281.15
		B	562.61	178.97			
		C	1754.27	-1140.94			
2	1290.19	A	45.62	1406.85	5776.49	148.92	5627.56
		B	1603.91	-168.13			
		C	1238.71	-1238.71			
3	/	A	-545.92	1930.41	5928.96	149.33	5779.63
		B	1635.70	-55.72			
		C	1874.70	-1874.70			
4	1327.24	A	244.38	1312.84	6497.15	/	6497.15
		B	1821.65	-130.30			
		C	1182.54	-1182.54			
5	/	A	-442.41	1387.74	6582.61	/	6582.61
		B	905.19	-8.81			
		C	2828.52	-1378.93			

The reserve capacity scheduling of SES is shown in Fig.7. In Fig.7, (a) and (b) respectively show the up and down reserve capacity reservation strategies adjusted for the scheduling strategy of VPPs under the pricing mechanism of DSO when the energy storage is running in the whole system. In the paper, transmission lines are set up between SES and VPPs to provide reserve capacity. In this case, three transmission lines are set up for SES, corresponding to three VPP A-C, to provide energy storage reserve capacity. (c) and (d) represent the energy storage reserve power called by each VPP when participating in the auxiliary reserve market scheduling under the up and down reserve capacity strategies set by SES.

From Table 6 and Fig. 7-9, it can be clearly seen that due to the increase of energy storage reserve capacity in Scheme 1 compared with Scheme 2, the benefit of SES is improved by using the characteristics of SES participating in the auxiliary reserve market. Compared with SES without considering the energy storage reserve capacity, SES considering the energy storage reserve increases the income by 236.82 CNY. This is a costly income for SES with a small income base in the VPP and even achieves the effect of doubling the income. In the previous load setting, the type of generator set of VPP A is relatively comprehensive compared with that of VPP B and VPP C. VPP B and C have different degrees of loss in

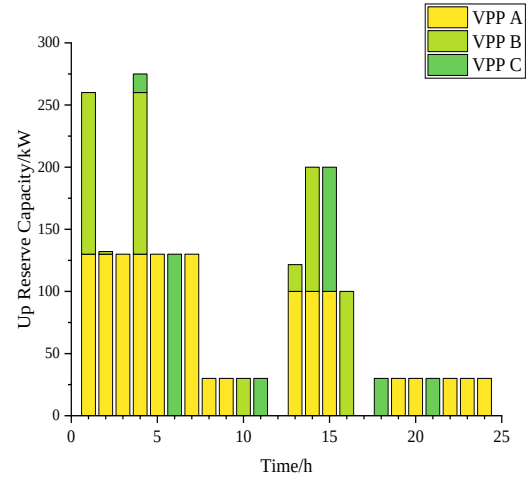
the type and quantity of units, while C has no new energy units at all. Therefore, in terms of operating costs and benefits, because VPP A has rich renewable energy generating units, the cost is the lowest, only 16.57 CNY. In addition, A can have more surplus electricity to be charged to SES or sold to the DSO to reduce operating costs. In the cooperative game of the lower VPPs, the profit of VPP A is 961.97 CNY. In the case of VPP C with high load demand and only equipping with thermal generation units. It is necessary to purchase electricity from other VPPs in the cooperative game and more electricity from SES and DSO to meet their load demand. In the VPP C operation, the daily operating cost reaching 1,754.27 CNY, and 1,140.94 CNY is spent on other VPPs in the cooperative game.

In the scheme without considering the reserve capacity, the scheduling trend of VPPs is still the same, but the total cost of the lower-level scheduling is 1,346.41 CNY higher than that of the system considering the reserve capacity. And the total scheduling cost of VPPs is also 1,109.6 CNY higher. At the same time, DSO can influence the SES reserve capacity scheduling strategy and the VPPs scheduling strategy through the master-slave game, which can make 518.73 CNY more profit than the system without considering the reserve capacity. This is because when considering the reserve capacity, the system can reserve space for increasing or decreasing the reserve power through energy storage, improve the utilization rate of energy storage, and help VPP obtain more power from SES to meet the load demand during scheduling. In this case, it can naturally increase the benefits of multi-agent parties in the system and reduce costs.

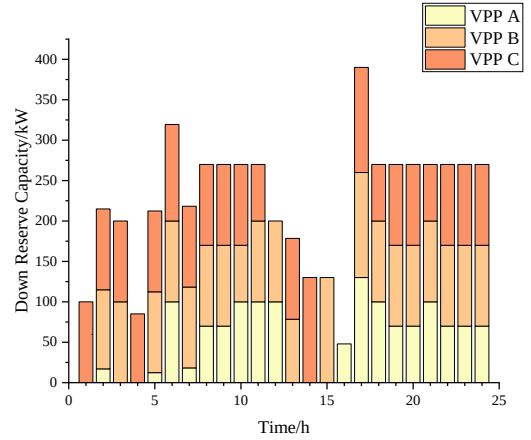
By comparing scheme 1 and scheme 3, it can be concluded that when there is no longer a master-slave game between DSO and the lower VPPs-SES alliance to adjust the purchase and sale price from it, but when VPPs directly enters the market for trading, it will increase the cost burden of purchasing electricity of the lower VPPs. The cost of VPPs consumption increases significantly, and the cost of VPPs expenditure in scheme 3 increases by 1,262.07 CNY compared with scheme 1. The total cost of the lower level also increases by 1,498.48 CNY. This is because DSO can analyse the price trend through the Stackelberg game, and formulate new electricity prices in the form of 'buy low and sell high', so as to help VPPs optimize their own generator sets and flexible load demand, which greatly improves the cost-saving ability of VPPs. It is precisely because of DSO's participation in the market that VPP and SES benefit more from the market.

Compared with the third and fifth schemes in table 6, without considering the adjustment of electricity price by DSO, the total cost of VPPs in the third scheme is 653.65 CNY lower than that in the fifth scheme when SES participates in the cooperative game, and the total cost of the lower level is reduced by 802.98 CNY. This is because the cooperative game between SES and each VPP also plays a full role in promoting the overall cost reduction.

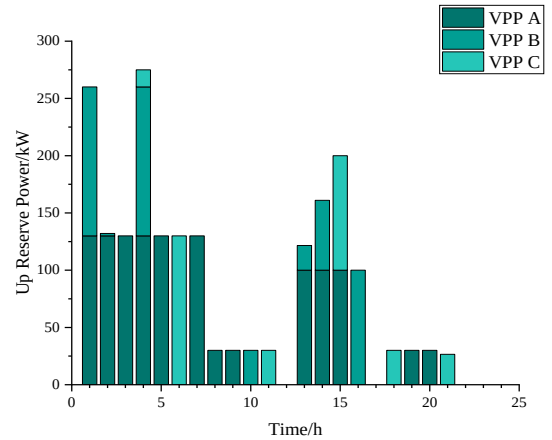
Finally, comparing scheme 1 with scheme 5, it can be concluded that scheme 1 adjusts the electricity price and energy storage strategy because it considers the game between DSO and SES to participate in the transaction, which greatly reduces the consumption cost of VPPs. Compared with scheme 4, the cost of VPPs in scheme 1 is reduced by 1,915.72 CNY.



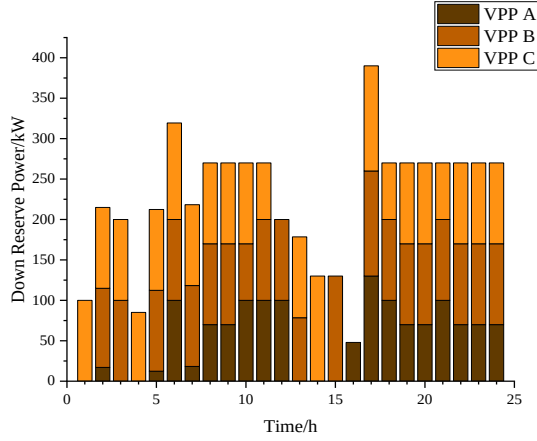
(a) Up reserve capacity set by SES for different VPPs.



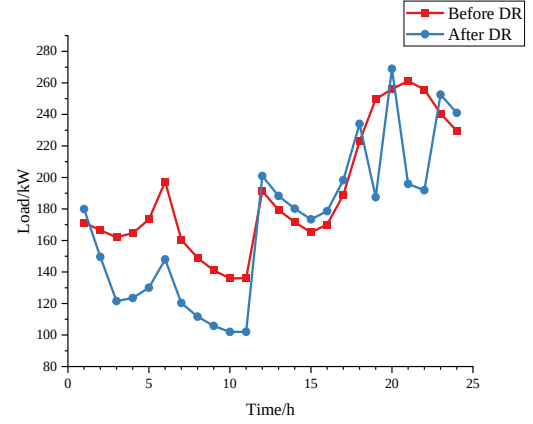
(b) Down reserve capacity dispatched by different VPPs.



(c) Up reserve dispatched by different VPPs.



(d) Down reserve dispatched by different VPPs.



(b) VPP B.

Fig. 7 SES reserve situation diagrams under the scheme 1.

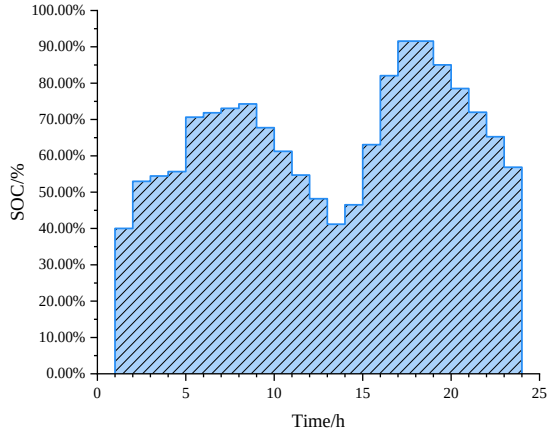
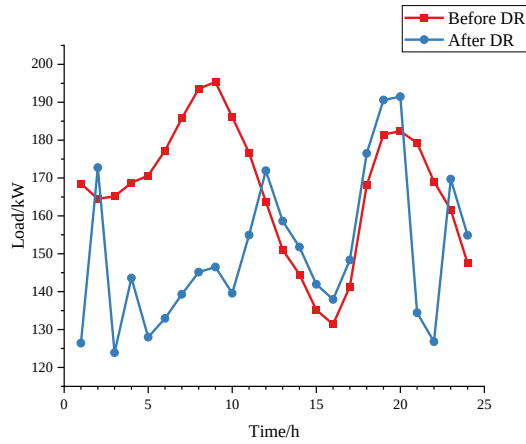
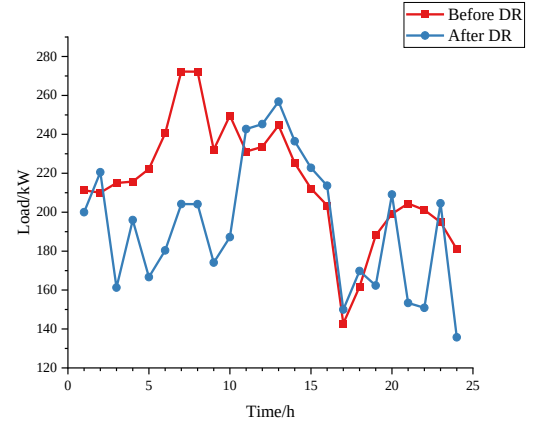


Fig. 8 SES's state of charge under the scheme 1.

Fig. 9 is a comparison chart of VPP's load dispatch adjustment according to the intraday electricity price transmitted by DSO under the load DR.



(a) VPP A.



(c) VPP C.

Fig. 9 The load demand responds of VPPs compared before and after under the scheme 1.

In this paper, the scheduling results of scheme 1 considering the SC-mixed game model are shown in Fig. 10.

Because there are enough generating units and the output of photovoltaic wind power in the dispatching of VPP A, the diversity of energy supply is greatly increased. It can be seen from Fig.9 (a) that because of the richness of the power supply unit, the VPP A is more of a generator role in the scheduling. On the output side, an average of 100kW or even higher than 100kW power is output to the VPP B or C at each moment. It not only meets its own load demand, but also supports the energy supply demand of other VPPs. There is also surplus energy that can be stored in a SES for subsequent use. Similarly, in Fig.9 (c), due to the high load demand of VPP C in the interval of 0:00, 9:00-11:00, 21:00-23:00, the power is not sold to other VPPs under the premise of short supply, and the power is charged to SES.

From the simulation experiment, it can be concluded that under the mixed game model, the addition of DSO and SES can fully optimize the scheduling cost and benefit distribution of prosumers, ensure the multi-party cooperative operation, reduce the cost and improve the income of each operator.

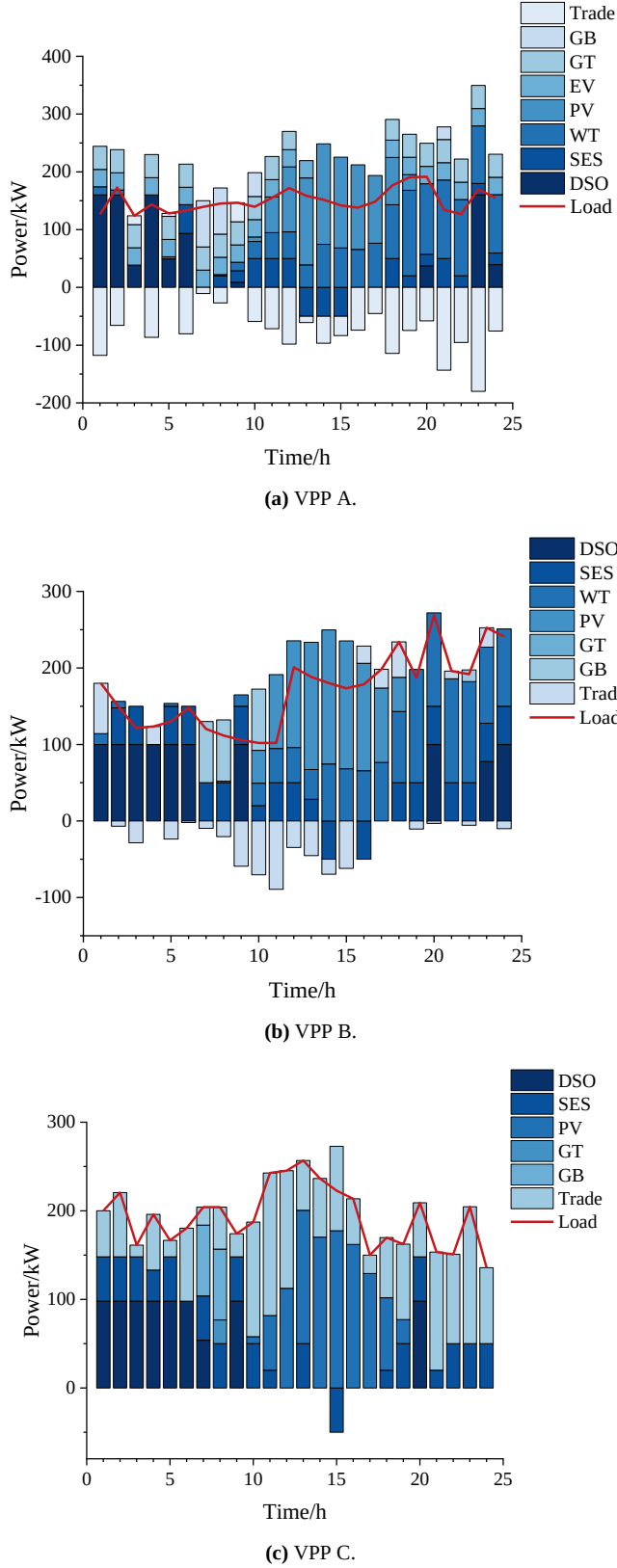


Fig. 10 The scheduling strategy of VPPs in scheme 1.

5.4 Algorithm comparison

In this paper, the combination of bisection and ADMM speeds up the calculation. We also use particle swarm optimization (PSO) and genetic algorithm (GA) for comparison. Table 7 shows the convergence speed of optimization using different algorithms.

Table 7 Convergence speed comparison of different algorithms

Method	Convergence time (s)
Bisection + ADMM	513.564
PSO	1834.461
GA	1693.727

The paper compares the iterations of the three algorithms mentioned above, and shows the number of iterations to obtain the optimization results under different algorithms in Fig. 11. It can be seen that the proposed method can reach the convergence condition and obtain the optimization results in only 21 iterations, but the convergence speed of PSO and GA is too slow, and it takes nearly 400 generations to stabilize the results. In addition, the optimization results of the three algorithms are similar, so the proposed method is more efficient.

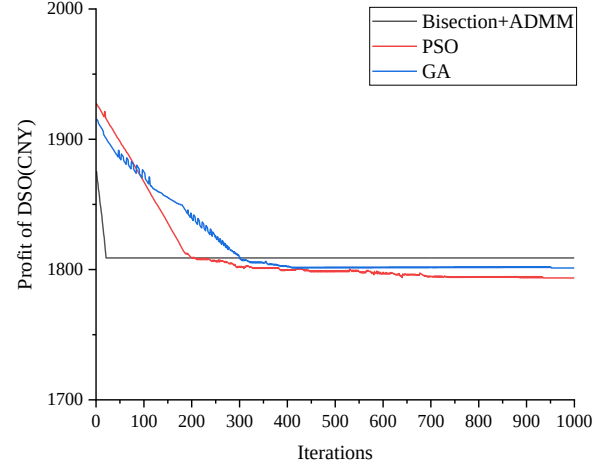


Fig. 11 The number of iterations under different algorithms.

6. Conclusion

This paper studies the coordinated operation mechanism of VPPs in the context of the energy-reserve joint market. An SC-mixed game model with DSO as leaders and SES-VPPs as followers is proposed based on Stackelberg theory. At the same time, based on Nash bargaining theory, a cooperative game model between VPPs and SES is established. Then a tailored ADMM algorithm is designed to solve and analyse the model to maximize the overall system operation benefits. The main conclusions obtained through the cases results under different operating schemes are as follows:

- 1) The DSO-VPP system under the leadership of DSO has formulated a more economic electricity price strategy for VPPs' coordinated operation. It not only ensures that DSO can make profits through the "Buy low, Sell high" mode, but also helps VPPs save electricity purchase costs.
- 2) Through the cooperative game with VPPs and SES, funds are saved and the phenomenon of power, wind and solar curtailment is reduced.

3) The proposed six-mode reserve model can maximize potential reserve capacity for SES. It can provide more reserve to the system which improve the operating efficiency of VPPs and SES.

4) VPPs and SES directly interact and cooperate with each other, so that VPPs can fully communicate with each other, fully dispatch the resources of all parties, so that the energy supply of VPPs with power shortage is no longer single, and VPPs with abundant capacity can also benefit from the transaction.

This paper contributes to the dispatch situation of VPPs participating in energy and reserve markets during a typical day. In the future, we will study the multi-time scale coupled optimal dispatch of the proposed DSO-VPP system, including day-ahead, intra-day, and real-time. In addition, we will consider the operation mechanism of DSO, VPP, and SES participating in the energy spot-auxiliary reserve-auxiliary frequency coupling market under the actual grid structure.

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Appendix A

The paper built the SES's general model:

$$E_{t+1}^{SES} = (1 - u)E_t^{SES} + \sum_{i=1}^{N^{VPP}} \left(\eta^{ch} P_{i,t}^{ch} - \frac{P_{i,t}^{dis}}{\eta^{dis}} \right) \Delta t \quad (A.1)$$

$$0 \leq P_{i,t}^{ch} \leq u_{i,t}^{ch} P_i^{ch,max} \quad (A.2)$$

$$0 \leq P_{i,t}^{dis} \leq u_{i,t}^{dis} P_i^{dis,max} \quad (A.3)$$

$$0 \leq u_{i,t}^{ch} + u_{i,t}^{dis} \leq 1 \quad (A.4)$$

$$u_{i,t}^{ch}, u_{i,t}^{dis} \in \{0,1\} \quad (A.5)$$

$$P_{1,t}^{ch} + P_{2,t}^{ch} + \dots + P_{N^{VPP},t}^{ch} \leq P^{ch,max} \quad (A.6)$$

$$P_{1,t}^{dis} + P_{2,t}^{dis} + \dots + P_{N^{VPP},t}^{dis} \leq P^{dis,max} \quad (A.7)$$

$$E_{t+1}^{SES,min} \leq E_t^{SES} \leq E^{SES,max} \quad (A.8)$$

where, E_t^{SES} and E_{t+1}^{SES} are the SES's capacity of SES in periods t and $t + 1$, respectively. u is the self-discharge rate of the SES. η^{ch} and η^{dis} the power transmission efficiency coefficients of the SES in charging and discharging process, respectively. $P_i^{ch,max}$ and $P_i^{dis,max}$ are the upper and lower limits of charging and discharging power of the i^{th} VPP when using the SES for charging and discharging behavior. $u_{i,t}^{ch}$ and $u_{i,t}^{dis}$ are Boolean variables, which represent the charging and discharging status of the i^{th} VPP in the period t . When $u_{i,t}^{ch} = 1$, $u_{i,t}^{dis} = 0$, it indicates a charging state. And when $u_{i,t}^{ch} = 0$, $u_{i,t}^{dis} = 1$, it indicates a discharging state. $P^{ch,max}$ and $P^{dis,max}$ are the maximum charging and discharging power per unit time of SES. When VPPs use the SES simultaneously, they are not allowed to exceed the upper limit. $E^{SES,max}$ and $E^{SES,min}$ are the maximum and minimum allowable capacity of the SES, respectively.

For SES to provide uninterrupted services, the paper assumes that the charging power and discharging power of SES in a typical day are equal:

$$\sum_{i=1}^{N^{VPP}} \sum_{t=1}^T \left(\eta^{ch} P_{i,t}^{ch} - \frac{P_{i,t}^{dis}}{\eta^{dis}} \right) = 0 \quad (A.9)$$

where T is the last period in which the system operates.

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