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Distributed energy storage hierarchical partition dispatch control of virtual power plant based on SaDE-BBO algorithm

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Abstract

To improve the response ability of the virtual power plant during operation and the adjustment ability when the load fluctuates, and ensure its stable operation, a virtual power plant distributed energy storage hierarchical partition dispatch control method based on the SaDE-BBO algorithm is proposed. This method is based on the operation structure of the virtual power plant, analyzes the operating characteristics of the distributed energy storage system and the output of uncertainty factors, considers the grid load, renewable energy and distributed energy storage on the time scale, and constructs hierarchical partitions of the virtual power plant. The dispatch model determines the day-ahead and day-in-day hierarchical partition dispatch control objective functions, and sets corresponding constraints; the dispatch control model based on the solution of the SaDE-BBO algorithm outputs the virtual power plant distributed energy storage hierarchical partition dispatch control optimization plan. The test results show that the maximum load peak value after dispatch control through this method is 40.9 MW; the active power loss results are all below 10 MW, real-time response to control instructions ensures the safety and stability of the voltage of the virtual power plant under the access of renewable energy, and the nodal voltage fluctuated within the permissible range of 0.95 to 1.05 p.u.

Keywords: SaDE-BBO algorithm; Virtual power plant; Distributed energy storage; Hierarchical partitioning; Dispatch control; Uncertainty factors

Received on 16 August 2024, accepted on 19 September 2024, published on 14 April 2025

doi: 10.4108/ew.9072

1. Introduction

A Virtual Power Plant (VPP) is a power supply coordination management system that uses advanced communication technology and software architecture to realize the aggregation and coordination optimization of various geographically dispersed distributed energy sources, thereby participating in the power market and grid operation as a special power plant. There are many types of VPP resources in the power grid, their internal resource aggregation methods are different, and the response characteristics of different resources are different [1]. Some response resources are seasonal, with different seasons and different response capabilities; some response resources are productive, with different production needs and different response capabilities; some response resources span different time and space regions. Therefore, demand resource indicators exhibit the characteristics of dynamic changes in space and time [2]. VPPs with different spatiotemporal characteristics in response to resource aggregation also exhibit different response characteristics to the power grid, and have an impact on regional power grids in different spatiotemporal contexts, resulting in impacts on grid stability, resource utilization levels, and operating costs [3]. In the scheduling control process of VPP, owing to the high degree of dispersion and heterogeneity of distributed resources, it significantly increases the difficulty of resource aggregation and

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scheduling. Moreover, there are significant differences in geographical location, equipment type, and operational characteristics among different resources, which makes it difficult for virtual power plants to perceive and interact with these resources [4], limiting the adjustment ability of VPP in response to grid load fluctuations. To ensure the effective dispatch of the power grid, Barala et al. proposed a two-stage hierarchical method. This method regards the total demand of the controlled load as a virtual energy storage system, divides the power grid into a distribution system and a transmission system, and uses virtual energy storage to collaboratively divide thr coordinated control of the two systems, enabling the power system to quickly respond to energy storage needs and improve system flexibility by maintaining a balance in power generation demand. During the application process of this method, it is necessary to ensure close coordination between different levels, that is, the power distribution system and transmission system can adapt to changes in grid operation and achieve effective coordination between the two. However, the high complexity and uncertainty of the grid operation will lead to instability in the response and coordination between the two systems, affecting the control effect [5]. Pandey et al. aimed to optimize the scheduling of virtual power plants (VPPs) and enhance their economic benefits by providing storage in the form of electric vehicles (EVs) as flexible reserves and energy storage systems (ESS) as rotating reserves. They also introduced the concept of risk management and utilized a popular risk measurement technique, Conditional Value at Risk (CVaR), to determine the optimization model of the VPP. The improved Harris Hawk optimization algorithm was used to solve the model and obtain the scheduling scheme of the VPP.. However, the virtual power plant its dispatching of power plants by a VPP involves multiple objectives, such as cost minimization, reliability maximization, environmental pollution minimization, etc. Although the Harris Hawks optimization algorithm can handle multi-objective optimization problems, how do we make trade-offs between these objectives? When there is conflict between them, it is still difficult to find the best trade-off solution [6]. To achieve effective dispatching of virtual power plants, Ghanuni et al. proposed a multi-objective programming model to weigh the regret degree of uncertainty risk and operating costs, taking into account the uncertain parameters of renewable energy, load, and market price. The scheduling strategy for the VPP to participate in the day-ahead market is determined, and combined with the fuzzy satisfaction method of the p-robust stochastic programming model, the optimal economic plan is provided according to the worst-case scenario while minimizing the regret level. However, the rules of the electricity market and policies may change frequently, and multi-objective optimization usually requires trade-offs between different objectives. It is difficult to find the best balance point among all objectives and cannot fully adapt to all major changes in market rules, affecting scheduling and quotation strategies [7]. Ebrahimi et al., in order to ensure the dispatching effect of the power system, mainly focus on the energy storage system, optimize its operating status, and use the optimized energy storage system to perform peak shaving and load smoothing of the power system to ensure the balance and power stability of load during the dispatching process. However, there are uncertainties in energy markets, weather conditions, grid loads and other factors, and new algorithms need to be able to effectively handle these uncertainties. However, this algorithm may have certain limitations when dealing with uncertainty and the response speed is significantly affected [8].

The BBO algorithm, named Biogeography-based Optimization, is a swarm intelligence optimization algorithm proposed by Professor Dan Simon in 2008. Inspired by the theory of biogeography, this algorithm solves optimization problems by simulating the migration and mutation processes of biological species between different habitats and has good application results in power system and distribution network optimization [9]. The SaDE algorithm is an evolution algorithm. It is based on a differential evolution algorithm, and introduces an adaptive mechanism. It can dynamically adjust the parameters of the algorithm according to the evolutionary status of the population, such as mutation factor, crossover probability, etc., thereby improving its search performance.and convergence performance [10]. Combining the advantages of the SaDE and BBO algorithms, adaptively adjusting the parameters of the DE algorithm and using the migration and settlement mechanism in the BBO algorithm to guide the evolutionary direction of the population and improve the search efficiency. During the optimization process, the SaDE algorithm is responsible for generating new candidate solutions and adjusting the algorithm parameters through an adaptive mechanism, the BBO algorithm determines the migration direction and settlement probability of species based on the fitness of each habitat, thereby guiding the population to a better solution. Regional evolution is suitable for solving a variety of complex optimization problems. Based on this, this paper proposes a distributed energy storage partition scheduling control method for virtual power plants based on the SaDE-BBO algorithm. This method adopts a hierarchical partition scheduling mode and takes advantage of the SaDE-BBO algorithm to combine distributed energy storage systems to obtain the optimal scheduling control solution.

2. Virtual power plant distributed energy storage hierarchical zonal scheduling control

2.1 Virtual power plant model

Virtual power plant operation structure

The VPP is a comprehensive distributed energy storage system and a load-responsive microgrid energy management system supported by smart-grid technology. As a bridge between power grid dispatching and demand-side resources, it is necessary to aggregate the response characteristics of demand-side resources and then participate in the schematic diagram of the power market or power grid dispatching and VPP operation, as shown in Figure 1.

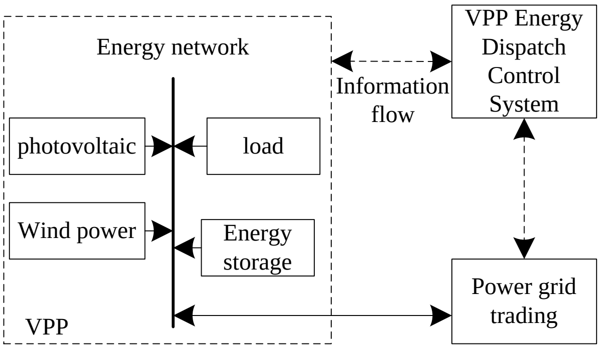

Figure 1. Schematic diagram of the operational structure of the virtual power plant

The VPP combines a comprehensive energy management system with dispatchable and nonschedulable distributed energy storage systems, traditional units, and controllable loads. It embeds the Internet and modern information technology into the management system to achieve the orderly adjustment and collaborative optimization of various resources. In particular, the support of new energy and renewable power to the power grid [11], including providing auxiliary services in the form of frequency and peak regulation, backup, and participation in new energy planning and optimization.

Modeling of distributed energy storage systems

During the operation of the virtual power plant, a large amount of renewable energy is distributed and connected to the grid. The configuration of a distributed energy storage system (ESS) is an important factor in the role of a virtual power plant, and the role of the ESS determines the configuration size of the distributed ESS to a certain extent. Therefore, a distributed ESS configuration model can be established based on the role of distributed ESS. The ESS functions involved in configuring the distributed ESS in this study mainly include the following aspects.

(1) Demand response for economic operation.

Because the VPP aggregates the renewable energy contained in it and directly participates in the operation of the power market, it can reasonably schedule distributed ESS charging and discharging according to electricity price signals to achieve a VPP demand response [12]. This increases the elasticity of the VPP power supply, improves economic returns, and realizes economic operation of the VPP.

(2) Peak reduction and valley filling to stabilize the power supplied by the network.

In a VPP with a large-scale distributed photovoltaic, the phenomenon of peak shifting between photovoltaic and load causes the difference curve between the two to have a huge peak-to-valley difference, which brings serious challenges to the operation of the VPP. A distributed ESS depends on its supply and demand characteristics. It can realize peak shaving and valley filling, coordinate photovoltaic output and user demand, reduce the peak and valley difference in network supply, and thereby stabilize the network supply power [13].

(3) Improve the voltage environment and voltage quality. After large-scale distributed photovoltaics are connected to the VPP, their intermittency, volatility, and irregular start and stop have a greater impact on the voltage quality of the VPP. However, distributed ESS with supply and demand characteristics can quickly respond and coordinate the photovoltaic output, improve the VPP voltage environment, and improve the VPP voltage quality [14].

Distributed energy storage systems are different from renewable energy generation systems in that can carry out two-way charging and discharging, and the output power can be freely adjusted and is not subject to external environmental constraints. However, the distributed energy storage model output active size is affected by its battery capacity, distributed energy storage system battery capacity indicates that the energy storage can be charged and discharged capacity size, and its main influence factor is the average discharge current. The size of the energy storage system battery capacity S_e can be expressed as:

$$S_e = S_o \frac{1.67}{1+1.67\left(\frac{\vec{I}}{I_0}\right)^{0.9}}\left(1+0.005\Delta T\right) \tag{1}$$

Where: ΔT is the difference in temperature between the actual outside temperature and the standard room temperature of 25°C; $\vec{I}$ is the average value of the discharge current of the storage battery. I_0 is the rated value of the charge/discharge current of the storage battery. S_o is the capacity of a standard battery.

Based on the capacity constraints of the storage battery, the output model of the energy storage system can be expressed as follows:

$$-P_i^{\min} < P_i^e\left(t\right) < P_i^{\max} \tag{2}$$

Where: $P_i^e\left(t\right)$ is the output of the i th energy storage system at time t . $P_i^{\min}$ and $P_i^{\max}$ are the lower and upper limits of the energy storage system output, respectively.

$$C_e = \sum_{t=1}^{T}\sum_{i=1}^{N} \tilde{c}_e P_i^e\left(t\right) \tag{3}$$

Where: C_e is the total operating cost of the energy storage system. $\tilde{c}_e$ is the operating cost of a single energy storage unit. N is the total number of energy storage units.

Uncertainty modeling

(1) Load probability model:

The load power fluctuations can be approximated as obeying a normal distribution, so the load power probability density function is calculated by the following formula:

$$f_L = \frac{1}{\sqrt{2\pi}\sigma_L} \exp\left[\frac{-\left(P_L - \mu_L\right)^2}{2\sigma_L^2}\right] \tag{4}$$

Where: P_L is the active power of the load; μ_L and σ_L are the expectation and variance of the load power probability density function.

(2) Probabilistic modeling of wind power output:

For wind power ratings is denoted by P_0, wind speed is modeled using the Weibull distribution probability density function, and the segmented function between the output power of wind power and wind speed is represented by P_{WP}, the probability density function of the wind power output, which is given by:

$$f_{WP} = \begin{cases} \frac{kh\bar{v}}{\upsilon P_o}\frac{\rho}{\upsilon P_o}\exp\left[-\left(\frac{\rho}{\upsilon P_o}\right)^k\right], P_{WP} \in \left[0, P_o\right] \\ 0, \text{ others} \end{cases} \tag{5}$$

$$h = v_0 - v_{ei} - 1 \tag{6}$$

$$\rho = \left(P_o + hP_{WP}\right)v_{ei} \tag{7}$$

Where: Rated wind speed is denoted by v_0; cut-in wind speed is denoted by $\bar{v}$; k denotes the shape parameter. υ indicates the speed parameter.

(3) Probabilistic modeling of PV output:

The PV output power is linearly related to the intensity of solar irradiation, thus it is considered that the PV output power obeys β distribution, therefore, the probability density function of the PV output power is calculated by the formula:

$$f_{PV} = \frac{\gamma(a+b)}{\gamma(a)\gamma(b)}\left(\frac{P_{PV}}{P_{PV}^{\max}}\right)^{a-1}\left(1 - \frac{P_{PV}}{P_{PV}^{\max}}\right)^{b-1} \tag{8}$$

Where: a and b respectively are the positional parameters of β distribution; P_{PV} denotes the output power of the PV; its maximum value is denoted by $P_{PV}^{\max}$; $\gamma(.)$ represents the Gamma function.

2.2 Virtual power plant hierarchical zonal scheduling control model construction

Stratified zonal regulation is based on spatio-temporal information to analyze the demand response capacity of virtual power plant resources in the region as an indicator, and considers the grid load, renewable energy, and distributed energy storage for stratified zoning on a time scale. Moreover, response resources with a large adjustable capacity, high adjustable elasticity, fast response speed, and good economy [15] have higher stratification and priority regulation. Stratified zonal regulation is a dynamic aggregation process with the purpose of avoiding the disorderly response of resources, guiding the virtual power plant to reasonably and scientifically play the value of demand response, and promoting the smooth load of the grid and the safe and stable operation of the system [16]. For a regional power grid with a number of virtual power plants, after stratified partitioning on the time scale, a virtual power plant stratified partitioning scheduling control model is constructed, which contains intraday scheduling and day-ahead scheduling, in which intraday scheduling is based on day-ahead scheduling, taking into account day-ahead scheduling plans and its own stability, correcting the errors that may be brought by day-ahead scheduling, and improving the accuracy and reliability of scheduling [17], while ensuring compliance with the scheduling arrangement, maximizing the benefits and ensuring the stability of operation and maximizing the use of renewable energy.

Day-ahead scheduling control objective function

Day-ahead dispatching of virtual power plants refers to the process of unified planning and optimal allocation of resources in virtual power plants in the Day-Ahead Market (DAM) stage of power market transactions. The purpose is to use market forecast information (such as load forecasting) , renewable energy output forecast, etc.) to formulate the power generation or power consumption plan of the virtual power plant to meet the transaction needs of the power market, adjust the operation plan of power production and transmission equipment, ensure the economic benefits of the operation of the power system [18], and reduce the system peak and valley difference with as little regulation cost.

Assuming that in the regional grid there are N virtual power plant participates in system regulation, each virtual power plant has different demand-side resources, and after the virtual power plant aggregates the internal resources, it presents the role of load unit with regulation capability to the grid, and the system peak-valley difference and system regulation cost are used, respectively $\min f_1$ and $\min f_2$ to expressed as:

$$\min f_1 = \sum_{i=1}^{N}\sum_{t=1}^{T}\left(P_L - Q_{i,t}^{VPP} - P_A\right)^2 \tag{9}$$

$$\min f_2 = \sum_{i=1}^{N}\sum_{t=1}^{T} Q_{i,t}^{VPP}\xi_p \tag{10}$$

Where: P_A is the average daily load; $Q_{i,t}^{VPP}$ is the amount of electricity the i virtual power plant exchanges with the grid during period t, a positive value indicating that electricity is supplied to the grid and a negative value indicating that electricity is absorbed from the grid. ξ_p is the peak-to-valley tariff coefficient. T indicates the scheduling control cycle.

Intraday scheduling control objective function

Intraday scheduling involves making real-time adjustments to the operation of power production and transmission equipment within one day according to the changes in the actual power demand and power supply, with the aim of ensuring that the power system can continuously maintain balance and stability, correcting the errors that may be brought about by the dispatch before the previous day, and coping with a variety of emergencies. Therefore, the objective function of intraday dispatch control is set to optimize the integrated FM performance of the virtual power plant $\max f_3$, voltage quality $\max f_4$ optimal as well as minimal optimization error penalties $\min f_5$ between the day-ahead and intraday optimization results and the real-time dispatch control instructions, which is calculated by the following formula:

$$\max f_3 = \frac{\sum_{t=1}^{T}\sum_{i=1}^{N} f_{WP} f_{PV}\left[0.25\times\left(2\times k_{1,i}^t + k_{2,i}^t + k_{3,i}^t\right)\times P_i^t\right]}{\sum_{t=1}^{T}\sum_{i=1}^{N} P_i^t} \tag{11}$$

$$\max f_4 = \left|1 - \frac{1}{U_j}\sum_{i\in\alpha_G} F_{ESS} U_i\right|, j\in\alpha_L \tag{12}$$

$$\min f_5 = \lambda \times \sum_{t=1}^{T}\left|P_\Sigma^t - P_r^t\right| \tag{13}$$

Where: $k_{1,i}^t$ 、 $k_{2,i}^t$ 、 $k_{3,i}^t$ are the regulation rate index, response time index and regulation accuracy index of each FM unit during the period t under the intraday short time scale. P_i^t represents the output result of each unit i in the virtual power plant during period t. α_G is the set of nodes for all generators; α_L is the set of nodes for the full load; U_i is the complex voltage of the i th generator node; U_j is the complex voltage of the j th load node; F_{ESS} is a participation factor in distributed energy storage; the P_Σ^t and P_r^t represents the actual output value and real-time dispatching control instruction value of the virtual power plant before and during period t. λ is the penalization factor.

2.3 Constraints

Combined with the operation mechanism of the virtual power plant and the uncertainty model, the constraints related to the hierarchical zonal scheduling control are set to ensure the rationality of the objective function, the details of which are as follows:

(1) Distributed energy storage operational constraints:

$$0 \le \overleftarrow{P}_e \le \overleftarrow{P}_e^{\max} \tag{14}$$

$$0 \le \overrightarrow{P}_e \le \overrightarrow{P}_e^{\max} \tag{15}$$

$$SOC_e^{\min} \le SOC_e \le SOC_e^{\max} \tag{16}$$

Where: $\overleftarrow{P}_e^{\max}$ and $\overrightarrow{P}_e^{\max}$ are the maximum charging power and maximum discharging power of the storage battery, respectively. SOC_e denotes the state of charge of the distributed energy storage system, and its maximum and minimum values are denoted by $SOC_e^{\max}$ and $SOC_e^{\min}$.

(2) Wind and solar new energy unit output constraints:

The constraints on the amount of demand response when the load increases or decreases is:

$$\begin{cases} P_{WT}^{\min} \le P_{WT} \le P_{WT}^{\max} \\ P_{PV}^{\min} \le P_{PV} \le P_{PV}^{\max} \end{cases} \tag{17}$$

Where: $P_{WT}^{\min}$ and $P_{WT}^{\max}$ are the minimum and maximum output of the wind turbine. $P_{PV}^{\min}$ and $P_{PV}^{\max}$ are the maximum output of the minimum output of PV.

(3) Scheduling control deviation constraints:

$$\left|P_\Sigma^t - P_r^t\right| \le \sigma \tag{18}$$

Where: σ is the maximum allowable error for dispatch control.

2.4 Solving the scheduling control model based on SaDE-BBO algorithm

The BBO algorithm is derived from optimization ideas contained in the migration process of species between habitats, and the activities of species in the ecological environment are called habitats. There are multiple factors in the ecological environment that affect the quality of habitat environment, which are called fitness index variables (SIV). The suitability of the habitat for the survival of the species and the quality of the environment are described by the fitness index (HSI). Each generation of habitats is called a population, and its fitness value is optimized using HSI as the function of fitness [19]. In the virtual power plant optimization dispatch, five objective functions are considered in each period within a dispatch cycle: system peak-valley difference and system regulation cost, best comprehensive frequency regulation performance of the virtual power plant, best voltage quality, and day-ahead and intraday optimization. The minimum optimization error penalty between the results and real-time scheduling control instructions is used as an optimization vector, which corresponds to a habitat, and the values of each objective function represented by the habitat HSI are optimized and solved.

A habitat represents a candidate solution, that is, a possible solution in the virtual power plant dispatch control optimization objective function. Each habitat contains a set of parameters or decision variables that together define the virtual power plant's power generation during different time periods. Scheduling plans, load distribution, etc. Each habitat has a corresponding habitat suitability index HIS. The HSI is an index used to evaluate habitat suitability for biological survival and reproduction. It is similar to the fitness function value in an optimization problem and is used to measure the quality of the solution. The exponent SIV corresponds to the characteristics or parameters of the solution. In the virtual power plant dispatch optimization problem, these SIVs may include the output power of the generating unit, charge and discharge status of the energy storage device, the amount of load reduction, etc. The value of SIV must satisfy constraint.

When the BBO algorithm is applied, as the number of iterations increases, the HSI of each candidate solution tends to saturate, and the convergence rate decreases and even converges locally, ultimately leading to premature maturity. The occurrence of this phenomenon is inseparable from the interaction between habitats and mutation operation of individual habitats (deindividuals). Therefore, the SaDE algorithm is used to optimize the migration and mutation operators of the BBO algorithm. The differential evolution algorithm generates new solution individuals through mutation operations. When optimizing the migration operator of BBO, the mutation mechanism of SaDE is introduced into the migration process to generate new candidate solutions through differential information; At the same time, the adaptive mechanism is introduced to dynamically adjust the parameter settings during the migration process to improve the performance of the algorithm [20]. The optimized formula for the migration operator is:

$$\begin{cases} X_i = X_{i,0}^M + F_i\left(X_k^M - X_{i,0}^M\right) + F_i\left(X_{c1}^M - X_{c2}^M\right) \\ F_i = rand\left[n\left(\lambda_i, 0.1\right)\right] \end{cases} \tag{19}$$

Where: X_i is the i th candidate solutions after the end of the migration. $X_{i,0}^M$ is the i th candidate solution of the M th iteration; X_k^M is the k th candidate solution of the M th iteration; X_{c1}^M 、 X_{c2}^M are randomly selected candidate solutions in the population, respectively; F_i denotes the difference coefficient.

The purpose of the SaDE algorithm to optimize the mutation operator is to reduce the randomness of SIV in the late iteration. The optimized differential migration operator $\kappa_i\left(d\right)$ formula is:

$$\kappa_i\left(d\right) = \kappa_i\left(d\right) + \eta\left\{\frac{\left[\kappa_{c1}\left(d\right) + \kappa_{c2}\left(d\right)\right]}{2 - \kappa_i\left(d\right)}\right\} \tag{20}$$

Where: c_1、 c_2 are different random numbers within $\left[1, N\right]$; η is adaptive adjustment parameters calculated for SaDE.

$$\beta = \frac{\sum_{i=1}^{N}\left(\kappa_i - \kappa_\Sigma\right)}{1 + \sum_{i=1}^{N}\left(\kappa_i - \kappa_\Sigma\right)} \tag{21}$$

Where: κ_Σ is the optimal fitness of the current population; κ_i denotes the optimal fitness of the individual; as the number of iterations increases, the closer κ_i to the optimal fitness, the smaller the adaptive tuning parameter is, and the more the original solution's good characteristics can be maintained.

After the above-mentioned adaptive differential mutation operation, calculate the HIS of different candidate solutions, sort the calculation results from large to small, and use the greedy selection method to complete the survival of the fittest habitat selection. The greedy selection method only needs to be selected after the survival of the fit test. Sorting the population once is a simple operation. Its essence is to compare the fitness κ_i of each candidate solution in the population with the fitness $\widehat{\kappa}_i$ of the new candidate solution after its own renewal, eliminating the bad ones, and retaining the good ones can effectively retain high-quality individuals, that is, obtain better solutions and enter them into the next generation population. According to the principle of the BBO algorithm, migration operations are allowed between the better solutions obtained, and certain mutation operations can be introduced to increase the diversity of the population to generate new solutions $\hat{x}_k^M$, which is calculated as follows:

$$\hat{x}_k^M = X_k^M Q_H \tag{22}$$

Where: Q_H denotes the eigenvector matrix of the solution; M denotes the number of iterations.

Determine whether the solution satisfies all the constraints. The differential evolution operation and biogeographic optimization operation are continuosly repeated until the maximum number of iterations is reached or other stopping conditions are met. During the iteration process, the currently found optimal solution (that is, the solution with the highest HSI value) is recorded and updated, and the final found optimal solution is output as the dispatching control scheme of the virtual power plant.

3. Test analysis

To verify the application effect of the method in the hierarchical partition dispatch control of distributed energy in virtual power plants, we select the IEEE30 node system as the test system. In this system, photovoltaic, wind power and distributed energy storage systems are connected, and the maximum interaction between VPP and the power grid is 500 kW, and the reserve price is 0.04 yuan/(kW.h); the carbon emission coefficient per unit power of the power grid is 0.93 kg/(kW.h), and the carbon emission quota is 0.88 kg/(kW.h). The IEEE28 node system structure is shown in Figure 2, and the relevant parameters of the system are shown in Table 1.

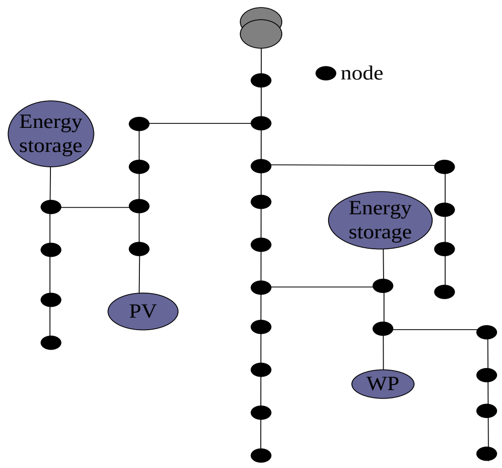

Figure 2. EEE28 Node System Structure

Table 1. System related parameters

Category	Parameter	Numerical value
Distributed energy storage system	Rated capacity /kW·h	150
	Maximum charging and discharging power /kW	60
	Charge/discharge efficiency	0.85
	Maximum charge capacity /kW·h	130
	Minimum charge capacity /kw·h	30
	Initial capacity /W·h	80
Wind turbine	Rated power /kW	500
	Rated wind speed /m.s	15
	Cut-in wind speed /m.s	3
	Cut-out wind speed /m.s	25
	Maintenance cost (yuan/kW.h)	0.08
Photovoltaic	Power upper limit /kW	670
	Conversion efficiency	0.093
	Maximum power /kW	600
	Capacity penetration rate /%	51
	Maintenance cost (yuan/kW. h)	0.06

The method in this study makes full use of the distributed energy storage system to participate in scheduling when a virtual power plant hierarchical zoning scheduling control is carried out, and the degree of the utilization of distributed energy storage system affects the scheduling control results. Based on this, the utilization degree of distributed energy storage system is analyzed, and the three methods in literature [5], literature [6], literature [7] are used as the comparison method of the method in the paper to obtain the peak shifting effect of the four methods under different adjustable load ratios, and the test results are shown in Table 2.

Table 2. Load peak shaving effects (MW) of the four methods

Adjustable load ratio/%	Reference [5] method	Reference [6] method	Reference [7] method	Proposed method
2	57.1	57.8	53.3	36.5
4	52.4	49.9	55.1	40.2
6	55.9	46.7	52.9	31.7
8	54.3	52.3	50.3	38.7
10	56.2	55.1	57.6	36.3
12	55.1	50.8	54.2	39.4
14	52.8	56.6	53.6	40.9
16	49.9	47.8	56.1	37.2
18	48.7	45.9	55.8	36.9
20	46.6	46.2	54.2	34.1

After analyzing the test results in Table 2, it can be concluded that with the gradual increase in the adjustable load proportion, after scheduling control through the four methods, the load peak value changes to a certain extent. Among them, literature [5], literature [6] In literature [7], the maximum load peak values after dispatch control by the three methods are 57.1 MW, 57.8 MW, and 57.6 MW respectively; the maximum load peak values after dispatch control by the method in this paper are 40.9 MW respectively. This result is significantly better than those of the other three methods. Scheduling control results of for the two contrasting methods. Because the method in this study uses a distributed energy storage system to participate in the hierarchical partition dispatch control of the virtual power plant, it has a load peak shaving capability even when the adjustable load ratio is low, and the load peak value drops significantly after adjustment. Therefore, when regulating a virtual power plant, making full use of distributed energy storage systems to participate in regulation can optimize resource utilization, promote new energy consumption, and improve the power system's regulation capabilities.

In order to further verify the effect of the method in the paper to control the virtual power plant by using distributed energy storage in hierarchical zoning, we obtain the active loss results of the virtual power plant after the distributed energy storage system participates in the scheduling control of the virtual power plant under different power fluctuation ratios in the method in the paper, and compare the results with the loss results before the scheduling control, so as to judge the effect of the application of its participation in the scheduling, and the test results are shown in Fig. 3.

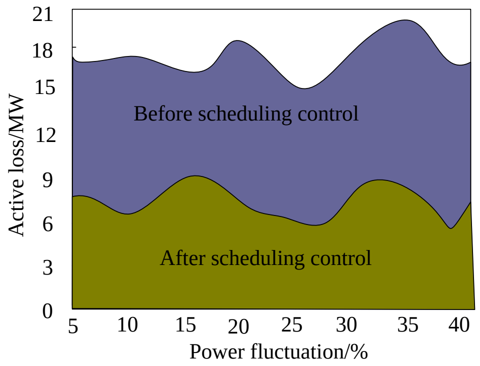

Figure 3. Active Loss Results of Virtual Power Plant

After analyzing the test results in Figure 3, it can be concluded that after the distributed energy storage system is used to participate in the virtual power plant dispatch control, under different fluctuation ratios, the active power loss results of the virtual power plant are all below 10 MW. Compared with the active power loss before scheduling control, there is a significant decrease. The distributed energy storage system can charge and discharge in both directions, and the output active power can be adjusted freely without being restricted by the external environment. Through the flexible scheduling of the energy storage system, it can more effectively participate in system peak shaving and optimize the load of the power grid. curve, making the power grid run more smoothly and reducing active power losses caused by load fluctuations.

The method in the paper minimizes the optimization error penalty $\min f_5$ between the day-ahead and intra-day optimization results and the real-time scheduling control instructions when performing the virtual power plant scheduling control as one of the scheduling control objective functions, the real-time scheduling control command response capability is used as a judgment criterion to obtain the actual scheduling control command response results of the virtual power plant when the method in the paper is used for scheduling control, as shown in Fig. 4.

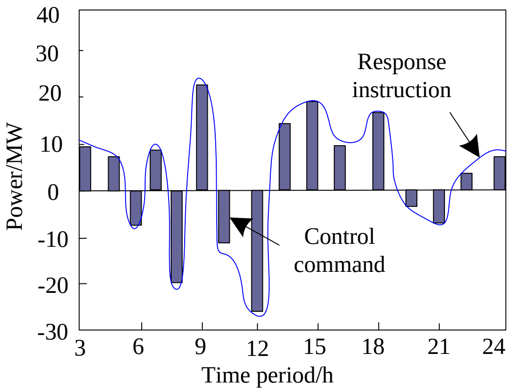

Figure 4. Actual Dispatch Control Instruction Response Results of Virtual Power Plant

After analyzing the test results in Fig. 4, it is concluded that after real-time scheduling control of the virtual power plant through the scheduling control method in this study, it can track the fluctuation of renewable energy power and load demand in the system, respond to the control instructions in real time to ensure that the virtual power plant can be combined with the changes in the actual power demand and power supply, and make real-time adjustments in the operation of the power production and transmission equipment to ultimately realize the scheduling control of the virtual power plant under the multi-temporal time scale.

In order to verify the effect of the method in the paper on the hierarchical zonal scheduling control of virtual power plants, the paper uses the loss factor ζ_e as an evaluation index, this index mainly describes the degree of power loss in the operation of the virtual power plant, which takes the value of 0~100, the larger the value indicates that the degree of loss is more obvious, the worse the scheduling control effect. The calculation formula of ζ_e is:

$$\zeta_e = \frac{1}{T}\sum_{t=1}^{T}\frac{Q(t)}{Y(t)} \tag{23}$$

Where: $Q(t)$ represents the loss of load power; $Y(t)$ represents the load demand power; T represents the total time period.

The hierarchical and partition scheduling control of virtual power plant is carried out by using the method in this paper, and the hierarchical scheduling results of virtual power plant before and during the day are obtained. The test results are shown in Table 3.

Table 3. Layered scheduling results of virtual power plants before and during the day (MW)

Period of time/h	Day ahead scheduling/MW		Daily scheduling/MW	
	Wind power output	Photovoltaic output	Wind power output	Photovoltaic output
2	32.5	11.7	27.8	16.2
4	35.1	10.6	33.3	15.8
6	49.3	15.9	35.2	15.5
8	16.6	16.8	20.8	20.2
10	15.8	24.4	19.6	25.1
12	14.7	48.3	21.3	33.6
14	13.5	45.5	22.1	32.7
16	18.8	25.1	15.9	27.4
18	24.3	24.4	24.1	20.2
20	22.6	22.1	25.1	19.7
22	25.1	20.8	20.7	18.3
24	20.8	20.2	21.1	16.6

After analyzing the test results in Table 3, it can be concluded that under different time periods, after the hierarchical partition control of the virtual power plant is carried out through the dispatch control method in this article, and after the day-ahead dispatch control, the output power of wind power and photovoltaic power changes within the range of 10~50 MW, in which wind power output fluctuates greatly; after intraday dispatch control, the output power of wind power and photovoltaic power changes within the range of 15~35 MW, and its fluctuation range decreases significantly. Therefore, when the method in this study performs hierarchical partition control of virtual power plants, intraday dispatch can correct errors that may be caused by day-ahead dispatch, cope with various emergencies, and better respond to control instructions.

To judge the effect of the hierarchical partition dispatch control of the virtual power plant, under different renewable energy outputs, after the hierarchical partition control of the virtual power plant is carried out through the method in this study, the fluctuation of the node voltage is obtained and compared with the standard voltage. (The allowable range of voltage is 0.95~1.05 p.u.) to judge the operational stability of the virtual power plant after dispatch control. The test results are shown in Figure 5.

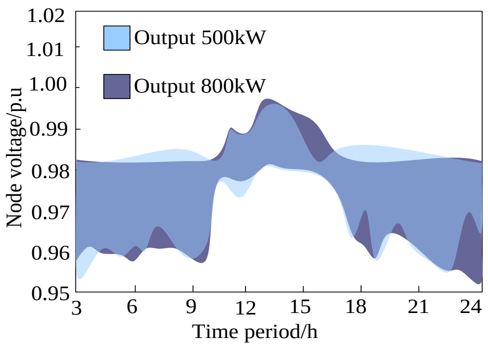

Figure 5. Voltage Dispatch Control Results of Virtual Power Plant Nodes

After analyzing the test results in Figure 5, it can be concluded that after the hierarchical partition dispatch control of the virtual power plant is carried out through the method in the article, the node voltages fluctuate within the allowed range of 0.95~1.05 p.u., because the method in this study uses distributed control during dispatch control. The energy storage system enables the virtual energy storage power plant to quickly and closely follow the dispatch signal provided by the power grid control center, participate in the active power balance of the power system, and provide active power auxiliary services at different time scales for the power grid; At the same time, the node voltages are controlled within the allowable range, to ensure the safety and stability of the voltage of the virtual power plant under the access of renewable energy.

4. Conclusion

In order to ensure the utilization and dispatching effect of energy and resources during the operation of a virtual power plant and to improve the operating efficiency and stability of the power system, this paper proposes a distributed energy storage hierarchical partition dispatch control method for virtual power plants based on the SaDE-BBO algorithm. This method can improve the dispatching control response capability of the virtual power plant, make full use of the advantages of the distributed energy storage system, and have the ability to participate in grid auxiliary services to achieve optimal operation and dispatch of the virtual power plant. After testing the method in this study, the application effect of the method was verified. This ensures ensure that the virtual energy storage power plant meets the regulation requirements of power system operation and can also provide local voltage support for the distribution network, effectively improving the efficiency and stability of power system operation.

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