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Resource Scheduling and Cluster Co-optimization of Virtual Power Plant Based on Large Scale Data Analysis

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Abstract The virtual power plant contributes to the safe and stable operation of the power system by aggregating distributed resources on the distribution network side to make it an aggregator with a certain degree of control. In order to optimize the utilization efficiency of multiple energy sources within a virtual power plant cluster as much as possible, this paper establishes a dynamic model of virtual power plant cluster under the premise of ensuring that each virtual power plant within the cluster has the ability to regulate. Taking the balance of power balance index, power complementarity index and regulation capacity index as the optimization target, the virtual power plant resources are dynamically dispatched, and the nodes of multi-energy systems are aggregated to build a virtual power plant cluster that meets the demand of the main grid. The virtual power plant cluster division problem is transformed into a multi-objective optimization problem, and by constructing different energy cooperation and non-cooperation game scenarios, the improved algorithm is used to solve the virtual power plant cluster synergy model, and analyze the economic benefits of the virtual power plants under different methods. The total benefits of per-capacity allocation, traditional method, and improved particle swarm method are 97.688 million yuan, 10.507 million yuan, and 107.94 million yuan, respectively. The benefit in the virtual power plant wind, light, combustion, and storage multi-type energy fully cooperative game scenario is 105.07 million yuan, which is 7.382 million yuan more than the benefit in the scenario of fully uncooperative game for each type of energy. The model constructed in this paper can promote the optimization of energy utilization rate of virtual power plant and take into account the economy of optimal scheduling strategy.

Index Terms virtual power plant, dynamic scheduling, multi-objective optimization, cluster coordination, cooperative game

I. Introduction

With the continuous development of social and economic development and the improvement of people's quality of life, carbon emissions have increased, forming a serious ecological and environmental problems, and even affecting human life [1], [2]. “Energy transition” has become a new theme in the development of the current power industry, and the development of a high proportion of renewable energy, optimization of energy use, and improving the utilization efficiency of customer-side loads and distributed generation resources can help to alleviate the pressure on the power grid and the environment [3]-[5]. However, with the increasing penetration of distributed renewable energy sources, their grid connection problems are becoming increasingly significant [6]. On the supply side, the coordination and cooperation of distributed energy sources with disorderly access is difficult, and the controllable loads in each region cannot respond to scheduling in a timely manner, which leads to difficulties in the consumption of distributed energy sources and the increase of system operation costs [7]-[9]. On the demand side, its large-scale grid-connected charging will have a greater impact on the planning and operation of the power grid, causing system scheduling difficulties, exacerbating the load peak-to-valley difference and other problems [10]-[12].

In order to cope with the new changes and challenges of the power system, while further guaranteeing the safe and stable operation of the power grid, the concept of virtual power plant (VPP) came into being [13]. As a common product of the power market reform and demand-side response, VPP is able to achieve the integration and scheduling of a variety of distributed energy sources, optimize the utilization efficiency of energy, realize intelligent energy management, and improve the efficiency of energy utilization [14]-[16]. However, due to geographic differences in the size and type of distributed power in each virtual power field, if only a single interaction between the virtual power plant and the grid is considered, it will lead to power imbalance problems when independently operating to participate in grid scheduling, thus facing the risk of damage to the interests [17]-[20]. Therefore, multi-regional virtual power plants can be united to form a cooperative scheduling cluster, which can realize the efficient use of distributed energy through the complementary and gradient utilization of power within the cluster, combined with refined evaluation and optimal scheduling methods [21], [22].

In this paper, by analyzing the operating characteristics of virtual power plants and the resource characteristics of virtual power plants, we propose the scheduling objective of optimizing the energy utilization rate within virtual power plant clusters, and use the power balance index, the power complementary degree index, and the regulating capacity index to aggregate the dynamic energy sources of virtual power plant clusters, and construct a virtual power plant cluster model applicable to multiple scenarios. The model is converted into a multi-objective dynamic construction model of virtual power plant cluster to supplement the equation constraints and imbalance constraints of the objective function. An improved particle swarm optimization algorithm is introduced to solve the model, and the scheduling benefits of the improved algorithm in the example are analyzed. Different scenarios of multi-energy cooperation are set up, and the improved particle swarm optimization algorithm is used to configure the capacity of each power source within the virtual power plant and calculate the economic benefits of the virtual power plant.

II. Dynamic modeling of virtual power plant clusters considering multi-energy synergies

II. A. Virtual power plant

The virtual power plant does not generate electricity directly, its essence is a set of distributed resource management system, which integrates a large number of scattered distributed resources in the grid, participates in the electricity market through cooperative control, and joins the grid scheduling to realize the goal of peak shaving and valley filling. It also provides auxiliary services such as frequency regulation, voltage regulation, and standby to enhance the security of the grid [23], [24].

Based on the realized functions, virtual power plants can generally be classified into two categories: one is commercial virtual power plant (CVPP) and the other is technical virtual power plant (TVPP).

CVPP mainly focuses on the trading function of virtual power plants in the energy market and auxiliary service market. By obtaining data such as operating parameters, marginal costs, measurements and forecasts of distributed energy sources and combining them with market information such as tariff forecasts, they optimize the potential returns of their portfolios and participate in market bids. TVPP focuses more on the direct participation of virtual power plants in the operation and management of the distribution grid according to the system scheduling commands. TVPP focuses on the management and scheduling of the virtual power plants as a whole in order to satisfy the distribution grid's operational needs. It focuses on coordinating and optimizing the use of distributed resources to achieve system stability, reliability and efficiency.

According to the operation characteristics of virtual power plants and the current development status, the operation control mode of virtual power plants can be divided into three types: centralized control, centralized-decentralized control and fully decentralized control. Among them, the centralized control mode means that all control operations are completed by a central control system. The centralized-decentralized control method is based on the central control system, and allocates part of the control power to the local control system of each constituent unit. Fully decentralized control means that all control is left to the local control system of each constituent unit to complete independently.

II. B. Characterization of virtual power plant resources

In this paper, the virtual power plant is defined as an aggregation of fossil-based energy, renewable energy, distributed energy storage, flexible loads represented by demand response and electric vehicles. The energy interaction with the grid is realized through information communication with the VPP control center.

In this paper, the virtual power plant resources are categorized into three main types, which are flexible loads, distributed generation resources and source loads. Among them, flexible loads are mainly loads that can participate in demand response. Distributed generation resources include renewable energy sources and gas turbines. Source loads include general distributed energy storage and electric vehicles.

II. B. 1) Flexible load characteristics

Load characteristic index refers to a kind of parameter that describes the change rule and characteristics of electric power load, and the establishment of a comprehensive load characteristic index system is an important prerequisite for user load classification, load modeling and load forecasting. Commonly used load characteristic indexes can be divided into three categories: descriptive, comparative, and curvilinear. Among them, the descriptive indicators are used to indicate the level of load with measurement units. Comparative indicators are the ratio of two load characteristics, relative physical quantities, mainly reflecting the degree of load change. Curve type indicators can reflect the change rule of load over time.

II. B. 2) Characterization of Distributed Generation Resources

At present, distributed photovoltaic is the fastest growing distributed power source, and photovoltaic power generation mainly adopts grid-connected operation. Its power generation model is usually equated with the series and parallel connection of solar photovoltaic panels, which is a flexible, simple and renewable way of energy utilization with small site limitations, green environmental protection and the advantages of small investment and large returns. However, its output power cannot be simply regarded as the superposition of the output power of PV panels, and the actual operation is complicated, which is related to the intensity of sunlight, the temperature of the environment, the angle of sunlight irradiation, the state of the solar cell and its photoelectric conversion coefficient. Therefore, photovoltaic power generation is characterized by stochasticity and volatility, and it is generally believed that the output power changes with the change of solar radiation intensity, which is in line with the Beta distribution, and its probability density function is expressed as equation (1):

$$f(r)=\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\left(\frac{r}{r_{\max}}\right)^{\alpha-1}\left(1-\frac{r}{r_{\max}}\right)^{\beta-1} \tag{1}$$

where $f(r)$ is the probability density function, α and β are the shape parameters of the Beta distribution, r and $r_{\max}$ denote the actual value and maximum value of the solar radiation intensity in the study time period, respectively, and $\Gamma(\cdot)$ denotes the gamma function.

The photovoltaic power output varies with the solar radiation intensity, which is expressed as equation (2):

$$P_{PV}(r)=\begin{cases}P_{PVr}(r/r_{rated}) & r\le r_{rated}\\ P_{PVr} & r>r_{rated}\end{cases} \tag{2}$$

where r_{rated} denotes the rated solar radiation intensity and P_{PVr} denotes the rated output power of photovoltaic power generation.

Since the output power of wind power generation mainly varies with the wind speed at the location of the wind farm, which is affected by the humidity of the environment, the weather, the topography where the wind farm is located, and is uncontrollable, the wind power generation is also characterized by a certain degree of volatility and rapid changes. However, in a longer time scale, the wind speed in most areas obeys the Weibull distribution, and its probability density function is expressed as equation (3):

$$f(v)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1}e^{-(v/c)^{k}} \tag{3}$$

where $f(v)$ is the probability density function of wind speed, v is the wind speed, and k and c are the shape parameter and scale parameter of the Weibull distribution, respectively, which are denoted as Eqs. (4) and (5):

$$k=\left(\frac{\sigma_w}{\mu_w}\right)^{-1086} \tag{4}$$

$$c=\frac{2\mu_w}{\sqrt{\pi}} \tag{5}$$

where σ_w and μ_w are the standard deviation and mean value of wind speed, respectively.

The actual wind power output P_W varies with the wind speed at the location of the wind turbine, which is expressed by equation (6):

$$P_W=\begin{cases}0 & v\le V_{c1}\le V_{co}\\ P_{Wr}\dfrac{v-V_{c1}}{V_r-V_{c1}} & V_{c1}\ge v\le V_r\\ P_{Wr} & V_r\le v\le V_{co}\end{cases} \tag{6}$$

where P_{Wr} denotes the rated power of the wind turbine, and V_{c1}, V_{co}, and V_r denote the cut-in, cut-out, and rated wind speed of the wind turbine, respectively.

Gas turbine is a kind of controllable power source, which is an effective auxiliary unit for renewable energy into the grid, and can smooth out the randomness and volatility of wind power and PV output. It has the flexibility of regulation, but in the operation stage of the gas turbine generator set, the generation power of the gas turbine cannot exceed the maximum generation power of the gas turbine, expressed as equation (7):

$$0 \le P_{g,t} \le P_{g,\max} \tag{7}$$

where $P_{g,t}$ denotes the generating power of the gas turbine at moment t and $P_{g,\max}$ denotes the maximum generating power of the gas turbine.

II. B. 3) Characterization of source loads

If a large number of PV and wind units are connected to the VPP, the stability of the VPP will be seriously affected due to the stochastic and fluctuating nature of PV and wind power generation, which can be utilized in addition to gas turbines, and source loads can also be used. Source load is a kind of load with two-way energy interaction, which can be used as a power source to deliver active power to the VPP, and can also be used as a load to dissipate renewable energy output, mainly including energy storage and EV.

We mainly take the battery as an example to analyze the characteristics of distributed energy storage. The charging state of the battery is constantly changing during the charging and discharging process, and the charging state at the t moment is expressed as Eqs. (8) and (9):

$$SOC_{t+1} = (1-d)SOC_t + \frac{P_{c,t}\eta_c}{E_s}\Delta t \tag{8}$$

$$SOC_{t+1} = (1-d)SOC_t - \frac{P_{d,t}\eta_d}{E_s}\Delta t \tag{9}$$

where SOC_t and SOC_{t+1} are the state of charge at the moment t and $t+1$, respectively, $P_{c,t}$ and $P_{d,t}$ are the charging and discharging power, η_c and η_d are the charging and discharging efficiencies, respectively, and d is the self-discharge rate of the battery. The state of charge and the charging and discharging power are subject to the following constraints. Namely:

$$SOC_{\min} \le SOC_t \le SOC_{\max} \tag{10}$$

$$0 \le P_{c,t} \le P_{c,\max} \tag{11}$$

$$0 \le P_{d,t} \le P_{d,\max} \tag{12}$$

where $SOC_{\max}$ and $SOC_{\min}$ denote the upper and lower limits of the charging state, and $P_{c,\max}$ and $P_{d,\max}$ denote the upper limit of charge and discharge, respectively.

II. C. Modeling the dynamics of virtual power plant clusters

In order to maximize the utilization of renewable energy within a virtual power plant cluster, the division of the cluster must be optimal. First, the paper ensures that the objects are coupled to each other for effective energy exchange. Secondly, the net power characteristics of the divided objects are used to achieve complementarity, so that the virtual power plants in the cluster have certain regulation capabilities and can participate in the main grid dispatch. Based on the above division principles, this paper proposes power balance index, power complementary degree index and regulation capacity index.

The dynamic division of virtual power plant clusters aims to form efficient virtual power plant clusters by optimizing the aggregation of energy states at nodes and points. Therefore, this paper transforms the virtual power plant cluster division problem into a multi-objective optimization problem, and constructs virtual power plant clusters suitable for various application scenarios to meet the system scheduling requirements.

(1) Power balance index

The power balance indicator can be used to represent the distributed power output and load supply and demand of a given virtual power plant.

(2) Power Complementarity Degree Indicator

The modularity function is a conventional division index, which is realized by defining different meanings of side weights and thus changes in the division results.

(3) Maximum Load Uniformity Indicator

The maximum load uniformity index is used to characterize the degree of uniformity of electricity, heat and gas loads of a single virtual power plant. The core of the dynamic division of virtual power plant clusters lies in the synthesis of various indicators to optimize the aggregation of node energy states to form an efficient virtual power plant. For the nodes to be divided, the problem can be defined as a multi-objective optimization task based on the indicators of power balance, power complementarity and maximum load uniformity. The objective is to balance these three metrics, aggregate multi-energy system nodes, and construct a virtual power plant cluster that meets the demand of the main grid.

The essential feature of the virtual power plant cluster dynamics problem is the optimization process in which the energy states of each node of the virtual power plant are aggregated to form a virtual power plant under the synergistic effect of the indicators. Therefore, the virtual power plant cluster dynamic division problem should coordinate the optimization of three indicators, and under the coordination of the indicators, the energy state of the nodes of multi-energy system is aggregated, and then form a virtual power plant cluster that meets the regulation needs of the main network. In this paper, the virtual power plant cluster dynamic division problem is expressed as the following multi-objective optimization problem:

$$\begin{aligned}&\min F(e)=\left(\varphi_p(e),-\varphi_m(e),-\varphi_q(e)\right)\\&s.t.\begin{cases}I_n(e)\le 0, n=1,\ldots,L\\E_m(e)=0, m=1,\ldots,R\\e_{i,\min}\le e_i\le x_{i,\max}, i=1,\ldots,N\end{cases}\end{aligned}\tag{13}$$

where $F(e)$ is the multi-objective vector space composed of $\varphi_p(e)$, $\varphi_m(e)$, $\varphi_q(e)$, i.e., the mapping of the energy state of the nodes of the virtual power plant cluster to the indicator of the degree of power balance $\varphi_p(e)$, the indicator of the degree of power complementarity $\varphi_m(e)$ and the maximal load The mapping of the uniformity index $\varphi_q(e)$, e constitutes the N-dimensional decision variable space of node energy states to be clustered $e=\{e_i\}_{i=1}^N$, and $E_m(e)$, $I_n(e)$ are the set of equational constraints and inequality constraints, respectively.

The equational constraints for the above objective function are as follows:

(1) The grid balance constraints for virtual power plant operation are:

$$\Delta P_{e_1,VPP}^{n,t}+P_{DP,e_1}^{n,t}+P_{FC,e_1}^{n,t}+P_{VPP,e_1}^{n,t}=L_{e_1}^{n,t}+P_{EH,e_1}^{n,t}+P_{MU,e_1}^{n,t}\tag{14}$$

where $\Delta P_{e_1,VPP}^{n,t}$ is the net input electric power of the virtual power plant, when it is greater than 0, the virtual power plant phase the main grid power supply, and vice versa, the power purchased from the main grid. $P_{DP,e_1}^{n,t}$, $P_{FC,e_1}^{n,t}$, and $P_{VPP,e_1}^{n,t}$ are the power supplied by the corresponding setups. $L_{e_1}^{n,t}$ is the electrical load. $P_{EH,e_1}^{n,t}$ and $P_{MU,e_1}^{n,t}$ are the electric power consumed by the corresponding equipment during operation.

(2) The gas network balance constraints for the virtual power plant operation are:

$$\Delta P_{e_2,VPP}^{n,t}+P_{MU,e_2}^{n,t}=L_{e_2}^{n,t}+P_{GT,e_2}^{n,t}+P_{FC,e_2}^{n,t}+P_{GS,e_2}^{n,t}\tag{15}$$

where $\Delta P_{e_2,VPP}^{n,t}$ denotes the net input natural gas power of the virtual plant, when it is greater than 0, the virtual plant phase the main grid supply, and vice versa, the gas is purchased from the main grid. $P_{MU,e_2}^{n,t}$ denotes the gas supply power of the corresponding plant. $L_{e_2}^{n,t}$ is the gas load. $P_{GT,e_2}^{n,t}$, $P_{FC,e_2}^{n,t}$, and $P_{GS,e_2}^{n,t}$ are the gas power output from the operation of the corresponding equipment.

(3) The thermal network balance constraints for virtual power plant operation are as follows:

$$P_{FC,e_3}^{n,t}+P_{EH,e_3}^{n,t}+P_{WHB,e_3}^{n,t}=L_{e_3}^{n,t}\tag{16}$$

where $P_{WHB,e_3}^{n,t}$, $P_{FC,e_3}^{n,t}$, and $P_{EH,e_3}^{n,t}$ are the thermal power output from the corresponding equipment in the thermal subsystem, and $L_{e_3}^{n,t}$ is the thermal load.

(4) In the virtual power plant, the operation constraints of the energy conversion devices are:

$$\sum_{i=1} P_{GT,e_1}^{n,t} + \sum_{i=1} P_{GT,e_2}^{n,t} = \omega_1 \sum_{i=1} F_{GT^{n,t}} H_{e_2} \tag{17}$$

$$\sum_{i=1} P_{FC,e_1}^{n,t} + \sum_{i=1} P_{FC,e_2}^{n,t} = \omega_2 \sum_{i=1} F_{FC}^{n,t} H_{e_2} \tag{18}$$

where ω_1, $F_{GT^{n,t}}$ are gas turbine operating efficiency and gas supply flow, respectively. $\zeta_{FC}^{j,t}$, ω_2 are solid fuel cell operating efficiency and gas supply flow, respectively. H_{e_2} is the calorific value of the corresponding equipment supply.

The imbalance constraints are as follows:

(1) Distributed power output constraint:

$$P_{DP,e_1,\min}^{n,t} \le P_{DP,e_1}^{n,t} \le P_{DP,e_1,\max}^{n,t} \tag{19}$$

where $P_{DP,e_1,\max}^{j,t}$ and $P_{DP,e_1,\min}^{j,t}$ are the upper and lower thresholds of distributed power output of the virtual power plant, respectively.

(2) Virtual power plant electric power change rate constraint:

$$\left| P_{e_1,G}^{n,t_e} - P_{e_1,G}^{n,t_o} \right| \le W_{e_1,G,\max}^{n,t} / \Delta t \tag{20}$$

$$\left| P_{e_1,VPP}^{n,t_e} - P_{e_1,VPP}^{n,t_o} \right| \le W_{e_1,VPP,\max}^{n,t} / \Delta t \tag{21}$$

where $P_{e_1,G/VPP}^{n,t}$ is the virtual power plant trading power with the main grid or other virtual power plants, $W_{e_1,G/VPP,\max}^{n,t}$ is the maximum value of the traded energy, and $\Delta t = t_e - t_o$.

(3) Virtual power plant thermal power rate of change constraint:

$$\left| P_{e_2,G}^{n,t_e} - P_{e_2,G}^{n,t_o} \right| \le W_{e_2,G,\max}^{n,t} / \Delta t \tag{22}$$

$$\left| P_{e_2,VPP}^{n,t_e} - P_{e_2,VPP}^{n,t_o} \right| \le W_{e_2,VPP,\max}^{n,t} / \Delta t \tag{23}$$

where $P_{e_2,G/VPP}^{n,t}$ is the virtual power plant trading thermal energy with the main grid or other virtual power plants, $W_{e_2,G/VPP,\max}^{n,t}$ is the maximum value of the traded energy, and $\Delta t = t_e - t_o$.

(4) Virtual power plant gas power rate of change constraint:

$$\left| P_{e_3,G}^{n,t_e} - P_{e_3,G}^{n,t_o} \right| \le W_{e_3,G,\max}^{n,t} / \Delta t \tag{24}$$

$$\left| P_{e_3,VPP}^{n,t_e} - P_{e_3,VPP}^{n,t_o} \right| \le W_{e_3,VPP,\max}^{n,t} / \Delta t \tag{25}$$

where $P_{e_3,G/VPP}^{n,t}$ is the virtual power plant trading gas energy with the main grid or other virtual power plants, $W_{e_3,Grid/VPP,\max}^{j,t}$ is the maximum value of the traded energy, and $\Delta t = t_e - t_o$.

(5) Virtual power plant electric and gas operating capacity constraints:

$$\begin{cases} 0 \le \sum_{t=1}^{T} \sum_{n=1} P_{e_1,G}^{n,t} \le \sum_{t=1}^{T} \sum_{n=1} P_{e_1,G,\max}^{n,t} \\ 0 \le \sum_{t=1}^{T} \sum_{n=1} P_{e_1,VPP}^{n,t} \le \sum_{t=1}^{T} \sum_{n=1} P_{e_1,VPP,\max}^{n,t} \end{cases} \tag{26}$$

$$\begin{cases} 0 \le \sum_{t=1}^{T}\sum_{n=1} P_{e_2,G}^{n,t} \le \sum_{t=1}^{T}\sum_{n=1} P_{e_2,G,max}^{n,t} \\ 0 \le \sum_{t=1}^{T}\sum_{n=1} P_{e_2,VPP}^{n,t} \le \sum_{t=1}^{T}\sum_{n=1} P_{e_2,VPP,max}^{n,t} \end{cases} \tag{27}$$

where $P_{e_1,G,\max}^{n,t}$, $P_{e_2,G,\max}^{n,t}$ are the maximum values of power trading between the virtual plant and the main power and gas grid. $P_{e_1,VPP,\max}^{n,t}$, $P_{e_2,VPP,\max}^{n,t}$ are the maximum values of power interactions between virtual power plants with electricity and gas.

(6) Energy storage device operation constraints:

$$Q_{GS,\min}^{i,j} \le Q_{GS}^{j,t} \le Q_{GS,\max}^{i,j} \tag{28}$$

$$Q_{WHB,\min}^{i,j} \le Q_{WHB}^{j,t} \le Q_{WHB,\max}^{i,j} \tag{29}$$

$$0 \le P_{GS}^{j,t} \le P_{GS,\max}^{j,t} \tag{30}$$

$$0 \le P_{WHB}^{j,t} \le P_{WHB,\max}^{j,t} \tag{31}$$

where $Q_{GS}^{i,j}$ is the gas storage capacity and $Q_{GS,\max}^{i,j}$, $Q_{GS,\min}^{i,j}$ are the upper and lower thresholds of its capacity. $Q_{WHB}^{i,j}$ is the heat storage capacity, $Q_{WHB,\max}^{i,j}$, $Q_{WHB,\min}^{i,j}$ are the upper and lower thresholds of its capacity. The $P_{GS}^{j,t}$, $P_{WHB}^{j,t}$ powers are the gas and heat storage powers, respectively. The $P_{GS,\max}^{j,t}$, $P_{WHB,\max}^{j,t}$ are the corresponding maximum values.

II. D.Multi-objective function processing and model solving

Particle swarm optimization algorithm is one of the most common methods used to find optimal solutions to equations. Each time it searches, it will adjust the direction and speed of its next search according to its previous results and the communication between populations, which simply means that it can record the optimal location of its own historical search and the optimal location of the population's historical search, and use this as the basis for its next search.

In this paper, a linear decreasing weight method is proposed: in view of the shortcomings of typical particle swarm algorithms in terms of computational speed and accuracy, the inertia weights ω are introduced into Eq. (32), and the inertia weights are defined as follows:

$$\omega = \omega_{\max} - \frac{t\left(\omega_{\max} - \omega_{\min}\right)}{\max x_d} \tag{32}$$

where $\omega_{\max}$ is the maximum inertia weight. $\omega_{\min}$ is the minimum inertia weight. Therefore, Eq. (33) is updated as:

$$v_{ij}(t+1) = c_1 r_1 (P_{ij}(t) - x_{ij}(t)) + c_2 r_2 (g_j(t) - x_{ij}(t)) + \omega x_{ij}(t) \tag{33}$$

From the formula, it can be seen that the larger the inertia weight ω, the smaller the chance that v_{ij} is close to the global optimal point $g_i(t)$ and the historical optimal point $P_i(t)$, and the v_{ij} will deviate from the current optimal point, and thus potentially skip out of the current local optimal region, but this is only more favorable early in the algorithm's computation, and the more likely that it will skip out of the global The more likely it is that the optimal position will also be skipped.

The linearly decreasing inertia weights ω still has the following 2 problems. ① Because the swarm randomly initializes the positions and velocities of the particles, it is possible to search for the global optimum at an early stage of the computation, and the linearly decreasing inertia weights ω will slow down the convergence of the algorithm. ② In the late stage of computation of the algorithm, the decreasing inertia weights ω will lead to a decrease in the global search ability, and it will be easier to fall into the local optimum.

It can be concluded that if the inertia weights ω can be automatically adjusted with the distance of each particle from the optimal particle, the performance of such particle swarm optimization algorithm will be greatly improved.

The specific design idea is: when the inertia weight ω decreases with the number of iterations, the inertia weight ω of different particles will also be automatically adjusted with the distance from the global optimal point, i.e., the inertia weight ω changes dynamically with different particles.

Assuming $f_{avg} = (sum(g_i(t)))/N$, when $g_i(t) \le f_{avg}$, the formula is updated as follows:

$$\omega = \omega_{\min} + \frac{(g_i(t) - \min g_i(t)) * (\omega_{\max} - \omega_{\min})}{f_{avg} - \min g_i(t)} \tag{34}$$

The hybridization algorithm is a part of the genetic algorithm, which is a stochastic global search and optimization method developed with reference to the principle of biological evolution in nature, which is based on the reference to Darwin's theory of evolution and Mendel's doctrine of heredity.

During the computation of the algorithm, the algorithm may fall into a local optimum when the global optimum g_{best} is not updated for consecutive N generations. The method of jumping out of the local optimum in the hybridization algorithm is to randomly select M better particles in the population including the optimal particles, and the selected particles are hybridized with the randomly generated new particles, so that the optimal particles may enter the new search area by changing the search direction and search speed, which may jump out of the local optimum to find the new individual extreme value. The hybridization process is defined as follows:

$$childx = c * poolx(seed1) + (1-c)\, poolx(seed2) \tag{35}$$

$$childv = \frac{\left(c * poolv(seed1) + c * poolv(seed2)\right) * norm\left(c * poolv(seed1)\right)}{norm\left(c * poolv(seed1) + c * poolv(seed2)\right)} \tag{36}$$

where c is the hybridization probability a random variable between $[0,1]$, independent of the adaptation value of the particle. $Poolx$ is the initial hybridization parent position in the hybridization pool. $seed1$ is the parent particle #1. $seed2$ is the parent particle #2. $childx$ is the position of the hybridized child particle. $childv$ is the velocity of the child particle after hybridization.

After combining the particle swarm algorithm with adaptive weights and the hybridized particle swarm algorithm, the hybridized particle swarm optimization algorithm with adaptive weights used in this paper can be obtained. The inertia weight of the particle swarm optimization algorithm ω is calculated by using formula (34), and at the same time, the judgment of the hybridization algorithm is added in the loop of the particle swarm calculation of the global optimum and the optimal particles are updated in accordance with formula (35) and formula (36) so that there is a certain possibility of jumping out of the local optimum.

Compared with the ordinary PSO algorithm, the hybridization algorithm can have a certain probability to jump out of the local optimum when the ordinary particle swarm falls into the local optimum. Therefore, in comparison with the ordinary PSO algorithm, it is necessary to set the ratio of hybridization probability and the size of the hybridization pool additionally bc, bs.

III. Analysis of examples

Distributed power generation grid-connected scale continues to expand, and the number of distributed power sources on the load side continues to grow. At the same time, the development and establishment of advanced measurement systems have made the load side observable, so that the controllable load on the load side has shown explosive growth. The small capacity, scattered location, and different output characteristics of these peak dispatchable resources make the dispatch management extremely tedious and complicated. Therefore, a virtual power plant is used to coordinate and optimize these different types of distributed energy sources, such as DG, energy storage units, controllable loads, and interruptible loads, so that the peaking resources can be reasonably and optimally allocated.

III. A. Multi-objective scheduling for virtual power plants

In this paper, a standard IEEE 33 node power distribution system is used for simulation and validation. The system is installed with fuel cells at nodes 6 and 15, micro gas turbines at nodes 17, 20 and 28, interruptible loads at nodes 26 and 32, and energy storage units at node 27. Wind turbines and photovoltaic plants are connected at node 7 and node 30, whose output is uncontrollable, and output power prediction is required for this intermittent renewable energy source.

In this paper, adaptive weight-based hybrid particle swarm optimization algorithm is used to solve the multi-objective scheduling optimization model of virtual power plant proposed in this paper. The optimized output power of each power source is shown in Fig. 1. The dispatchable DG includes fuel cell FC, micro gas turbine MT.

From the output power value curves of each dispatchable unit in the figure, it can be seen that the distributed grid load is lighter in the trough time from 1:00-8:00, and the output of FC and MT is relatively low. 8:00 is the peak of MT output. The load FC and MT outputs climb gradually in the flat periods of 9:00-16:00 and 23:00-24:00. The interruptible load output is 0 in the period of 1:00-16:00, and the two controllable DGs, FC and MT, are maintained at a smooth output in the peak period of 17:00-22:00 due to the combined effect of the interruptible loads and the energy storage units.

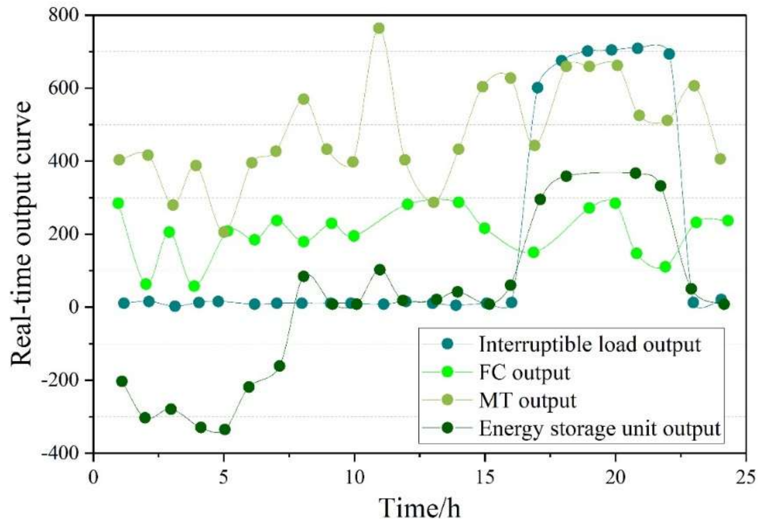

Figure 1: Real-time output curve of each scheduling unit

III. B. Multi-type resource mix planning for virtual power plants

III. B. 1) Selection of typical scenes

Game theory is a discipline that uses mathematical tools to study optimal decision-making in adversarial and conflict situations, with particular emphasis on rational choice in interactive situations. Compared with conventional decision analysis, game theory focuses more on the strategic actions taken by the parties to the game, and each participant is committed to the pursuit of maximizing their own interests.

This chapter mainly selects five typical investor cooperation modes as the scenarios for solution analysis, the selected scenarios and explanations are as follows:

Scenario 1: wind, light, fuel, storage, that is, No. 1 (taking into account the current electricity market system under this scenario wind power, photovoltaic power generation, gas turbine power generation and energy storage equipment often have different interests, each pursuing their own maximization of economic benefits, for the non-cooperative game.)

energy storage investors both cooperation, and wind, light investors game analysis, gas turbine and energy storage investors both in the virtual power plant to play the role of wind and light consumption as well as participation in auxiliary services.)

Scenario 3: wind-photovoltaic and fuel-storage, i.e., No. 3 (Considering that in order to optimize the resource allocation, wind and photovoltaic investors both cooperate. Gas turbine investors and storage investors both cooperate in the game.)

Scenario 4: wind-storage and photovoltaic-fuel, i.e., No. 4 (Considering the game between wind-storage cooperation and photovoltaic-fuel cooperation, since the total load of the region is certain, i.e., the total amount of electricity is certain, the decrease of the annual O&M cost of the wind-storage or the increase of the revenue will definitely cause the increase of the annual O&M cost of the photovoltaic-fuel or the decrease of the revenue, and vice versa.)

Scenario 5: wind-optical-fuel-storage, i.e., No. 5 (Considering that wind-optical-fuel-storage is a typical cooperative game model, the main emphasis is on overall rationality, i.e., aiming at maximizing the overall revenue of the virtual power plant.)

III. B. 2) Basic data

The analysis of the arithmetic examples in this paper is mainly carried out on the example of a typical area in the Northeast region. The fan model used for planning is BZD80-2000, with a rated power of 2MW, and cut-in, cut-out, and rated wind speeds of 3.0, 25.0, and 13.5m/s, respectively, and a photovoltaic array with a rated power of 1.2kW is selected, with a power temperature coefficient of 0.41%, a standard solar irradiance of 1.2 kW/m^2, and a standard battery temperature of 26℃. The government subsidies for wind power and photovoltaic are taken as 0.1935 and 0.4861 Yuan/kWh, respectively, and the unit price of wind and light abandonment penalty is set as 180 Yuan/MW, and the parameters such as maximum capacity, investment cost, operation and maintenance cost, service life, and use efficiency of each equipment are shown in Table 1.

Table 1: Equipment parameters

Device name	Wind generator	Photovoltaic generator	Microgas turbine	Energy storage equipment
Maximum capacity/ MW	65	35	20	12
Initial investment cost/ (RMB/KW)	3600	11000	1500	900
Operational cost/ (RMB/kw/year)	452	1200	300	85
Service life/ year	26	23	18	13
Efficiency / %	/	/	60	100

III. B. 3) Simulation results and analysis

Utilizing the solution method to configure the capacity of each power source within the virtual power plant, the results of the capacity configuration for the wind, light, fuel, and storage investors under the five typical scenarios mentioned above are shown in Table 2.

It can be seen that the trend of the installed capacity of the power sources of each investor shows a common trend characteristic to a certain extent. The installed capacity of wind turbines is the largest in all five typical modes, followed by the installed capacity of photovoltaics and energy storage, and the smallest installed capacity of microfuel turbines.

Scenario 5 forms a wind-photovoltaic-combustion-storage cooperative gaming alliance, and the total installed capacity drops significantly compared with the non-cooperative alliance (Scenario 1), with a difference of 38.4 MW. Compared with Scenario 3, the total installed capacity is slightly lower, which achieves the effect of saving investment.

Table 2: Distributed power installed capacity in different scenarios

Scene pattern	Installed capacity /MW	Fan capacity /MW	Photovoltaic capacity /MW	Energy storage capacity /MW	Gas turbine capacity /MW
Scenario 1	114.2	58	29.4	20.6	6.2
Scenario 2	103.9	52	30.2	18.3	3.4
Scenario 3	76.1	41.3	23.5	7.2	4.1
Scenario 4	95.8	50.9	26.5	13.2	5.2
Scenario 5	75.8	36.4	22.1	14.6	2.7

In accordance with the theoretical analysis of the virtual power plant revenue allocation, the revenue allocation of the internal members of the virtual power plant is carried out in two extreme cases, namely, the completely non-cooperative game and the completely cooperative game. The typical scenarios 1 and 5 selected for this simulation analysis are taken as examples, and the results of gain distribution are shown in Table 3.

The gain generated by the cooperative game of the virtual power plant is 105.07 million yuan, which is 7.382 million yuan more than the gain of the non-cooperative game, and the proportion of the gain is increased by 7.56%, the gain is improved obviously, and the gain generated by the cooperative game is better.

The above preliminary allocation results only consider the economic value of each member, without taking into account the safety and environmental protection, etc. According to the improved particle swarm method for redistribution, the main consideration of the main members of the safety, environmental protection, the degree of contribution, has been to achieve the effect of equalization. The coefficients of safety and environmental protection in this analysis are taken as 0.45 and 0.62 respectively, and the benefits of the participants under different allocation methods are shown in Figure 2.

Table 3: Revenue distribution

Participant	Cooperation income / 10,000 yuan	Non-cooperative income / 10,000 yuan	Difference value/ 10,000 yuan	Increase the proportion / %
Wind power investors	7856.3	7359.9	496.4	6.74
Photovoltaic power generation investors	1325.4	1143.0	182.4	15.96
Microgas turbine generation investors	412.8	379.7	33.1	8.72
Energy storage investors	912.5	886.2	26.3	2.97
Total income / 10,000 yuan	10507	9768.8	738.2	7.56

The total benefits under the three allocation methods are 97.688 million yuan, 10.507 million yuan and 10.794 million yuan, respectively. The improvement ratio of traditional particle swarm method and improved particle swarm method is 7.56% and 11.89% in that order.

As can be seen from the comparison of the above gain results, when the allocation is made according to the tolerance, each investor does not participate in the cooperation, which leads to the overall poor gain. When allocating according to the traditional method, the gains of each investor are improved than when they do not participate in the cooperation, and the overall gains are also improved compared with the non-cooperation. When the improved particle swarm method is adopted for allocation, their overall returns increase substantially. The wind and PV investors' returns are all higher than the traditional allocation method, and the microfuel turbine and energy storage investors' returns are lower compared to before the improvement, mainly due to the fact that the improved particle swarm method takes into account environmental friendliness as well as safety, and that wind is a relatively environmentally friendly form of energy.

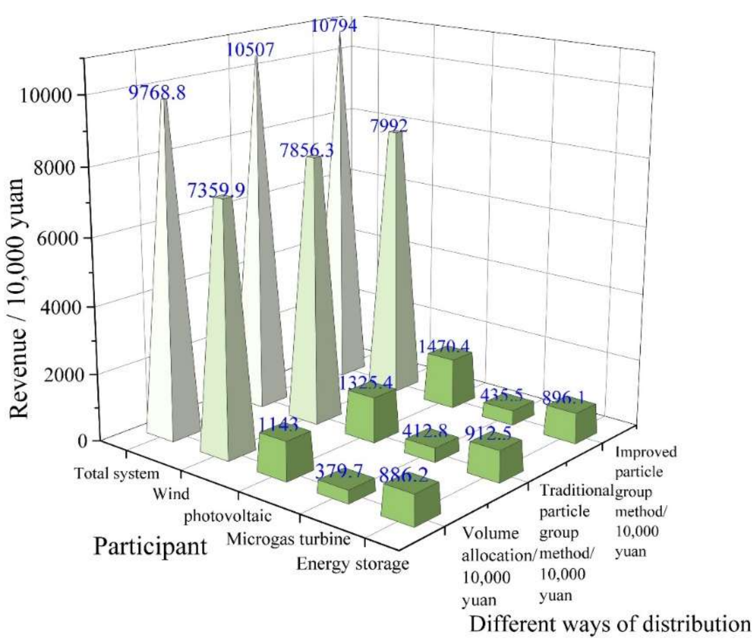

Figure 2: The participants' benefits of different distribution methods

IV. Conclusion

This paper combines the virtual power plant resource characteristics, in order to achieve the optimization of resource utilization within the virtual power plant cluster, set the power balance degree, power complementary degree and maximum load uniformity index balance objective function, and construct the virtual power plant cluster dynamic model of multi-energy system synergy.

(1) Adaptive weights of the hybrid particle swarm optimization algorithm is used to solve the multi-objective scheduling model of the virtual power plant cluster, from the power of each scheduling unit in each time period, it can be obtained that the power of interruptible loads in the 1:00-16:00 time period and the 23:00-0:00 time period is zero, and at this time, the energy storage unit and interruptible loads participate in the grid peaking, and the controllable DGs can be controlled to maintain a smooth power, optimize the grid operation cost, the network loss of the grid is reduced, and the economy of grid peaking is improved.

(2) In the example analysis of the virtual power plant multi-type cooperative model, game theory is added to set up a virtual power plant scheduling scenario with different wind, light, fuel and storage multi-energy cooperation. Scenario 5 is the wind-optical-fuel-storage cooperative game model, and the scenario 5 model reduces 38.4 MW in total installed capacity and increases 7.382 million yuan of economic benefits than the completely non-cooperative game scenario (Scenario 1). The coordinated scheduling of various types of resources improves economic benefits while reducing operating costs, and reaches a win-win situation for multiple types of resources in virtual power plants, which is beneficial to the stable development of the virtual power plant market.

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