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Scheduling method based on multi-objective dynamic planning for virtual power plants to participate in regional grid auxiliary services

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Abstract As an emerging energy aggregation management technology, virtual power plant can integrate multiple distributed resources such as wind power, photovoltaic and energy storage. Aiming at the multi-objective optimization and uncertainty handling problems in the participation of virtual power plants in the auxiliary services of regional power grids, the study proposes a virtual power plant scheduling method based on multi-objective dynamic planning. The method constructs a virtual power plant model containing micro gas turbine, energy storage unit, wind power generation and demand response, establishes a multi-objective optimization function with the objective of minimizing the operating cost, and solves it with an improved particle swarm algorithm. Through the simulation verification of the IEEE33 node distribution system, the results show that, compared with the traditional peaking method, the proposed method is able to reduce the load variance from 2251kW to 2071kW, the operating cost from 41845.3 yuan to 39,574.63 yuan, and the network loss from 3041kW to 2711kW. In the analysis of the different confidence levels, the system operating benefit reaches 16753 when the confidence level is 0.87 When the confidence level is 0.87, the system operation benefit reaches 16753.68 RMB, while the benefit is 16148.47 RMB when the confidence level is 0.97, which verifies the negative correlation between the confidence level and the operation benefit. The research results show that the multi-objective dynamic planning method can effectively improve the economy and operational stability of virtual power plants, which provides theoretical support for virtual power plants to participate in the electricity market.

Index Terms Virtual power plant, multi-objective dynamic planning, particle swarm algorithm, auxiliary service, operation cost, confidence level

I. Introduction

In recent years, major changes have occurred in the power structure and network structure of China's electric power industry, and the complexity of system operation and management has subsequently increased greatly, putting forward higher requirements for the safe and stable operation of the system [1]-[3]. At the same time, local wind, light, water abandonment and system peaking, and electricity and heat conflicts in the heating season in the northern region are prominent, and the necessity of establishing a regional grid auxiliary service market mechanism is becoming more and more prominent [4]-[6]. Virtual power plant as a new energy unit to participate in the power market operation of the new form, effective aggregation of load-side distributed power generation, energy storage, adjustable loads and other types of adjustable resources, so as to participate in the power auxiliary services market, to promote the source network load storage interactive operation [7]-[9].

Virtual power plant is a collection of multiple distributed power sources, loads, and energy storage devices, which can be operated as a special power plant, and is an emerging technology for solving the problem of grid-connection of distributed power sources, which can be controlled and managed like a traditional power plant, submit power generation plans to the grid, and participate in the power market as well as auxiliary services, such as peak shifting and frequency regulation [10]-[13]. Meanwhile, as an integrated energy management system with multiple functions such as self-coordination, self-management, self-control, and self-recovery, it provides a real-time feasible solution for grid-connected operation of renewable energy [14]-[16]. The virtual power plant does not change the grid-connected mode of distributed power sources, but realizes the coordinated and optimized operation of multiple distributed power sources through advanced control, communication, and metering technologies at a higher level of software architecture [17]-[19]. The virtual power plant presents the overall function and effect to the outside world, and can stabilize power transmission without transforming the grid, thus it can provide rapid response auxiliary services for the regional grid, and is a safe and effective method for distributed power sources to be integrated into the grid [20]-[23].

This study proposes a scheduling method based on multi-objective dynamic planning for virtual power plants to participate in the auxiliary services of regional power grids. Firstly, the mathematical models of each unit inside the virtual power plant are established, including the Weibull distribution model of wind power generation, the charge state model of energy storage unit and the cost efficiency model of micro gas turbine, to construct the overall characterization framework of the virtual power plant. Then a multi-objective optimization model is established with the goal of minimizing the operating cost, and multiple constraints such as power balance constraints, equipment output constraints, and hill-climbing constraints are considered comprehensively. Aiming at the problem that the traditional particle swarm algorithm is easy to fall into the local optimum, an improved particle swarm optimization algorithm is proposed, which improves the global search capability and convergence accuracy of the algorithm through the improvement of the initial population distribution, the adaptive inertia weight adjustment and the particle selection and replacement mechanism.

II. Modeling of the characteristics of virtual power plants and a framework for their participation in market transactions

II. A. External characteristics of the virtual power plant

II. A. 1) Output randomness

The virtual power plant integrates a large number of wind power, photovoltaic and other renewable distributed energy sources, their output is affected by the environment, geography, etc., which is manifested in the stochastic nature of the output, which makes the virtual power plant in the output plan development of a large uncertainty, and other controllable distributed power sources are needed to cooperate to reduce the impact of the stochastic nature of the wind power, photovoltaic and so on.

II. A. 2) Schedulability

Although the virtual power plant integrates a variety of distributed power sources, including wind power, photovoltaic and other uncontrollable and stochastic distributed power sources, but as a whole, due to its internal energy storage, gas turbines, controllable loads and other dispatchable resources, and thus the overall performance of the virtual power plant has a dispatchable condition under certain conditions.

II. A. 3) Independence

As a collection of integrated distributed resources, the virtual power plant has independence, i.e., it has its own independence in terms of organization, interests, and transactions, and it can independently participate in transactions and obtain benefits, but at the same time, since the distributed power sources integrated by the virtual power plant are usually distributed in the distribution grid, usually the virtual power plant has to accept the scheduling of the distribution grid when it formulates its plan in order to meet the safe and stable operation of the distribution grid.

II. A. 4) Scalability

In the face of a large number of distributed power supplies with scattered locations, the virtual power plant can integrate distributed power supplies through advanced communication technology, measurement technology and other means to form a whole that is not directly connected physically, but unified in its role, so that the distributed power supplies in the virtual power plant have flexible expandability, and different types of distributed power supplies and distributed power supplies in different locations can be integrated into the virtual power plant through communication technology, measurement technology and other means. Different types of distributed power supplies and distributed power supplies in different locations can be integrated into the virtual power plant through communication technology, measurement technology, etc. Similarly, members of the virtual power plant can flexibly withdraw from the virtual power plant, thus realizing the flexible expansion and withdrawal of the virtual power plant.

II. B. Internal units and modeling of the virtual power plant

II. B. 1) Wind power

Wind speeds have been subjected to extensive statistics and analysis to derive the law that wind speeds obey a Weibull distribution [24].

Wind speed distribution function and probability density function:

$$F(v)=1-\exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{1}$$

$$f(v)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1}e^{-\left(\frac{v}{c}\right)^{k}} \tag{2}$$

where v is the wind speed, k is the shape parameter and c is the scale parameter.

If the mean and variance of the wind speed are known, then the calculation of the shape parameter k and scale parameter c of the Weibull distribution can be carried out according to the following equation.

$$k=\left(\frac{\sigma}{\overline{v}}\right)^{-1.086}(1\le k\le 10) \tag{3}$$

$$c=\frac{\overline{v}}{\Gamma\left(1+\frac{1}{k}\right)} \tag{4}$$

where $\overline{v}$ is the mean value of wind speed; σ is the standard deviation of wind speed; and $\Gamma(x)$ denotes the Gamma function.

II. B. 2) Energy storage units

Generally the state of charge (SOC) is used to indicate the state of the energy storage unit, the state of charge is the ratio of the current residual power of the energy storage device to the rated capacity of the device, which is between 0 and 1. The expression is shown in the following equation. The following formula indicates the relationship between the state of charge and the charging and discharging power, in the charging and discharging, there will be a certain amount of energy loss in the conversion process, the amount of loss of power per unit is expressed in terms of the charging and discharging efficiency, generally speaking, for the chemical battery energy storage equipment, the newer the equipment, the higher the efficiency, and with the use of the equipment, the aging phenomenon will gradually occur, making the charging and discharging efficiency becomes lower.

$$SOC_t=\frac{E_t^{ESS}}{E_{rated}}\times 100\% \tag{5}$$

$$SOC_t=SOC_{t-1}-\frac{P_t^{dis}}{\eta_{dis}E_{rated}}\Delta t \tag{6}$$

$$SOC_t=SOC_{t-1}-\frac{\eta_{chr}P_t^{chr}}{E_{rated}}\Delta t \tag{7}$$

where SOC_t,SOC_{t-1} is the state of charge at t and $t-1$, respectively; E_{rated} is the rated capacity of the energy storage device; η_{chr},η_{dis} is the efficiency of charging and discharging, respectively; P_t^{chr},P_t^{dis} are the power of charging and discharging, $P_t^{chr}\le 0,P_t^{dis}\ge 0$, respectively.

II. B. 3) Micro gas turbine model

The cost of the gas turbine considered in this paper consists of two parts, which are fuel cost and operation and maintenance cost. The fuel cost of its power generation can be expressed in terms of the amount of natural gas consumed as well as the efficiency, where the efficiency is a quantity that varies with the output power of the gas turbine, which usually increases as the power generated increases, so that in the operation of the micro gas turbine, the marginal cost is generally lower at higher load factors, and greater economic benefits can be achieved.

$$C_t^{MT}=C_{MTJ}^{m}+C_{MTJ}^{fuel} \tag{8}$$

$$C_t^{MT,m}=\sum_{i=1}^{N_{MT}}k_i^{MT,m}(P_{i,t}^{MT})\Delta t \tag{9}$$

$$C_t^{MT,fuel} = \sum_{i=1}^{N_i} \frac{\lambda_{LNG}(P_{i,t}^{MT})\Delta t}{\eta_{i,t}^{MT} L} \tag{10}$$

where $C_t^{MT,fuel}, C_t^{MT,m}$ are the fuel cost and operation and maintenance cost of the gas turbine in time period t, respectively; $k_i^{MT,m}$ is the unit operation and maintenance cost of the i gas turbine in time period t; $P_{i,t}^{MT}$ is the i gas turbine's power; λ_{LNG} is the price of natural gas; $\eta_{i,t}^{MT}$ is the power generation efficiency of the i th gas turbine in time period t; L is the low calorific value of natural gas; and N_{MT} is the number of gas turbines.

The output power and output efficiency of a gas turbine are usually expressed by the following equation.

$$\eta_{MT} = m_0 + m_1 P_{MT^*} + m_2 P_{MT^*}^2 + m_3 P_{MT^*}^3 \tag{11}$$

where m_0, m_1, m_2, m_3 are the characteristic parameters related to the efficiency of the micro-gas turbine power generation, and P_{MT^*} is the standardized value of the output power of the micro-gas turbine.

II. C.Electricity market trading framework

Due to the uncertainty of wind power, photovoltaic and other renewable energy sources in the virtual power plant, the output of the power in the actual transaction may have a certain error with the power declared earlier, so in the balancing market, we have to penalize the over-generation or under-generation of power, and sell the part of the virtual power plant's actual power generation that is higher than the declared amount earlier at a lower price, and buy the power that is lower than the declared amount earlier at a higher price to make up for the power deficit. The power that is lower than that declared earlier will be purchased at a higher price to make up for the power shortfall.

The framework structure of the virtual power plant participating in market trading is shown in Figure 1. The virtual power plant, as a power market trading organization, can participate in the mid- and long-term market, the day-ahead market, the intra-day market, the real-time balancing market, the auxiliary service market and other trading to obtain profits.

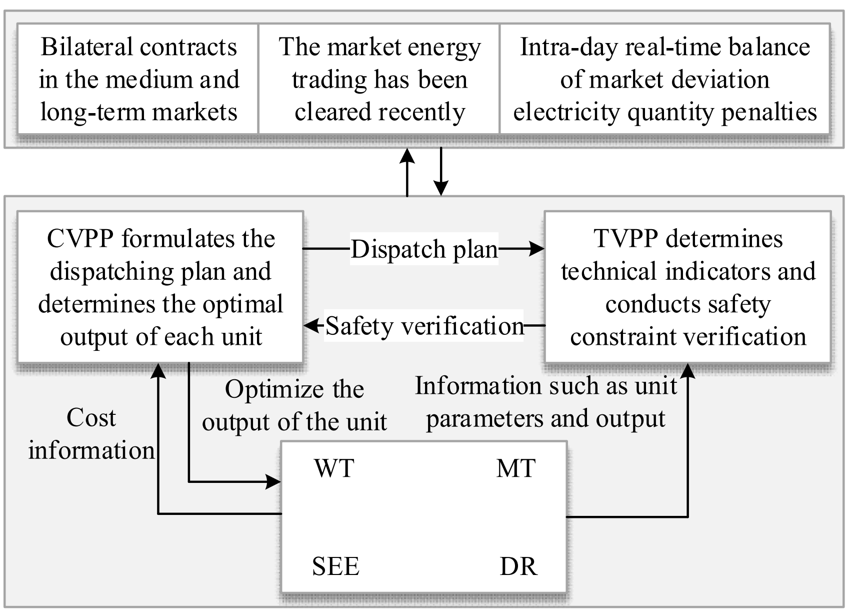

Figure 1: Framework of virtual power plant participating in electricity market transactions

III. Participation of virtual power plants in the dispatch optimization of ancillary services in the regional grid

III. A. Multi-objective dynamic scheduling planning modeling

III. A. 1) Objective function

Virtual power plant cost function, due to the new energy generation mainly using wind and solar power generation, the cost is low, so the virtual power plant cost is mainly considered the following three parts: micro-gas unit cost, electric vehicle storage unit cost (charging is equivalent to the load to provide revenue for the virtual power plant, this part of the cost of the negative value, the equivalent of the unit when discharged to provide electricity for the virtual plant, the cost of the positive value). Demand response contains interruptible loads and controllable loads. The objective function is to minimize the total cost of the virtual power plant:

$$\min C = C_F + C_S + C_{IL} \tag{12}$$

where C_F denotes the cost of micro gas units, C_S denotes the cost of electric vehicle energy storage units, and C_{IL} denotes the cost required to mobilize demand response.

The cost of micro gas units in Eq. mainly includes start-stop cost, fuel cost.

$$C_F = C_F^g + C_F^q \tag{13}$$

where C_F^g denotes the fuel cost of the MGU, and C_F^q denotes the start-stop cost of the MGU.

The specific formula for fuel cost is:

$$C_f^g = (a_f \times P_{f,t}^2 + b_f \times P_{f,t} + c_f) \times u_{f,t} \tag{14}$$

where a_f, b_f and c_f denote the fuel cost coefficients for power generation by the MGUs, respectively; $P_{f,t}$ denotes the power generation output of the thermal power unit at moment t; $u_{f,t}$ denotes the power generation state parameter of the MGUs at moment t, $u_{f,t} = 1$ indicates that the thermal unit is enabled, and $u_{f,t} = 0$ indicates that the thermal unit is not enabled.

The startup and shutdown cost of the micro gas unit is calculated as:

$$C_F^q = \sum_{t=1}^{T} u_{f,t}(1 - u_{f,t-1}) C_f^q \tag{15}$$

C_f^q denotes the cost required for a single start-stop, and C_F^q denotes the total start-stop cost. The cost of the energy storage unit is mainly determined by the charging and discharging state and the amount of charging and discharging as follows:

$$C_s = p_s \times u_{s,t} P_s \tag{16}$$

p_s denotes the price of electricity when mobilizing power from EV storage units and charging EVs on the same day.

III. A. 2) Constraints

The constraints mainly include system operation constraints and unit output constraints, and the system operation constraints include power balance constraints and system standby constraints.

(1) Power balance constraints

At any moment t, the actual output of the virtual power plant should be equal to the load:

$$F_t = Q_t \tag{17}$$

F_t denotes the virtual power plant output at the moment t, and Q_t denotes the system load at the moment t.

The output of the virtual power plant at the moment of t is equal to the sum of the output of the wind turbines, PV generating units, thermal generating units, and demand response within the virtual power plant at the moment of t, which is expressed as Equation (18):

$$F_t = P_{L,t} + P_{W,t} + u_{s,t} P_{S,t} + P_{F,t} + P_{IL,t} \tag{18}$$

$$F = P_L + P_W + P_S + P_F + P_{IL} \tag{19}$$

where $P_{L,t}, P_{W,t}, P_{S,t}, P_{F,t}, P_{IL,t}$ denote the outputs provided by the wind turbine, solar turbine, energy storage unit, micro-gas turbine, and the demand response in the virtual power plant at the moment t, respectively. $P_L, P_W, P_S, P_F, P_{IL}$ denote the sum of outputs provided by the wind turbine, solar turbine, energy storage unit, micro gas unit, and demand response within the virtual power plant at the time of the cycle respectively.

(2) Output constraints

For wind and solar generating units, the moment t output should be greater than 0 less than the predicted value of the moment t output:

$$0 \le P_L^t \le P_{l,t}^{\max} \tag{20}$$

$$0 \le P_W^t \le P_{w,t}^{\max} \tag{21}$$

There are upper and lower constraints on the output of micro gas units:

$$P_F^{\min} \le P_F \le P_F^{\max} \tag{22}$$

For the energy storage unit, the output of the storage unit can be either positive or negative, therefore, according to the previous modeling of the energy storage unit, it is only necessary to satisfy that at any moment t the battery charge state is greater than 0 less than 1:

$$0 < SOC_t < 1 \tag{23}$$

For demand response, it should be greater than 0 and less than 1.

$$0 \le P_{IL} \le P_{IL}^{\max} \tag{24}$$

(3) Thermal power unit climbing constraints

The change in output of a miniature gas-fired unit from moment $t-1$ to moment t is constrained by the upward and downward creeping power.

$$Ramp_f^d \le P_{f,t} - P_{f,t-1} \le Ramp_f^u \tag{25}$$

(4) Rotating standby constraints

$$\begin{cases} P_{f,t}^{\max} - P_{f,t} \ge RES + RES_t^u \\ P_{f,t} - P_{f,t}^{\min} \ge RES + RES_t^d \end{cases} \tag{26}$$

III. B. Scheduling Model Solution Algorithm

III. B. 1) Introduction to the Particle Swarm Algorithm

The basic principle of particle swarm algorithm is to make the particles search along the current best particle by initializing a group of particles [25]. In the iterative process, the particles update themselves by tracking the optimal solution found by themselves and the optimal solution found by the whole particle swarm, and the solution speed is fast. However, the particle swarm algorithm generates the initial population randomly, which may result in poor diversity of the particle swarm due to the concentration of particles in a certain region. At the same time, similar to other algorithms, the particle swarm algorithm is prone to fall into local optimization when solving high-dimensional complex problems, and it is difficult to balance the depth and breadth of the search ability.

III. B. 2) Algorithmic improvements

For the problems of the basic particle swarm algorithm mentioned in the previous section, this section proposes to screen the distribution of the initial population of the particle swarm algorithm, so that the particles can be uniformly distributed in space; adjust the inertia weights according to the actual situation of the particle evolution, and increase the weights to accelerate the speed of evolution when the success rate of the particle evolution is high, and vice versa reduce the weights and increase the depth of the global search of particles so that the algorithm jumps out of the local optimal points: after the the end of each iteration, replace the speed and position of the particles to speed up the search speed of the particles.

Suppose the position of the i th particle in N -dimensional space is:

$$X_i = (x_i^1, x_i^2, x_i^3 \cdots x_i^N) \tag{27}$$

The velocity of particle i is:

$$V_i = (v_i^1, v_i^2, v_i^3 \cdots v_i^N) \tag{28}$$

The current optimal position found by particle i is:

$$P_i = (p_i^1, p_i^2, p_i^3 \cdots p_i^N) \tag{29}$$

The current optimal position found by the particle swarm is:

$$P_g = (p_g^1, p_g^2, p_g^3 \cdots p_g^N) \tag{30}$$

Based on the above introduction, the specific algorithm steps are as follows:

(1) Generation of initial population

The particles are discretized according to the variation interval of the independent variables and the discrete accuracy of the independent variables, so that all the particles can be uniformly distributed in each discrete interval. For the selection of the number of particles N, it is decided according to the complexity of the specific problem under study, and the dimension m of the particles is the dimension of the solution of the problem under study.

(2) Initialize the optimal position of each particle and the particle swarm

Select the appropriate fitness function and calculate the fitness of each particle. And store the current particle fitness and position in the particle's P_i, and the fitness and position of the optimal individual among all particles are stored in P_g. In order to make the particles with better fitness have a large enough chance of survival, the fitness function is generally selected with respect to the objective function.

(3) Update the inertia weights

Taking the example of solving the minimization problem, there is the following definition:

$$S(i,t) = \begin{cases} 0 & fit(p_i) \geq fit(p_g) \\ 1 & fit(p_i) < fit(p_g) \end{cases} \tag{31}$$

which denotes the success rate of particle i in the t th iteration; $fit(p)$ is the fitness function. Then the success rate of the whole particle swarm in the t th iteration, i.e., the success rate of converging to the better solution is:

$$f(t) = \frac{\sum_{i=1}^{N} S(i,t)}{N} \tag{32}$$

When the particle swarm tends to have a larger proportion of superior solutions during the iteration process, then the particles should be accelerated in that direction for global search, i.e., the weight coefficients should be increased. Therefore, there is the following definition:

$$\omega(t) = (w_{\max} - w_{\min}) f(t) + w_{\min} \tag{33}$$

where $\omega_{\max}$ and $\omega_{\min}$ are the boundary values of the set inertia weights.

(4) Update particle position and velocity

After finding the two optimal values, the velocity and position of the particle are updated using the following equation:

$$v_{ij}(t+1) = \omega(t) v_{ij}(t) + c_1 r_1 [p_{ij} - x_{ij}(t)] + c_2 r_2 [p_{gj} - x_{ij}(t)] \tag{34}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{35}$$

where $j = 1, 2 \cdots m$; ω is the inertia weight, which determines the degree of velocity inheritance to the current particle. If chosen appropriately, it can make the particle have balanced exploratory and exploitation ability; c_l, c_2 is the positive learning factor, which can make the particle have the ability of self-summarization and learning from the excellent individuals, so that the particle tends to the optimal point; r_l, r_2 is a uniformly distributed random number between 0 and 1.

(5) Selecting the individual optimal position

For each particle, compare its current adaptation value with the previous response value and select the better and most current optimal position of the particle.

(6) Update the group optimal position

After updating the individual optimal position, compare the current optimal value of all particles with the overall optimal value, and select the better one as the group optimal position.

(7) Select and replace particles

Sort the whole particle swarm according to the adaptation value and select the best half of the particles in the group. And replace the velocity and position of the worst half particle with the velocity and position of this particle.

III. C. Solution flow

By improving the generation of initial population W and the updating of weights in the selection-based particle swarm algorithm, the scenario of falling into local optimality due to too high dimensionality can be effectively avoided. The improved algorithm can not only make the particles uniformly distributed in the solution space range, and speed up the search speed, increase the search range and coordinate the local search capability when approaching the optimal solution with the global search level when far away from the optimal solution, which improves the algorithm's solving speed and solving accuracy. The specific flow of the algorithm is shown in Figure 2.

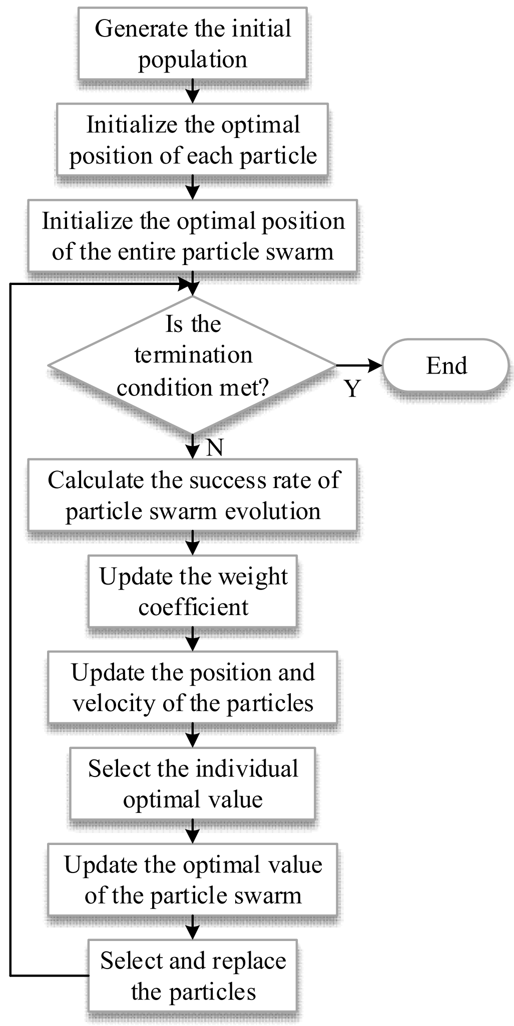

Figure 2: Algorithm flowchart

IV. Analysis of examples

IV. A. Description of the algorithm

In this paper, a standard IEEE33 node power distribution system is used for simulation verification and the system wiring is shown in Fig. 3. The system installs fuel cells at nodes 7 and 15, micro gas turbines at nodes 17, 20 and 28, interruptible loads at nodes 25 and 32, and energy storage units at node 24. Access to wind turbines and photovoltaic panels at node 7 and node 30, whose output is uncontrollable, is required to forecast the output power of this intermittent renewable energy source, whose wind turbine and photovoltaic output are shown in Fig. 4, and the daily load forecast curve is shown in Fig. 5.

As can be seen from Fig. 4 and Fig. 5, wind power and PV output have obvious anti-peaking characteristics, which increases the difficulty of power system peaking. In terms of time-sharing tariff setting: the price of electricity is 0.63 yuan/(kw·h) for the peak period from 17:00 to 22:00; the price of electricity is 0.36 yuan/(kw·h) for the trough period from 1:00 to 7:00; and the levelized price for the rest of the period is 0.50 yuan/(kw·h). The compensation price of interrupted unit power is 0.15 yuan, and the power purchase price from the controllable load dg is 0.76 yuan/(kw·h); the operation and maintenance price of the energy storage unit is 0.07 yuan/(kw·h).

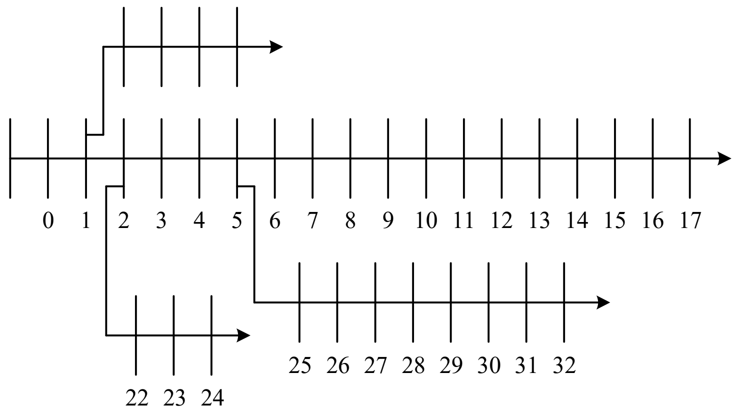

Figure 3: IEEE33 Node distribution system

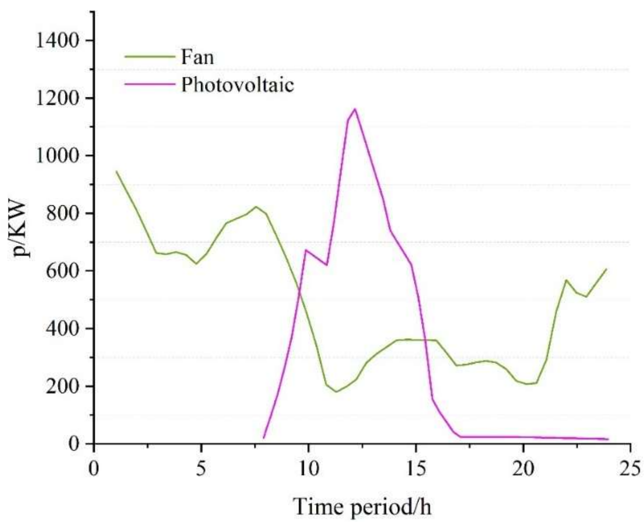

Figure 4: Output power of fan and photovoltaic power station

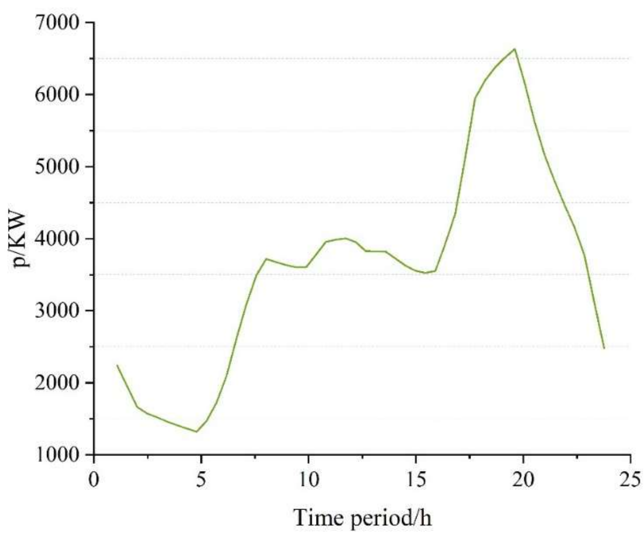

Figure 5: Daily load forecast curve

IV. B. Calculation results and analysis

In this paper, the multi-objective particle swarm algorithm based on gray correlation is used to solve the peak optimization model proposed in this paper. The optimized output of each power source is shown in Fig. 6. From the figure, it can be seen that: in 1:00~7:00 trough time the distributed grid load is lighter, the FC and MT outputs are relatively low, and the energy storage units start to charge; in 8:00~16:00 and 23:00~24:00 equal time, the load FC and MT outputs are gradually climbing; in 17:00~22:00 peak time, due to the interruptible loads and the energy storage units, the two controllable DGs, FC and MT, maintain a smooth output. During the peak hours from 17:00 to 22:00, the interruptible loads and storage units work together to maintain the smooth output of the two controllable DGs, FC and MT.

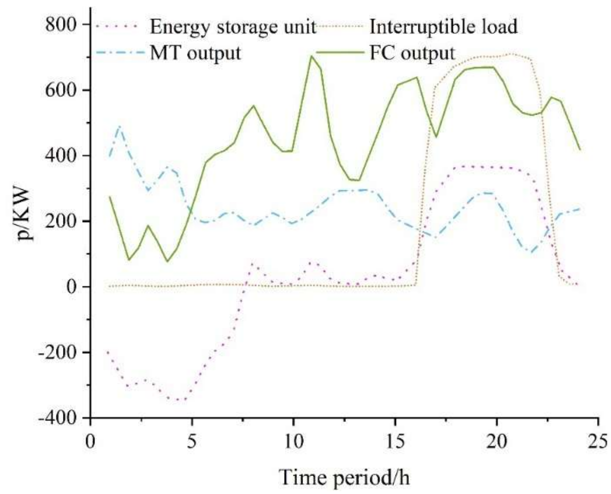

Figure 6: Real-time output curve of each scheduling unit

In order to verify the feasibility of the proposed peaking model, this paper divides three kinds of peaking scheduling methods according to the participation of each DER in grid peaking, and analyzes and compares them in terms of load variance, grid operation cost and network loss, and its simulation results are shown in Table 1.

From the table, it can be seen that although the way of DG full generation can effectively reduce the load variance, the cost consumed is huge and not economical. The way of only DG participating in peak shifting is also the traditional peak shifting method commonly used nowadays, i.e., the two controllable loads, FC and MT, respond to the load demand of the grid, and due to the high cost of purchasing power from DG, the output of DG is cut down during peak shifting, and the load demand is satisfied by purchasing power from the higher-level grid. In this paper, the proposed approach of the energy storage unit and interruptible loads participating in the virtual power plant grid peaking together not only reduces the load variance to a greater extent, but also reduces the cost of the virtual power plant grid operation in comparison with the traditional peaking approach. When the energy storage unit is discharged, it is equivalent to connecting to the power source, and at the same time, the interruptible load reduces part of the load demand, which makes the network loss of the virtual power plant grid can be greatly reduced, and further improves the economy of the virtual power plant grid peaking.

Table 1: Simulation results of three kinds of peak load regulation modes

Peak mode	Load variance /kW	Power grid operating cost /yuan	Net speed /kW
DG is fully developed	1034	51184.4	2457
Only DG participates in peak regulation	2251	41845.3	3041
All DER participates in peak regulation	2071	39574.63	2711

IV. C. Economic analysis

IV. C. 1) Analysis of virtual power plant operation results with different uncertainty conditions

The following five operational scenarios are constructed to further illustrate the impact of accounting for multiple uncertainties on the operation of the virtual power plant, of which Scenario 5 is the uncertainty considered in this chapter. Scenario 1: The volatility of the market price of electricity is not taken into account, while the volatility of the new energy output, load demand, and the uncertainty of the price of carbon emission rights are taken into account; Option 2: Consider only the uncertainty of new energy output, load demand, and market price of electricity, without considering the volatility of the price of carbon emission rights; Scenario 3: Does not take into account the stochastic nature of the new energy output, but only the volatility of the load demand and the uncertainty of the price of electricity and carbon emission rights; Scenario 4: Does not take into account the uncertainty of load demand, but takes into account the volatility of new energy output and the uncertainty of the price of electricity and carbon emission rights; Scheme 5: For the current research status of VPP uncertainty factors, this paper considers the volatility of new energy output and load demand as well as the uncertainty of electricity price and carbon emission right price.

With the above scenarios determined, the confidence level is set to 0.90, and the PSGA algorithm is used to solve the model, and the objective function values for each optimized operation scenario are obtained as shown in Table 2.

Based on the comparison of Scenario 1 and Scenario 5, it can be seen that the model economics may not be optimal if the uncertainty of electricity price is not considered. However, when the fluctuation of electricity price and the fluctuation of carbon emission right price are considered at the same time, the model is closer to the reality. Optimizing the model to take into account the uncertainty of electricity price helps the VPP make timely adjustments in response to real-time changes in electricity market prices in order to optimize the economic efficiency.

By comparing Scenario 3 and Scenario 5, it can be seen that the overall economic benefit of the VPP decreases from 18,151.38 yuan to 16,379.57 yuan when considering the impact of the uncertainty of wind and solar power generation, and at the same time, the cost of the carbon emission right increases from 639.42 yuan to 647.01 yuan. Compared to the case where wind stochasticity is not taken into account, once wind output stochasticity is included in the analysis, both the economic and environmental benefits of the system show a downward trend.

According to the comparison of Scenarios 4 and 5, it can be seen that compared to the case where the uncertainty of load demand is not taken into account, when the uncertainty of load demand is considered, the economic and environmental performance of the system is enhanced, and the uncertainty of load forecasting and the uncertainty of the new energy output are compensated for each other to a certain extent, which promotes the virtual power plant to more efficiently integrate the diversified energy equipments and resources, and to take advantage of their temporally complementary characteristics for optimization.

Table 2: The value of the target function in the situation

Inconclusive factors	System operating income(yuan)	The cost of carbon emissions(yuan)
Plan 1	16474.41	682.12
Plan 2	16583.27	685.72
Plan 3	18151.38	639.42
Plan 4	16083.61	671.28
Plan 5	16379.57	647.01

IV. C. 2) Confidence level setting analysis

Taking the confidence level ζ as three values of 0.86, 0.92 and 0.97 respectively, the operating benefits of the VPP at each moment under different confidence levels can be derived as shown in Fig. 7. As can be seen, under the consideration of the four uncertainty factors described in this chapter, the overall operating benefits of the virtual power plant at all moments when setting a lower confidence level are higher than the benefits of the virtual power plant when setting a higher confidence level. This indicates that the operational benefits of the virtual power plant are negatively correlated with the confidence level, i.e., the lower the confidence level setting, the higher the operational benefits of the virtual power plant.

The VPP at different confidence levels of VPP and carbon emission cost at different confidence levels are shown in Table 3. It can be seen that there is a 92% probability that the expected value of the operating benefits of the virtual power plant exceeds 16379.57 yuan and the target expected value of the cost of carbon emission rights is lower than 647.01 yuan, taking into account the four uncertainty factors. As the confidence level increases, the system benefit target expectation value decreases and the carbon cost target expectation value increases, indicating that the VPP scheduling scheme becomes more conservative in order to reduce the risk. At the same time, the magnitude of this change in the target values of benefits and costs decreases as the confidence level increases, indicating that the decision maker is less sensitive to risk and the dispatch scheme tends to be more robust. Decision makers can balance the operational benefits, environmental benefits and system reliability by setting different confidence levels to achieve an optimal dispatch strategy.

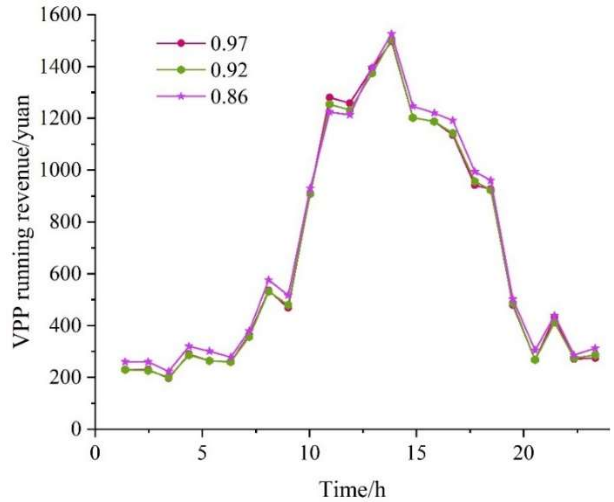

Figure 7: The performance of VPP at all times in different confidence levels

Table 3: Comparison of the scheduling results of VPP in different confidence levels

Confidence level	Operational benefit	Carbon cost
0.87	16753.68	637.58
0.92	16460.41	643.68
0.97	16148.47	649.61

IV. C. 3) Impact of the way the virtual power plant is constructed on economics

In order to verify that the introduction of equipment such as electricity to gas and participation in multiple markets is more economical for the virtual power plant, three scenarios are constructed in this paper as shown in Table 4. The Yalmip toolbox + Cplex commercial solver is invoked in Matlab to simulate with a 24h scheduling cycle with an interval of 1h, and the benefits and costs of VPP under each scenario are obtained as shown in Table 5.

In Scenario 1, VPP does not convert electricity into gas, and only participates in three markets: electricity, heat and natural gas, while the carbon trading market has no benefits. Compared with scheme 3, the revenue of the electric heat trading market in scheme 1 increased by 1168.79 yuan, and the overall cost increased by 412 yuan.

In Option 3, the virtual power plant participates in the carbon trading market, and because the P2G equipment can absorb carbon dioxide, it is equivalent to increasing the carbon emission quota of the VPP, thereby improving the profitability of the carbon trading market. Compared with Option 2, the total revenue of VPP participating in the electricity and heat markets in Scheme 3 remains basically unchanged, but the revenue from the natural gas market increases from -49,783.12 yuan to -49,573.81 yuan. Overall, compared with Option 2, the overall operating cost of VPP is reduced by 243.84 yuan.

Table 4: Different composition of VPP and participate in market plan

	Plan 1	Plan 2	Plan 3
CHP unit	Have	Have	Have
Electric rotating gas equipment	Nothing	Have	Have
Gas boiler	Have	Have	Have
Power market	Participate in	Participate in	Participate in
Thermal market	Participate in	Participate in	Participate in
Gas market	Participate in	Participate in	Participate in
Carbon market	Nonparticipation	Nonparticipation	Participate in

Table 5: The benefits and costs of VPP in different scenarios

	Plan 1	Plan 2	Plan 3
Thermal market income (yuan)	41754.21	40373.11	40585.42

Gas market income (yuan)	-51084.11	-49783.12	-49573.81
Carbon trading market income (yuan)	0	0	0
Alternative load cost (yuan)	361.22	361.31	330.78
Electrical equipment cost (yuan)	0	663.47	993.21
Final running cost (yuan)	16384.73	16216.57	15972.73

In summary, virtual power plants can maximize economy and environmental protection when they incorporate power-to-gas equipment and participate in the electricity, heat, gas, and carbon trading markets at the same time.

V. Conclusion

In this study, by establishing a virtual power plant dispatch optimization model based on multi-objective dynamic planning, the multi-objective coordination and uncertainty handling problems in the participation of virtual power plants in the auxiliary services of regional power grids are effectively solved. Simulation results verify the effectiveness and practicality of the proposed method.

In terms of scheduling optimization effect, compared with the traditional way in which only distributed power supply participates in peak shifting, the scheduling scheme in which energy storage units and interruptible loads are jointly involved can reduce the system operating cost from 41845.3 yuan to 39574.63 yuan, with a cost saving rate of 5.4%, and at the same time, the load variance is reduced from 2251kW to 2071kW, which effectively improves the system operation stability.

In terms of uncertainty analysis, the optimization results at different confidence levels show that the system operation benefit is 16,753.68 yuan when the confidence level is 0.87, while the benefit drops to 16,148.47 yuan when the confidence level is raised to 0.97, with a difference of 605.21 yuan, which confirms the trade-off relationship between risk control and economic benefits.

The analysis of the benefits of multi-market participation shows that the final operating cost of the virtual power plant when it simultaneously participates in the four markets of electricity, heat, gas, and carbon is 15972.73 yuan, which is a reduction of 411.84 yuan compared with the cost of the scenario when it participates in only the three markets of electricity, heat, and gas, reflecting the economic advantage of the synergistic participation in multi-markets.

The improved particle swarm algorithm shows good convergence and stability when dealing with high-dimensional complex optimization problems, and provides reliable technical support for real-time scheduling of virtual power plants.

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References

[1] Soares, J., Pinto, T., Lezama, F., & Morais, H. (2018). Survey on complex optimization and simulation for the new power systems paradigm. Complexity, 2018(1), 2340628.
[2] Chakrabarti, A., & Halder, S. (2022). Power system analysis: operation and control. PHI Learning Pvt. Ltd..
[3] Machowski, J., Lubosny, Z., Bialek, J. W., & Bumby, J. R. (2020). Power system dynamics: stability and control. John Wiley & Sons.
[4] Hu, J., Yan, Q., Kahrl, F., Liu, X., Wang, P., & Lin, J. (2021). Evaluating the ancillary services market for large-scale renewable energy integration in China's northeastern power grid. Utilities Policy, 69, 101179.
[5] Jiang, M., Guo, Q., Sun, H., & Ge, H. (2021). Leverage reactive power ancillary service under high penetration of renewable energies: An incentive-compatible obligation-based market mechanism. IEEE Transactions on Power Systems, 37(4), 2919-2933.
[6] Oureilidis, K., Malamaki, K. N., Gallos, K., Tsitsimelis, A., Dikaiakos, C., Gkavanoudis, S., ... & Demoulias, C. (2020). Ancillary services market design in distribution networks: Review and identification of barriers. Energies, 13(4), 917.
[7] Gulotta, F., Daccò, E., Bosisio, A., & Falabretti, D. (2023). Opening of ancillary service markets to distributed energy resources: A review. Energies, 16(6), 2814.
[8] Pollitt, M. G., & Anaya, K. L. (2021). Competition in markets for ancillary services? The implications of rising distributed generation. The Energy Journal, 42(1_suppl), 1-28.
[9] Zapata, J., Vandewalle, J., & D'haeseleer, W. (2014). A comparative study of imbalance reduction strategies for virtual power plant operation. Applied Thermal Engineering, 71(2), 847-857.
[10] Minai, A. F., Khan, A. A., Ndiaye, M. F., Alam, T., Khargotra, R., & Singh, T. (2024). Evolution and role of virtual power plants: Market strategy with integration of renewable based microgrids. Energy Strategy Reviews, 53, 101390.
[11] Wang, Y., Gao, W., Qian, F., & Li, Y. (2021). Evaluation of economic benefits of virtual power plant between demand and plant sides based on cooperative game theory. Energy Conversion and Management, 238, 114180
[12] Naval, N., Sánchez, R., & Yusta, J. M. (2020). A virtual power plant optimal dispatch model with large and small-scale distributed renewable generation. Renewable Energy, 151, 57-69.

[13] Panda, S., Mohanty, S., Rout, P. K., & Sahu, B. K. (2022). A conceptual review on transformation of micro-grid to virtual power plant: Issues, modeling, solutions, and future prospects. International journal of energy research, 46(6), 7021-7054.

[14] Baringo, A., Baringo, L., & Arroyo, J. M. (2023). Robust virtual power plant investment planning. Sustainable Energy, Grids and Networks, 35, 101105.

[15] Ochoa, D. E., Galarza-Jimenez, F., Wilches-Bernal, F., Schoenwald, D. A., & Poveda, J. I. (2023). Control systems for low-inertia power grids: A survey on virtual power plants. IEEE Access, 11, 20560-20581.

[16] Ninagawa, C. (2022). Virtual power plant system integration technology. Springer.

[17] Vasirani, M., Kota, R., Cavalcante, R. L., Ossowski, S., & Jennings, N. R. (2013). An agent-based approach to virtual power plants of wind power generators and electric vehicles. IEEE Transactions on Smart Grid, 4(3), 1314-1322.

[18] Li, B., Wang, J., Bai, X., Tang, T., Zhao, J., Liu, C., ... & Ali, R. (2022). Overview and prospect of information and communication technology development in virtual power plants. Energy Conversion and Economics, 3(6), 368-380.

[19] Ruan, G., Qiu, D., Sivaranjani, S., Awad, A. S., & Strbac, G. (2024). Data-driven energy management of virtual power plants: A review. Advances in Applied Energy, 100170.

[20] Kolenc, M., Nemček, P., Gutschi, C., Suljanović, N., & Zajc, M. (2017). Performance evaluation of a virtual power plant communication system providing ancillary services. Electric Power Systems Research, 149, 46-54.

[21] Etherden, N., Bollen, M. H., & Lundkvist, J. (2013, October). Quantification of ancillary services from a virtual power plant in an existing subtransmision network. In IEEE PES ISGT Europe 2013 (pp. 1-5). IEEE.

[22] Abbasi, E. (2017). Coordinated primary control reserve by flexible demand and wind power through ancillary service–centered virtual power plant. International Transactions on Electrical Energy Systems, 27(12), e2452.

[23] Zhang, G., Ouyang, L., & Yang, S. (2021). The evaluation of solely renewable energy based virtual power plants potential for ancillary services provision. In IOP Conference Series: Earth and Environmental Science (Vol. 621, No. 1, p. 012064). IOP Publishing.

[24] Muhammad Aslam Mohd Safari,Nurulkamal Masseran,Muhammad Hilmi Abdul Majid & Razik Ridzuan Mohd Tajuddin. (2025). Robust estimation of the three parameter Weibull distribution for addressing outliers in reliability analysis. Scientific Reports,15(1),11516-11516.

[25] Xuelin Zhang,Xiaobin Xu,Song Sun,Qinghua Zhong,Hong He,Georg Brunauer & Felix Steyskal. (2025). An Improved Adaptive Particle Swarm Optimization Based on Belief Rule Base. International Journal of Fuzzy Systems,(prepublish),1-20.