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Power-to-gas-based VPP Stochastic Scheduling Optimization Model in View of Carbon Emission Constraints

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Abstract: *Combining P2G and virtual power plant (Virtual power plant, VPP), this paper proposes a new concept of electrical interconnection virtual power plant (Power-to-gas-based VPP, GVPP). In addition, this paper proposes a GVPP low-carbon economic dispatch optimization model considering carbon emission rights trading. Furthermore, in view of the strong uncertainty of wind power and PV power generation in GVPP, the information gap decision theory is used to measure the uncertainty tolerance threshold of decision makers under different expected target deviations. In addition, a GVPP near-zero carbon random scheduling optimization model is established under the conventional and worst-case scenarios. In order to verify the feasibility and effectiveness of the proposed model, a 9-node energy hub was selected as the simulation system. The results show that: (1) GVPP can coordinate and optimize the output of electricity-to-gas and gas turbines according to the difference in gas and electricity prices in the electricity market and the natural gas market at different times. Moreover, it can use the two-way conversion of gas and electricity energy to form an electricity-gas-electricity cycle, thereby improving the system's clean energy absorption capacity, reducing its own carbon emissions and the volatility of net output. (2) The IGDT method can be used to describe the impact of wind and wind uncertainty in GVPP. Decision makers can obtain the maximum tolerance for wind and wind uncertainty by setting a reasonable expected target deviation coefficient. For example, when the expected target deviation coefficient is 0.5, the corresponding degree of uncertainty is 0.142. In the worst scenario, the scheduling results obtained by this method are in line with the actual scheduling experience, which reflects the effectiveness of the method in this paper. In summary, the models and methods presented in this paper can be used to formulate optimal scheduling decision-making schemes for GVPP considering carbon trading and uncertainty.*

Keywords: *Virtual power plant (VPP); Information Gap; Power-to-gas-based; Near Zero Carbon; Random Scheduling*

1. Introduction

In recent years, with the continuous strengthening of resource and environmental constraints, the centralized energy development model has gradually become difficult to meet the requirements of transmission loss, utilization efficiency and environmental pollution. Therefore, distributed energy with gold users and high performance is developing rapidly. In the "13th Five-Year Plan for Energy", it is specified that the installed capacity of distributed natural gas power generation and PV power generation will reach 15 million kilowatts and 60 million kilowatts by the end of 2020, and it is necessary to actively develop decentralized wind power [1]. However, the small-capacity, large-volume, and low-density characteristics of distributed energy sources have caused their large-scale access to bring great challenges to the safe and stable operation of the power grid. By using advanced intelligent computer technology and communication systems, VPP aggregates a variety of distributed power sources, energy storage and flexible loads, etc., so as to achieve the goal of overall participation in the optimal operation of the power system [2]. In particular, power-to-gas (P2G) technology is becoming more and more mature. Therefore, electrical energy can be used to convert CO_2 into methane to achieve flexible electrical conversion [3]. If it is combined with VPP (power-to-gas-based VPP, GVPP), it will produce electricity-gas-electricity recycling utility and carbon emission reduction effect. This has important theoretical value and practical significance for promoting the optimal utilization of distributed energy and the clean, low-carbon, efficient and safe utilization of energy.

Many researches have been carried out on the optimization of distributed energy utilization with

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P2G at home and abroad. The main operating process of P2G includes two processes: water electrolysis and methanation. Electrolyzed water uses electricity to split water into hydrogen and oxygen. Methanation is a chemical reaction between hydrogen and CO_2 to produce CH_4. The consumption and production of water in the two processes are equal [4]. Literature [5] established a power-to-gas-based system with P2G, and proposed the concept of energy flow integrating electricity and natural gas. Literature [6] established a P2G-containing power system scheduling optimization model with strong versatility and scalability, and analyzed the application space of P2G from the level of large-scale power systems. Furthermore, Literature [7] discussed the cooperative operation of P2G and distributed energy, established a P2G-containing multi-source microgrid operation optimization model, and analyzed the effect of P2G on the utilization of distributed energy. Literature [8] constructed a P2G-containing multi-level energy system scheduling model, and discussed the optimization effect of P2G technology in improving system operation economy and reducing natural gas node pressure. The above-mentioned research provides a prerequisite foundation for the construction of the optimal operation model of GVPP. However, the existing literature seldom considers the fusion effect of P2G and carbon emission rights trading, and only considers P2G's own operating cost issues and system economic issues. In fact, China’s unified carbon trading market is already under planning and construction, and 8 pilot projects have completed a considerable transaction scale [9]. If carbon emission rights trading and P2G can be combined with each other, and the optimization of GVPP operation is considered, it will help to improve the economic and environmental benefits of GVPP operation, and it will also help promote the market to absorb distributed clean energy enthusiasm [10]. Based on the above analysis, this paper focuses on the research of GVPP scheduling optimization in the context of carbon emissions trading.

Based on the above analysis, this paper constructs a GVPP near-zero carbon random scheduling optimization model based on IGDT theory. The model comprehensively considers the effects of carbon emission rights trading and P2G on the use of distributed energy, and describes and model the uncertainties of wind power and PV power generation. By introducing the deviation coefficient of the decision makers’ expected target, the maximum uncertainty tolerance threshold of decision makers with different risk attitudes is measured. The feasibility and effectiveness of the proposed model and method are verified through the analysis of examples, in order to provide an effective decision-making tool for the optimization of GVPP.

2. GVPP Carbon Transaction Cost Model

2.1 Constitution of the GVPP System

GVPP integrates Power-to-gas devices (P2G) and gas storage tank (GST) with conventional VPP wind power plant (WPP), PV (Photovoltaic Station), gas turbine unit and distributed energy such as conventional gas turbine (CGT), power storage device (PSD) and controllable load. Among them, the controllable load participates in system scheduling through an incentive demand response method, which is mainly provided by a demand response provider (DRP). They are generally industrial loads, electric vehicle loads and part of commercial loads with flexible power consumption characteristics. PSD and GSD select discharge/gas or charge/gas based on real-time electricity prices and gas prices, so as to earn “price difference”. Figure 1 is a schematic diagram of the structure of GVPP.

Fig.1 Composition Diagram of VPP

In GVPP, P2G operations are divided into two processes: electrolysis and methanation. Electrolysis is the direct injection of hydrogen into natural gas pipelines or hydrogen storage equipment after the excess electric energy is produced by electrolyzing water to produce hydrogen, and its energy

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conversion efficiency can reach 75% to 85%. The methanation process is based on electrolysis. Under the action of a catalyst, the hydrogen and carbon dioxide generated by the electrolysis of water react to form methane and water. The specific chemical reactions are as follows:

$$2H_2O \rightarrow 2H_2 + O_2 \quad (1)$$

$$CO_2 + 4H_2 \rightarrow CH_4 + 2H_2O \quad (2)$$

Through the above-mentioned two-stage chemical reaction, the comprehensive efficiency of electricity-to-natural gas conversion is between 45% and 60%. After the electricity is converted into natural gas, it can be injected into a natural gas network or gas storage device. It can be seen that the H_2O input and output of the P2G chemical reaction are the same, and only CO_2 is consumed, which is conducive to reducing the carbon emissions of GVPP power generation.

2.2 GVPP Carbon Transaction Cost

Carbon trading is a trading mechanism that allows participants to trade carbon emissions as commodities by establishing a fair, open, and just carbon trading market, thereby achieving the goal of systematic carbon emission reduction. Generally speaking, the allocation of carbon emission allowances is mainly based on free allocation. Participating entities formulate and adjust production plans based on the carbon emission allowances they have obtained. If the actual carbon emissions are higher than the allocated allowances, they need to purchase excess shares in the carbon trading market. On the contrary, the remaining allowances can be sold in the carbon trading market. For GVPP, the initial free carbon emission allowances are directly related to the power generation of different components, and carbon trading can be carried out for the excess or deficiency. GVPP carbon emission sources include two channels, namely traditional power generation resources and purchased power. Among them, traditional power generation resources include gas-fired power generation and biomass fuel power generation. At the same time, for the convenience of analysis, it is assumed that the electricity purchased by GVPP is thermal power. At this time, the carbon emission allowances obtained by GVPP are calculated as follows:

$$\tilde{E} = \sum_{t=1}^{T} \delta(1\text{-}\lambda)\left(\eta_{CGT,t} g_{CGT,t} + \eta_{BPG,t} g_{BPG,t} + g_{UPG,t}\right)\Delta t \quad (3)$$

In the formula, $\tilde{E}$ refers to free carbon emission allowances obtained by GVPP; T is the total number of time periods in the scheduling cycle; Δt is unit time duration; δ is carbon emissions per unit of electricity. Refer to Literature [10] and set it to 0.648. $\eta_{CGT,t}$ and $\eta_{BPG,t}$ are conversion efficiency of natural gas and biomass fuels; $g_{CGT,t}$ and $g_{BPG,t}$ are the power generation of CGT and BPG at time t; $g_{UPG,t}$ are GVPP purchased electricity at time t; λ is the government or regulatory authority sets the carbon emission reduction allocation rate; Furthermore, in order to calculate the carbon emission cost of GVPP, it is necessary to calculate the actual carbon emission of GVPP. According to Literature [10], the carbon emissions of CGT and BPG power generation are actually a quadratic function of one yuan, which is calculated as follows:

$$\begin{aligned} E = {} & \sum_{t=1}^{T}\left[a_1 + b_1\left(g_{CGT,t} + g_{CGT,t}^{P2G} + g_{CGT,t}^{GST}\right) + c_1\left(g_{CGT,t} + g_{CGT,t}^{P2G} + g_{CGT,t}^{GST}\right)^2\right] - \\ & E_{CO_2,t}^{P2G} + \sum_{t=1}^{T}\left[a_2 + b_2 g_{BPG,t} + c_2 g_{BPG,t}^2\right] + \sum_{t=1}^{T}\left[a_3 + b_3 g_{UPG,t} + c_3 g_{UPG,t}^2\right] \end{aligned} \quad (4)$$

In the formula, E is the actual carbon emissions of GVPP; $g_{CGT,t}^{P2G}$ and $g_{CGT,t}^{GST}$ are CGT uses methane provided by P2G and GST to generate power at time t; a , b and c are CGT, BPG and UPG power generation carbon emissions calculation coefficient; $E_{CO_2,t}^{P2G}$ is the carbon emissions that can be converted by P2G which belongs to carbon emission reductions.

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In order to carry out differentiated cost accounting for different carbon emission status, build a stepped carbon transaction cost calculation model. That is, based on the free carbon emission amount calculated in formula (3), a number of different carbon emission ranges are divided. When the carbon emissions are higher, the carbon trading settlement price is also higher. The calculation formula of GVPP ladder carbon transaction cost is as follows:

$$C_{\mathrm{CO_2}}=\begin{cases} P_{\mathrm{CO_2}}\left(E\text{-}\tilde{E}\right), & \tilde{E}\le E+d \\ \sigma P_{\mathrm{CO_2}}d+\left(1+\sigma\right)P_{\mathrm{CO_2}}\left(E\text{-}\tilde{E}\text{-}d\right), & E+d\le\tilde{E}\le E+2d \\ \left(2+\sigma\right)P_{\mathrm{CO_2}}d+\left[\left(1+2\sigma\right)P_{\mathrm{CO_2}}\left(E\text{-}\tilde{E}\text{-}2d\right)\right], & E+2d\le\tilde{E}\le E+3d \\ \vdots & \\ \left(n-1+\sigma\right)P_{\mathrm{CO_2}}d+\left[\left(1+\left(n-1\right)\sigma\right)P_{\mathrm{CO_2}}\left(E\text{-}\tilde{E}\text{-}\left(n-1\right)d\right)\right], & E+\left(n-1\right)d\le\tilde{E}\le E+nd \end{cases} \tag{5}$$

In the formula, $C_{\mathrm{CO_2}}$ is GVPP carbon trading costs; $P_{\mathrm{CO_2}}$ is the carbon trading price in the market; d is the length of the carbon emission growth interval; σ is the growth rate of the carbon trading price of each tier; n is the price range of carbon emissions; When $E<\tilde{E}$, $F_{\mathrm{CO_2}}$ is negative, itt indicates that the actual carbon emissions of the system will be lower than the free carbon emissions. At this time, you can purchase and store at the initial carbon trading price to obtain carbon trading benefits.

3. GVPP Near-Zero Carbon Scheduling Optimization Model

3.1 Objective function

Considering that GVPP participates in power system dispatch as a whole, that is, it is a low-carbon economic dispatch optimization problem 24 hours before the day. According to formula (4), it can be known that at the end of the scheduling cycle, if $E=0$, all the CO_2 produced by GVPP is converted into CH_4, which enters the gas grid or is stored in GST. It is believed that GVPP has achieved the goal of zero carbon emissions. However, zero carbon emissions requires P2G to fully use clean energy to generate electricity and convert CO_2 in the last period of the dispatch cycle, which is difficult to achieve. Therefore, this article pursues the goal of nearly zero carbon emissions, i.e., considering the maximum limit of $E\rightarrow 0$, carbon trading costs are as small as possible. At the same time, the operating cost of GVPP also includes the cost of power generation fuel and the cost of outsourcing electricity. Therefore, this paper chooses to minimize the operating cost as the optimization objective. The specific objective function is as follows:

$$F_{\mathrm{cost}}=\min\sum_{t=1}^{T}\left(C_{\mathrm{CO_2},t}+C_{CGT,t}+C_{BPG,t}+P_{UPG,t}g_{UPG,t}\right) \tag{6}$$

In the formula, F_{cost} is GVPP's operation cost, $P_{UPG,t}$ and $g_{UPG,t}$ are GVPP's purchased electricity and purchased electricity price at time t; $C_{CGT,t}$ and $C_{BPG,t}$ are rhe power generation cost of CGT and BPG at time t mainly includes fuel cost and start-up and stop cost. Taking CGT as an example, the specific calculation is as follows:

$$C_{CGT,t}=\left[a_{CGT}+b_{CGT}g_{CGT,t}+c_{CGT}\left(g_{CGT,t}\right)^{2}\right]+C_{CGT,t}^{\mathrm{sd}} \tag{7}$$

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$$C_{CGT,t}^{\text{sd}}=\left[u_{CGT,t}(1-u_{CGT,t-1})\right]\times\begin{cases}N_{CGT}^{hot},T_{CGT}^{\min}<T_{CGT,t}^{\text{off}}\le T_{CGT}^{\min}+T_{CGT}^{cold}\\ N_{CGT}^{cold},T_{CGT,t}^{\text{off}}>T_{CGT}^{\min}+T_{CGT}^{cold}\end{cases}+ \left[u_{CGT,t-1}(1-u_{CGT,t})\right]\times\begin{cases}N_{CGT}^{off},T_{CGT,t}^{\text{on}}\ge T_{CGT}^{\text{off,min}}\\ 0,T_{CGT,t}^{\text{on}}<T_{CGT}^{\text{off,min}}\end{cases} \tag{8}$$

In the formula, a_{CGT}, b_{CGT} and c_{CGT} are calculation coefficient of CGT power generation fuel cost; $C_{CGT,t}^{\text{sd}}$ is the start and stop cost of CGT at time t; $u_{CGT,t}$ is the running state of CGT at time t, 0-1 variable; N_{CGT}^{hot}, N_{CGT}^{cold} and N_{CGT}^{off} are CGT's hot start cost, cold start cost and shutdown cost; $T_{CGT,t}^{\text{on}}$ and $T_{CGT,t}^{\text{off}}$ are CGT's continuous running time and down time at time t; $T_{CGT}^{\min}$, T_{CGT}^{cold} and $T_{CGT}^{\text{off,min}}$ are the shortest hot start time, cold start time and down time of CGT.

3.2 Constraint condition

In the process of GVPP operation, it is necessary to consider the load supply and demand balance constraints, the operation of each component unit and the spinning reserve constraints. The specific constraints are as follows:

(1) Load supply and demand balance constraint

$$g_{WPP,t}+g_{PV,t}+g_{CGT,t}+g_{CGT,t}^{P2G}+g_{CGT,t}^{GST}+g_{BPG,t}+\left(g_{PSD,t}^{\text{dis}}\text{-}g_{PSD,t}^{\text{chr}}\right)+\Delta L_{DRP,t}+g_{UPG,t}=L_t+\Delta L_{P2G,t} \tag{9}$$

In the formula, $g_{PV,t}$ and $g_{WPP,t}$ are the power output of WPP and PV at time t, which mainly depends on the natural wind and PV radiation intensity; $g_{PSD,t}^{\text{dis}}$ and $g_{PSD,t}^{\text{chr}}$ are discharge and charge power of energy storage at time t; $\Delta L_{DRP,t}$ is the output provided by the demand response integrator (DRP) at time t; $g_{UPG,t}$ is GVPP's outsourced power output at time t; L_t is load demand at time t; $\Delta L_{P2G,t}$ is P2G power load at time t.

(2) P2G-GST joint operation constraints

$$0\le Q_{\text{P2G},t}\le Q_{\text{P2G}}^{\text{rated}} \tag{10}$$

$$Q_{\text{GST},t}^{\text{P2G, min}}\le Q_{\text{GST},t}^{\text{P2G}}\le Q_{\text{GST},t}^{\text{P2G, max}} \tag{11}$$

$$Q_{\text{P2G},t}^{\min}\le Q_{\text{P2G},t}^{\text{CH}_4}+g_{CGT,t}^{\text{P2G}}\big/\varphi_{\text{CGT}}\text{H}_{\text{g}}\le Q_{\text{P2G},t}^{\max} \tag{12}$$

$$Q_{\text{GST},t}^{\min}\le Q_{\text{GST},t}^{\text{CH}_4}+g_{\text{CGT},t}^{\text{GST}}\big/\varphi_{\text{CGT}}\text{H}_{\text{g}}\le Q_{\text{GST},t}^{\max} \tag{13}$$

$$S_{\text{GST},t}=S_{\text{GST,T}_0}+\sum_{t=1}^{T}\left(Q_{\text{GST},t}^{\text{P2G}}-Q_{\text{GST},t}^{\text{CGT}}-Q_{\text{GST},t}^{\text{CH}_4}\right) \tag{14}$$

$$S_{\text{GST},t}^{\min}\le S_{\text{GST},t}\le S_{\text{GST},t}^{\max} \tag{15}$$

In the formula, $Q_{\text{P2G}}^{\text{rated}}$ is rated gas production power of P2G; $Q_{\text{P2G},t}$ is the amount of natural gas produced by P2G at time t; $S_{\text{GST},t}$ is the gas storage capacity of GST at time t; $S_{\text{GST,T}_0}$ is the gas storage capacity of GST at the initial moment; $Q_{\mathrm{GST},t}^{\mathrm{P2G}}$ is the amount of natural gas entering GST at time t; $Q_{\mathrm{GST},t}^{\mathrm{CGT}}$ is the amount of natural gas input from GST to CGT at time t; $Q_{\mathrm{GST},t}^{\mathrm{CH_4}}$ is the amount of natural gas that GST enters the natural gas network at time t; $S_{\mathrm{GST},t}^{\min}$ and $S_{\mathrm{GST},t}^{\max}$ are the maximum and minimum gas storage capacity of GST at time t; $Q_{\mathrm{GST},t}^{\mathrm{P2G,\,min}}$ and $Q_{\mathrm{GST},t}^{\mathrm{P2G,\,max}}$ are the minimum and maximum power of the gas storage of GST at time t; $Q_{\mathrm{P2G},t}^{\min}$ and $Q_{\mathrm{P2G},t}^{\max}$ are P2G outputs the minimum and maximum power of natural gas at time t; $Q_{\mathrm{GST},t}^{\min}$ and $Q_{\mathrm{GST},t}^{\max}$ are the GST outputs the minimum and maximum power of natural gas at time t.

(3) CGT and PBG operating constraints

Both CGT and BPG are traditional power generation resources, and their power generation needs to face maximum output power constraints, up and down climbing power constraints, and start-stop time constraints. Take CGT as an example, the details are as follows:

$$u_{CGT,t}g_{CGT}^{\min} \le g_{CGT,t} \le u_{CGT,t}g_{CGT}^{\max} \tag{16}$$

$$\Delta g_{CGT}^{-} \le g_{CGT,t} - g_{CGT,t\text{-}1} \le \Delta g_{CGT}^{+} \tag{17}$$

$$(T_{CGT,t-1}^{\mathrm{on}} - M_{CGT}^{\mathrm{on}})(u_{CGT,t-1} - u_{CGT,t}) \ge 0 \tag{18}$$

$$(T_{CGT,t-1}^{\mathrm{off}} - M_{CGT}^{\mathrm{off}})(u_{CGT,t} - u_{CGT,t-1}) \ge 0 \tag{19}$$

In the formula, $g_{CGT}^{\max}$ and $g_{CGT}^{\min}$ are CGT maximum and minimum power generation; Δg_{CGT}^{+} and Δg_{CGT}^{-} are CGT's up and down climbing power; M_{CGT}^{on} is the shortest start-up time of CGT; $T_{CGT,t-1}^{\mathrm{on}}$ is the continuous running time of CGT at t+1. M_{CGT}^{on} is the shortest start time of CGT. $T_{CGT,t-1}^{\mathrm{off}}$ is the CGT continuous stop time at time *t*–1. M_{CGT}^{off} is CGT minimum downtime.

(4) Energy storage equipment operation constraints

The operation of energy storage equipment needs to consider the maximum charge and discharge power constraints and its own battery capacity constraints. The specific constraints are as follows:

$$g_{PSD,t}^{\min} \le g_{PSD,t} \le g_{PSD,t}^{\max} \tag{20}$$

$$S_{PSD,t}^{\min} \le S_{PSD,t} \le S_{PSD,t}^{\max} \tag{21}$$

$$S_{PSD,t+1} = S_{PSD,t} + \left[g_{PSD,t}^{chr}\left(1-\eta_{PSD,t}^{\mathrm{chr}}\right) - g_{PSD,t}^{\mathrm{dis}} \Big/ \left(1-\eta_{PSD,t}^{\mathrm{dis}}\right) \right] \tag{22}$$

In the formula, $g_{PSD,t}^{\max}$ and $g_{PSD,t}^{\min}$ are the maximum charge and discharge power of the PSD at time t; $S_{PSD,t}^{\max}$ and $S_{PSD,t}^{\min}$ are the maximum and minimum power storage capacity of the PSD at time t; $S_{PSD,t+1}$ is the power storage capacity of the PSD at time t+1; $\eta_{PSD,t}^{\mathrm{chr}}$ and $\eta_{PSD,t}^{\mathrm{dis}}$ are PSD charge and discharge power at time t; $\eta_{PSD,t}^{\mathrm{chr}}$ and $\eta_{PSD,t}^{\mathrm{dis}}$ are PSD charge and discharge power at time t.

(5) DRP operating constraints

This paper considers that the flexible and controllable load involved in GVPP operation is mainly completed by the way that DRP provides IBDR. Generally speaking, DRP distributes demand response according to the relationship between power supply and demand. It is a multi-stage output method. The specific calculation is as follows:

$$D^{j,\min} \le \Delta L_t^j \le D_t^j,\ j=1 \tag{23}$$

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$$0 \le \Delta L_t^j \le \left(D_t^j - D_t^{j-1}\right), j = 2,3,\ldots,\mathrm{J} \tag{24}$$

$$\Delta L_{DRP,t} = \sum_{j=1}^{J} \Delta L_t^j \le \Delta L_{DRP,t}^{\max} \tag{25}$$

In the formula, ΔL_t^j is the actual power generation output provided by DRP at time t and step j; $D^{j,\min}$ is the minimum power output provided by DRP in step k; D_t^j is the power generation output that DRP can provide at time t and step j; ΔL_t^j is the cumulative power generation output provided by DRP at time t step j; $\Delta L_{DRP,t}^{\max}$ is the maximum power output allowed by DRP at time t.

(6) Spinning Reserve Constraint

$$g_{GVPP,t}^{\max} - g_{GVPP,t} + \min\left\{\left(g_{PSD,t}^{\mathrm{dis,max}} - g_{PSD,t}^{\mathrm{dis}}\right), \left(S_{PSD,t} - S_{PSD,t}^{\min}\right)\right\} \ge r_L \cdot L_t + r_{WPP} \cdot g_{WPP,t} + r_{PV} \cdot g_{PV,t} \tag{26}$$

$$g_{GVPP,t} - g_{GVPP,t}^{\min} + \max\left\{\left(g_{PSD,t}^{\mathrm{chr,max}} - g_{PSD,t}^{\mathrm{chr}}\right), \left(S_{PSD,t}^{\max} - S_{PSD,t}\right)\right\} \ge r_{WPP} \cdot g_{WPP,t} + r_{PV} \cdot g_{PV,t} \tag{27}$$

In the formula, $g_{GVPP,t}$ is the output power of GVPP at moment *t*; $g_{GVPP,t}^{\max}$ and $g_{GVPP,t}^{\min}$ are the maximum and minimum output power of GVPP at moment *t*; $g_{PSD,t}^{\mathrm{dis,max}}$ and $g_{PSD,t}^{\mathrm{chr,max}}$ are the maximum discharge power of PSDat moment *t*; r_L , r_{WPP} and r_{PV} are backup rate of load, WPP and PV.

4. GVPP Stochastic Scheduling Optimization Model

4.1 Introduction to IGDT Theory

There are uncertain variables such as wind power and PV power generation in GVPP, because its scheduling optimization decision is based on the forecast information of uncertain variables. When the actual value of the uncertainty variable deviates from the predicted value, it is considered that the uncertainty variable has an information gap. Yakov Ben-Haim et al. proposed and continuously improved the Information Gap Decision Theory (IGDT) in the 1980s, which is used to describe the gap state between the known and unknown uncertain information. When the information gap is generated, if the actual value deviates in a bad direction, it will have a negative impact on the decision-making system. Conversely, when the actual value deviates in a good direction, it will bring opportunity benefits to the decision-making system. The IGDT method forms an open decision-making optimization strategy by separately constructing a risk aversion (robust) model and a risk speculation (opportunity) model corresponding to the above two directions. Analyze the degree of uncertainty and its consequences, so as to formulate a more realistic decision-making plan. The basic model of IGDT includes system model, uncertainty model and minimum demand model, which are described as follows:

For any initial system model, it can be written in the form of objective function, inequality constraint, and equality constraint, as follows:

$$\begin{cases} \min R(q,v) \\ s.t. \quad H(q,v) \le 0 \\ \qquad G(q,v) = 0 \end{cases} \tag{28}$$

In the formula, R is the target function, q is the set parameter, v is the uncertain parameter, $H(q,v)$ is inequality constraints; $G(q,v)$ is equality constraints.

Consider uncertain variables v , the corresponding expected value is $\tilde{v}$. The range can be used to

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describe the flotation of the uncertain variable $U(\alpha,\tilde{v})$, the specific description is:

$$U(\alpha,\tilde{v})=\left\{v(t):\left|\frac{v(t)-\tilde{v}(t)}{\tilde{v}(t)}\right|\le\alpha\right\}\quad \alpha\ge 0 \quad (29)$$

In the formula, α is the uncertainty of parameter v, i.e., for v in the set $U(\alpha,\tilde{v})$, the maximum disturbance corresponding to the expected value $\tilde{v}$ is $\alpha\ \tilde{v}$.

The minimum demand model is mainly used to describe the influence of the deviation of the predicted value of the uncertainty variable on the system decision-making, considering the parameter r_c as the lower limit of the target value acceptable to the decision maker. For any parameter v, the target function $R(q,v)$ can meet the following constraints:

$$R(q,v)\le r_c \quad (30)$$

According to formulas (28) to (29), the original initial system decision-making model can be transformed into an uncertain decision-making model, as follows:

$$\begin{cases}\max\alpha \\ s.t.\quad \underset{v\in U(\alpha,\tilde{v})}{R(q,v)}\le r_c \\ \qquad\quad H(q,v)\le 0 \\ \qquad\quad G(q,v)=0\end{cases} \quad (31)$$

Through the above-mentioned optimal model, it can be ensured that under the premise of the target value acceptable to the decision maker, the maximum fluctuation of the uncertainty parameter can be withstood. Calculate the decision value q by formula (31). In this way, it can be ensured that when the v is disturbed in the set $U(\alpha,\tilde{v})$, the target value r_c acceptable to the decision maker can be obtained.

The IGDT stochastic scheduling optimization model shown in formula (31) ensures that the obtained decision-making scheme has strong applicability by considering the extreme situations of uncertain variables, which is also called robustness. However, the prerequisite for the optimal scheme determined by formula (39) is that the objective function changes monotonously with the wind and wind uncertainty parameters, which can be calculated by using formula (38). However, in the GVPP low-carbon random dispatch, when carbon transaction costs are considered, wind power and PV power generation have carbon emission reduction effects, causing the uncertain cost of wind and solar and carbon transaction costs to offset each other. This may cause the objective function to show a non-monotonic change with the uncertainty variable. This leads to the inability to directly apply formula (38) to obtain the extreme value, that is, the decision cost corresponding to the scene with the largest or smallest wind power is not necessarily the largest. At this time, it is necessary to establish a method for seeking the worst scenario.

4.2 GVPP Random Scheduling Model

This section uses the IGDT theoretical method to deal with the determinism of wind power and PV power generation, and proposes a GVPP stochastic scheduling optimization model considering the state of information gaps. The specific process is as follows:

(1) Landscape uncertainty model

$$U(\alpha,g_{WPP,t})=\left\{g^{*}_{WPP,t}:\left|\frac{g^{*}_{WPP,t}-g_{WPP,t}}{g_{WPP,t}}\right|\le\alpha\right\}\quad \alpha\ge 0 \quad (32)$$

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$$U\left(\alpha, g_{PV,t}\right)=\left\{g_{PV,t}^{*}:\left|\frac{g_{PV,t}^{*}-g_{PV,t}}{g_{PV,t}}\right|\leq\alpha\right\} \quad \alpha\geq 0 \tag{33}$$

In the formula, $g_{WPP,t}^{*}$ and $g_{PV,t}^{*}$ are the actual output power of wind power and PV power generation; α is relative forecast bias.

(2) GVPP Uncertainty Decision Model

According to the GVPP near-zero carbon scheduling optimization model in Section 2, the optimal target value $F_{\text{cost}}^{\text{opt}}$ of GVPP can be established under deterministic scenarios. 当 When considering the impact that uncertain variables may have on the optimal decision-making scheme, according to formula (32) and formula (33), the maximum perturbation of wind power and PV power generation relative to the predicted value is $\alpha g_{WPP,t}$ and $\alpha g_{PV,t}$, respectively. In order to overcome this part of the fluctuation, GVPP needs to call conventional units or purchase electric energy from UPG, which will bring new peak shaving costs. At this time, the decision makers expect the target value to be adjusted to:

$$F_{\text{risk}}=\left(1+\sigma_{\text{risk}}\right)\left\{F_{\text{cost}}^{\text{opt}}+\sum_{t=1}^{T}P_{R,t}\left(\alpha g_{WPP,t}+\alpha g_{PV,t}\right)\right\} \tag{34}$$

In the formula, F_{risk} is the decision maker's expected target value; $P_{R,t}$ is the peak shaving cost of wind power and PV power generation in response to power deviation at time t; σ_{risk} is the expected target deviation coefficient; When the decision-maker's target value F_{risk} is higher $F_{\text{cost}}^{\text{opt}}$, the value of σ_{risk} is greater than 0. According to formula (34), the scheduling decision value of GVPP should not be higher than F_{risk}, the specific constraints are:

$$\min\left[\max_{\substack{g_{WPP,t}^{*}\in U\left(\alpha, g_{WPP,t}\right)\\ g_{PV,t}^{*}\in U\left(\alpha, g_{PV,t}\right)}} F\left(g_{WPP,t}, g_{PV,t}, g_{DRP,t}\boldsymbol{g}_t, \boldsymbol{u}_t\right)\right]\leq F_{\text{risk}} \tag{35}$$

In the formula, $\boldsymbol{g}_t$ and $\boldsymbol{u}_t$ are the output and start-stop state of traditional power generation resources outside the scenery at time t; Under the condition that the peak shaving transaction decision cost is not higher than the expected target F_{risk}, the maximum uncertainty degree α is solved to establish the GVPP random scheduling decision model, as follows:

$$\begin{cases}\hat{\alpha}\left(F_{\text{risk}}\right)=\max\alpha\\ \min\left[\max_{\substack{g_{WPP,t}^{*}\in U\left(\alpha, g_{WPP,t}\right)\\ g_{PV,t}^{*}\in U\left(\alpha, g_{PV,t}\right)}} F\left(g_{WPP,t}, g_{PV,t}, g_{DRP,t}\boldsymbol{g}_t, \boldsymbol{u}_t\right)\right]\leq F_{\text{cost}}^{\text{opt}}\\ \text{s.t.formula (9)- (27)}\\ \dfrac{g_{WPP,t}^{*}-g_{WPP,t}}{g_{WPP,t}}\leq\alpha\\ \dfrac{g_{PV,t}^{*}-g_{PV,t}}{g_{PV,t}}\leq\alpha\end{cases} \tag{36}$$

The IGDT stochastic scheduling optimization model shown in formula (36) ensures that the obtained decision-making scheme has strong applicability, which is also called robustness, by considering the extreme situations of uncertain variables. However, the prerequisite for the best

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solution determined by formula (39) is that the objective function changes monotonously with the wind and the indeterminate parameters, so formula (38) can be used for extreme value calculation. However, in the GVPP low-carbon random dispatch, when carbon transaction costs are considered, wind power and PV power generation have carbon emission reduction effects, causing the uncertain cost of wind and solar and carbon transaction costs to offset each other. This may cause the objective function to show a non-monotonic change with the uncertainty variable. This leads to the inability to directly apply formula (38) to obtain the extreme value, that is, the decision cost corresponding to the scene with the largest or smallest wind power is not necessarily the largest. In this case, it is necessary to establish a method for obtaining the worst case.

5. Calculation Analysis

5.1 Basic Data

In this paper, a 9-node energy hub system is selected as the simulation system, and H1 to H9 are 9 energy hubs [2]. Among them, H1 is equipped with 2×1MW WPP, H5 is equipped with 2×0.5MW PV and 1×1MW BPG, and H6 is equipped with 1×1MW CGT and 1×1 MW•h PSD. H7 is equipped with 1×0.2MW P2G and 200 m^3 GSD. Set the maximum charge and discharge power of ESD to be 02MW, the electrical energy conversion efficiency of P2G is 60%, the calorific value of natural gas is 39MJ/m^3, and the gas storage loss rate is 5%. It is assumed that BPG power generation fuels are mainly user biogas digesters and large pig farms. The daily biogas output of a typical load is about 4746m^3, and the relationship between biogas and output power is about 0.55~0.62 m^3/kW•h. The power generation cost parameters and emission coefficients of CGT and BPG are selected with reference to Literature [2], and the carbon emission rights transaction price is set to 45 yuan/ton.

Furthermore, considering that WPP, PV, CGT, and BPG equipment are all dispatched by GVPP, set the on-grid electricity price for power generation and the price of natural gas sales for a typical load day. When GVPP cannot meet its own load demand, it can purchase electricity from UPG, and the purchase price is set at 0.8 yuan/kW•h. Use the scenario production and reduction strategy proposed in Literature [2] to set WPP and PV power generation output parameters, simulate the power generation output scenarios of WPP and PV on a typical load day, and select the scenario with the highest probability as the input data. At the same time, considering the flexibility of end users to participate in GVPP power generation scheduling through DRP agents, the maximum positive and negative output provided by DRPs does not exceed 10% of the original load. Figure 2 shows the forecast values of wind power, PV power generation and load demand on a typical load day.

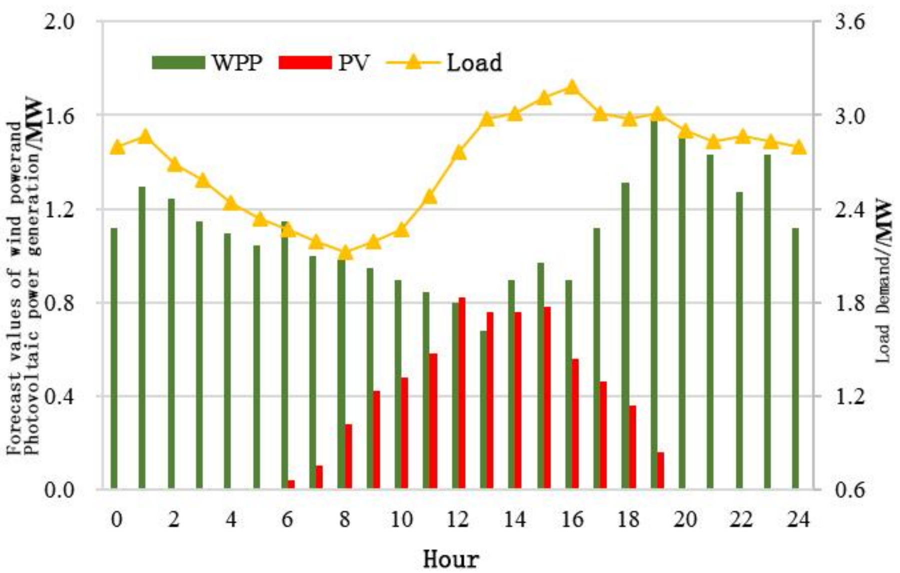

Fig.2 Forecast values of wind power, photovoltaic power generation and load demand on typical load days

Finally, in order to analyze the effectiveness of IGDT in dealing with the uncertainty of WPP and PV, the initial value of the expected target deviation coefficient for decision makers is set to 0.5, and

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the sensitivity analysis of the predicted deviation coefficient is performed to verify the effectiveness of the IGDT method. After the above-mentioned input data are obtained, GAMs software is used to mathematically model and solve the proposed model by calling the CPLEX solver to establish the GVPP optimal scheduling strategy.

5.2 Result Analysis

5.2.1 Calculation Results

The IGDT method is used to describe the optimal operation of GVPP scheduling considering the uncertainty of wind and solar, and the degree of uncertainty under different expected target deviation coefficients is measured. On the whole, the degree of uncertainty has a linear relationship with the predicted target deviation coefficient, that is, as the expected target deviation coefficient increases, that is, the decision makers can bear the increase in cost, the allowable degree of uncertainty in the scenery also increases. For example, when the prediction target deviation coefficient is 0.5, the degree of uncertainty $\sigma_{\text{risk}}=0.142$. This shows that when the wind and solar output power fluctuates within the range of [0.858, 1.142] times the predicted value, the decision-making scheme obtained by the method in this paper can ensure that the cost of the dispatching decision-making scheme is less than the expected cost of the decision maker. Figure 3 shows the relationship between the tolerance of GVPP and the expected target deviation coefficient.

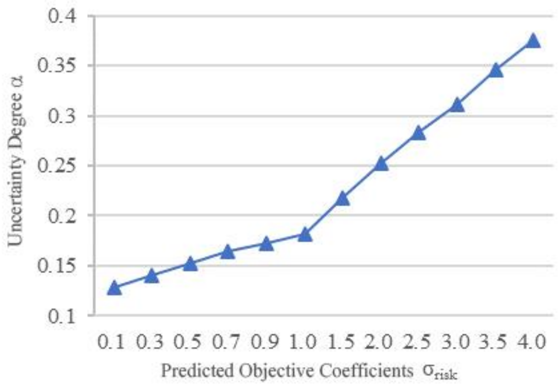
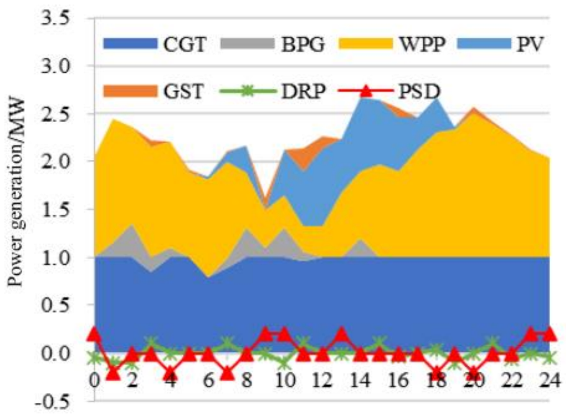


Fig.3 Relationship between Uncertainty Degree α and Predicted Objective Coefficient σ_{risk}

Further, consider the GVPP scheduling optimization scheme in deterministic scenarios and uncertain scenarios respectively. When $\sigma_{\text{risk}}=0$, the decision maker believes that the predicted value of wind and solar output power is consistent with the actual value; when the decision maker considers the uncertainty of wind and solar, this paper sets the initial prediction target deviation coefficient to 0.5. The degree of uncertainty obtained at this time is $\sigma_{\text{risk}}=0.142$. Accordingly, calculate the optimal scheduling plan of GVPP in deterministic and uncertain scenarios respectively. Figure 4 shows the optimal scheduling scheme of GVPP under different prediction target deviation coefficients.



($\alpha=0\&\sigma_{\text{risk}}=0$)

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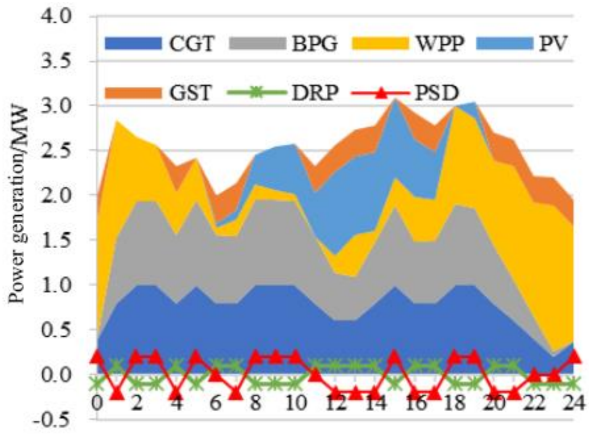

(α=0.5 & σ_{risk} =0.142)

Fig.4 Dispatching Optimization Results of GVPP under Different Object Deviation Coefficients

According to Figure 5, if we do not consider the uncertainty of the scenery, GVPP will give priority to the use of WPP and PV for power generation in order to pursue the goal of minimizing power generation costs. CGT is mainly used to meet the basic load, GST, DRP and PSD mainly provide peak shaving services. When considering the uncertainty of wind and solar, in order to increase the flexibility of the system, CGT began to participate in wind and solar peak shaving. At this time, in order to reduce the overall cost of power generation, BPG power generation output increased, and P2G converts more CO2 into CH4, reducing the carbon emission cost of GVPP, and the range of DRP and PSD calls are significantly increased to improve GVPP's ability to cope with the uncertainty of scenery. Table 1 shows the GVPP scheduling optimization scheme under different scenarios.

Table 1 Dispatching optimization results of GVPP under different scenarios

Scenario	Power generation /MW·h				P2G	Regulation generation/MW·h		Carbon emissions/ton	Target value	
	CGT	BPG	WPP	PV		PSD	DRP		F_{cost}	σ_{risk}
Certainty	24.32	1.92	22.67	5.58	-1.39	±1	±0.54	13.75	4875.10	0
Uncertainty	28.00	16.56	14.79	6.97	-7.86	±2	±1.2	0	6512.19	0.142

According to Table 1, considering the uncertainty of wind and solar output power, the power output of CGT and BPG increased by 4.68MW•h and 14.64MW•h, while the output of wind power decreased by 7.88MW•h. At the same time, because P2G and PSD have the ability to use energy abandonment during the valley period and supply power during the peak period, DRP has the ability to provide negative output during the peak period. Therefore, in order to pursue the goal of the lowest power generation cost, PV power generation increased by 1.39MW•h during the peak hours during the day. In addition, when the expected target deviation coefficient is 0.5, the corresponding degree of uncertainty is 0.142. At this time, the carbon emissions have been reduced to 0 tons, that is, zero carbon emissions have been achieved.

In summary, this paper proposes to apply the IGDT method to the uncertainty of the scenery and establish a GVPP low-carbon random call optimization model. The results of the above calculation examples verify that the optimization results are in line with the actual scheduling experience and reflect the effectiveness of the method in this paper. In general, the GVPP low-carbon stochastic scheduling optimization model proposed in this paper can reasonably set the expected target deviation coefficient for decision-makers based on their own risk attitudes, and then obtain the optimal decision-making plan that meets their own requirements and provide effective decision-making tools.

5.3 GVPP Zero Carbon Dispatching Scheme

By applying the GVPP low-carbon stochastic scheduling optimization model based on the IGDT method proposed in this article, this section takes zero carbon emissions from GVPP operations as the goal, and calculates the corresponding prediction target deviation coefficient and uncertainty cost. When the predicted target deviation coefficient is equal to 0.326, GVPP achieves near-zero carbon scheduling, and the degree of uncertainty at this time is equal to 0.131. Figure 5 shows the GVPP optimal dispatch plan under the zero carbon emission scenario.

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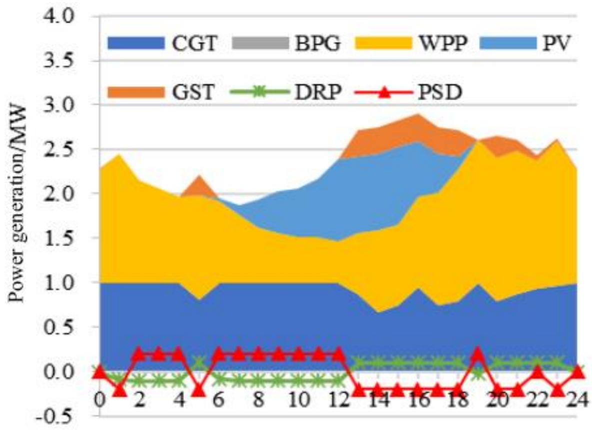

Fig.5 Dispatching optimization results of GVPP under the zero-carbon emission scenario

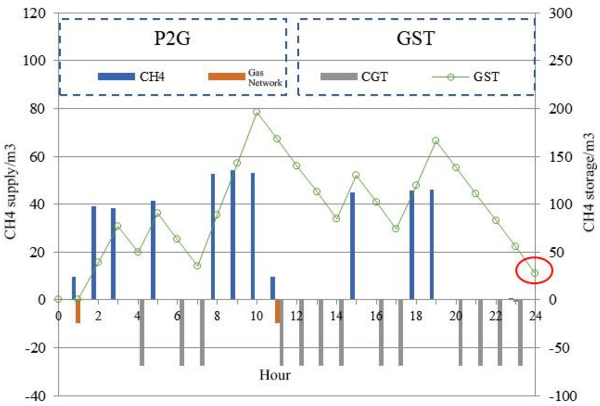

Fig.6 Operation output of P2G-GST under the zero-carbon emission scenario

According to Figure 6, when the decision maker expects that the target deviation coefficient is set to 0.326, GVPP operation can reach the critical value of zero carbon emissions. At this time, GVPP can sell carbon emission allowances through the trading market. At this time, in order to achieve the goal of zero carbon emissions, BPG was not used due to high carbon emissions per unit of power generation. Peak shaving services for wind power and PV power generation are mainly satisfied by P2G, PSD and DRP. It is particularly noteworthy that the PSD and DRP operation basically strictly match the peak and valley distribution of the load curve at this time. Further, through analyzing the operation of P2G-GST, it can be seen that P2G mainly converts electricity to gas to generate CH4 during the low period, most of which are stored in GST, and a small part is directly sold to the gas network. GST inputs natural gas into CGT during peak hours for gas-to-electricity conversion, thereby providing peak shaving output for wind power and PV power generation. Until the end of the dispatch period, the remaining CH4 is stored in the GST to achieve zero carbon emissions during the dispatch period. Furthermore, the sensitivity analysis of carbon trading prices is carried out. Table 2 shows the cost value and degree of uncertainty of GVPP operations under different carbon trading prices.

Table 2 Operation Scheme of GVPP under Different Carbon Price

Carbon transaction price	Cost value/¥			Degree of uncertainty σ_{risk}	
	Certainty	Near zero carbon	The worst	Near zero carbon	The worst
30	5046.06	5550.67	6310.22	0.121	0.224
35	5009.54	5510.49	6285.07	0.128	0.216
40	4945.35	5439.89	6906.94	0.136	0.210
45	4875.10	6512.19	7585.97	0.142	0.203
50	4811.99	5293.19	8021.27	0.145	0.194
55	4825.08	5307.59	8653.07	0.134	0.187
60	4875.92	5363.51	9733.92	0.129	0.181

According to Table 1, the sensitivity analysis of carbon trading prices is carried out, and the scheduling costs and uncertainty levels of GVPP under certain, near-zero carbon and worst-case scenarios under different carbon trading prices are measured. When the carbon trading price is lower than 50 yuan./ton, the GVPP scheduling cost will decrease as the carbon trading price increases, and the degree of uncertainty will gradually decrease in the near-zero carbon scenario. This is because P2G converts more CO2 into CH4 and provides greater peak shaving capabilities, so GVPP has an increased ability to cope with the uncertainty of the scenery. However, when the carbon trading price is higher than 55 yuan/ton, CGT and BPG generate electricity to generate CO_2, which is used to obtain carbon trading income, which reduces the ability of GVPP to deal with the uncertainty of the scenery. For the worst scenario, due to the extremely magnified risk of wind and solar uncertainty, as the carbon trading price increases, as more CGT and BPG power generation brings higher carbon trading costs, the GVPP dispatch cost gradually increases. And the degree of uncertainty is gradually increasing. This shows that the tolerance of decision makers to the uncertainty of scenery is gradually decreasing. In summary, the actual load dispatch experience of the sensitivity analysis results in Table 2 reflects the effectiveness of the method in this paper.

6. Conclusions

Considering the electrical transformation and spatio-temporal suppression characteristics of P2G, this paper integrates it with VPP into GVPP, and uses the IGDT method to describe the impact of wind and wind uncertainty, and then proposes a GVPP near-zero carbon random scheduling optimization model based on IGDT theory. Different types of decision makers establish the maximum tolerance threshold range of wind and wind uncertainty by setting deviation coefficients in line with their own expectations, and then establish the optimal decision-making plan for GVPP. By selecting a 9-node energy hub as the simulation system to verify the feasibility and effectiveness of the proposed approach to low GVPP near-zero carbon stochastic scheduling, the following conclusions can be drawn:

(1) GVPP can coordinate and optimize the output of electricity-to-gas and gas turbines according to the difference in gas and electricity prices in the electricity market and the natural gas market at different times, and use the two-way conversion of gas-electric energy to form an electricity-gas-electric cycle. This can not only give play to the characteristics of VPP to achieve complementary utilization of distributed energy, but also improve the system's clean energy absorption capacity through PGST, reduce its own carbon emissions and reduce the volatility of net output.

(2) The IGDT method can be used to describe the influence of wind and wind uncertainty in GVPP. Decision makers can obtain the maximum tolerance of wind and wind uncertainty by setting reasonable expected target deviation coefficients. For example, when the expected target deviation coefficient is 0.5, the corresponding degree of uncertainty is 0.142. In the worst scenario, the scheduling results obtained by this method are in line with the actual scheduling experience, which reflects the effectiveness of the method in this paper.

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