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Original Research

Virtual Power Plant Operation Based on Entropy-Weight-Improved Cloud Risk Assessment Model

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Abstract

Many virtual power plant demonstration projects are currently in operation in China, but research on the risk assessment of virtual power plants is insufficiently deep. Virtual power plants are complex systems operated by multiple participants and can provide a variety of products or services. Based on the operation practices of virtual power plants, in this study, we considered the characteristics of different components of virtual power plants and their impact on the operation process. We developed a risk assessment model for virtual power plants from many aspects involved in their operation processes. First, we analyzed the operation modes that can be selected during the operation of a virtual power plant, including the scenario in which electric vehicles participate and considering the comprehensive demand response. Second, we considered the risk faced by a virtual power plant from five dimensions: external policy, participation, coupling technology, bidding transaction, and credit management risk; we then designed an operation risk indicator system for virtual power plants with 29 indicators. Third, based on the entropy weight order relation method and cloud model for determining the index uncertainty in the process of risk assessment, we developed a cloud risk assessment model and specific algorithm flow based on the entropy weight order relation method are proposed. Finally, we compared the optimal economic operation strategies of a virtual power plant under different operating characteristics. The results showed that the comprehensive risk in the operation of gas virtual power plants can be effectively reduced when considering various uncertainties, electric vehicles, and comprehensive demand response

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risk. The results verify the effectiveness and scientificity of the improved cloud model risk assessment model proposed in this paper.

Keywords: virtual power plant1, entropy weight correction2, cloud model3, operational risk4, economic risks

Introduction

In recent years, the installed capacity of distributed wind power, photovoltaic, and micro gas turbines in China has been increasing; however, the seasonal contradiction on the demand side has become increasingly prominent, which provides opportunities and resources for the development of virtual power plants. The strong coupling between the energy equipment of virtual gas-electric power plants, the uncertain outputs of clean energy, and the unstable conversion efficiency between the energy equipment in the system have posed considerable challenges when deciding to bid on virtual power plant projects [1]. Additionally, many influencing factors are involved in the process of bidding on virtual coupled gas-electric power plants in the market, which increases the difficulty of virtual power plant operation, regulation, and decision making. The many potential risks and the values of relevant evaluation indicators are difficult to quantify, which directly leads to a certain variation in the final risk evaluation results [2]. Based on this, we need to better understand the bidding relationship of multiple energy subsystems such as electricity, heat, and gas in virtual coupled gas-electricity power plants, clarify the impact of multiple characteristics on the bidding optimization of these plants, and identify relevant operation bidding risk indicators. With this information, we can take full advantage of the utility of virtual power plants for the large-scale consumption of renewable energy and to ensure power system stability, thereby markedly improving the overall market competitiveness of virtual power plants.

In the literature, some studies have been conducted on the key technologies and bidding optimization for virtual power plants, but relatively few studies have been published on the risk evaluation of virtual power plants or multienergy systems. Liu et al. focused on the economic risks in the investment in virtual power plants. Considering the time-of-use electricity price, construction subsidies, and other factors, conditional value at risk was used to measure the economic risks caused by the uncertainty in wind, light, and load [3]. According to the characteristics and functions of virtual power plants, Xu et al. developed a comprehensive evaluation system composed of seven indices from the aspects of reliability, economy, and schedulability [4]. Liu et al. systematically described the ability of a power grid to accept renewable energy from three time scales, short, medium, and long term; they constructed an index system to evaluate the power grid's ability to accept renewable energy considering economic and security factors [5]. Zhang et al. proposed a risk assessment method of load aggregators based on fuzzy simulation technology, analyzed the economic risk level of load aggregators under different confidence and different penalty coefficients, measured the scheduling reliability of load aggregators from two indicators: response credible capacity and response capacity credibility, and discussed the accuracy of resource prediction The influence of configuration proportion and confidence on reliability index [6]. Luo et al. established a day-ahead fuzzy optimal scheduling model of source load interactions based on the impact on the uncertainty of the price demand response, considering the uncertainty of wind power output and system load [7]. According to the power consumption characteristics of load aggregators, power consumption contribution and power consumption confidence evaluation indices were established to quantify risk; the weight of each index was comprehensively evaluated, and the dispatching priority from both subjective and objective perspectives was determined by combining the analytic hierarchy process and entropy weight method [8]. However, researchers have focused more on the impact of the uncertainty of virtual power plants or multienergy systems on the economy, considering demand response load evaluation indices. Less attention has been paid to the coupling and interconnection relationship between multiple energy types, and an operation scheduling evaluation index of the whole process of market bidding and credit management that reflects the system architecture has not been established.

Many scholars have studied the weighting objectivity of risk evaluation indicators and the authenticity of the results in depth. A double fuzzy evaluation model was applied to combine a single evaluation result and repeat the test, which effectively reduced the random deviation and systematic error of uncertain information in the evaluation process, and provided risk evaluation and grade values with high convergence and reliability [9]. Liang and Dai calculated index weights based on an improved analytic hierarchy process with a combined method, and they designed a fuzzy comprehensive evaluation method to calculate the satisfaction with a platform [10]. Liu and Zhao adopted a fuzzy evaluation method to comprehensively evaluate the energy efficiency of a multienergy system with energy storage equipment by considering the difference in energy taste, multienergy complementarity, and renewable energy consumption [11]. A fuzzy comprehensive energy evaluation method was studied for a microgrid in a park, and the index calculation was combined with the system operation, but an analysis of the impact of a single index on the final evaluation results was lacking [12]. Yang et al. considered the operation of an integrated energy system under the background of new and old kinetic energy conversion, constructed an improved fuzzy evaluation model, and compared and selected operation schemes for an integrated energy system [13]. However, when using the traditional fuzzy comprehensive evaluation method, using the membership function instead of each fuzzy information involves a certain subjectivity, and the randomness of each evaluated piece of information is ignored. To overcome the above problems, some scholars introduced cloud models to replace the membership function in the evaluation method. In Li and Wang study, the characteristics of cloud models were applied, and the problems of randomness and fuzziness of qualitative indicators were solved [14]. Li et al. applied a cloud model as the dependent variable of characteristic parameters and the influencing factors of different states as independent variables to construct a method of evaluating system reliability cloud model under variable-factor environments, which effectively converted the uncertain information between qualitative and quantitative indicators [15].

To summarize, although many scholars have conducted in-depth studies on the evaluation of virtual power plants or multienergy systems, many deficiencies remain to be overcome, which are mainly reflected in unrepresentative and unsystematic index systems, the deviation between the index's calculation method and the actual situation, the ambiguity and randomness among multiple indices, and the evaluation methods paying more attention to the final evaluation results with insufficient evaluation and analysis of some key indicators. Based on this, by analyzing the bidding risk of gas-and-electricity virtual power plants with multidimensional characteristics, in this study, we constructed a system for evaluating the risk of coupled gas and electricity virtual power plants considering 29 evaluation indices from five dimensions of risk: external policy, participant, coupling technology, bidding transaction, and credit management risk. We adopted a cloud risk evaluation model that we improved using the entropy weight order relationship. The uncertainty and randomness in the risk evaluation of gas and electricity virtual power plant were effectively addressed, and the typical virtual power plant demonstration base as selected as a case study to obtain risk evaluation results, thereby providing a suitable basis for decision makers to formulate relevant systems.

Materials and Methods

Bidding Risk Analysis of Virtual Power Plants

Focusing on the research on the bidding optimization of gas-electricity coupled virtual power plant, in order to comprehensively consider the risks in the bidding process, combined with the operation architecture and operation characteristics of coupled gas-electricity virtual power plants, the bidding risks of coupled gas-electricity virtual power plant are analyzed from multiple perspectives with multiple uncertainties, including electric vehicle characteristics and comprehensive demand response, as shown in Fig. 1.

Fig. 1 shows that in the actual bidding process of gas virtual power plants, the energy supply system directly meets the needs of users with renewable energy such as wind and photovoltaic power. Here, the output of the renewable energy participating in the grid connection fluctuates and is intermittent, so accurately predicting the internal and external energy demands of a virtual power plant is difficult. To effectively reduce the wind

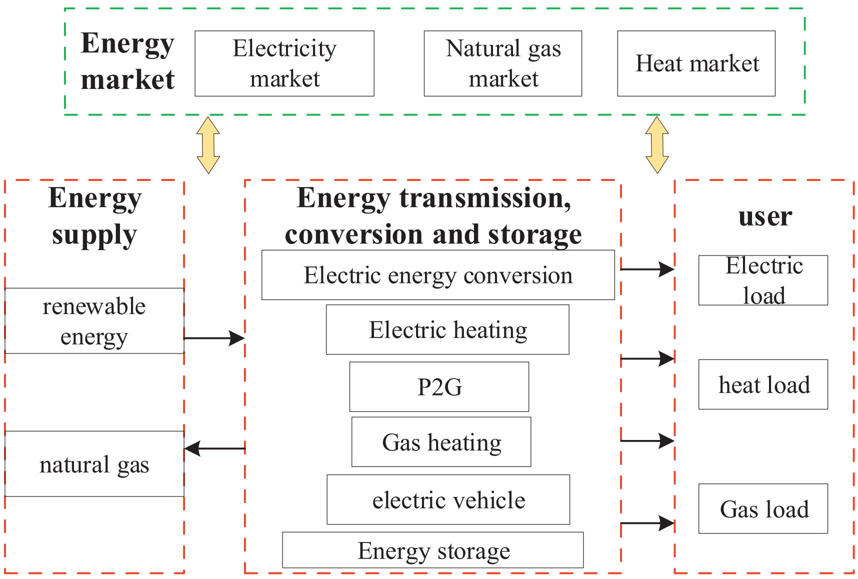

Fig. 1. Infrastructure of coupled gas-electric virtual power plants.

and light energy rejection rate and the cost of purchasing all energy types from the large power grid and natural gas market, the excess electric energy must be converted through heating, gas, and other equipment to enable the diversified use of energy. All energy storage devices in the system, including electric vehicles, can store excess electricity, heat, and gas, but different energy storage equipment have different characteristics. Economic use can be achieved through the reasonable coordination and arrangement of charging and discharging. Internal power and heat and gas networks at the user end meet the energy demand. Users can adjust multiple loads and participate in the comprehensive demand response through aggregation. However, the comprehensive demand response involves a range of energy response characteristics and uncertainties, which are difficult to accurately regulate. Therefore, to more effectively select and evaluate the risk indicators of the whole bidding process of virtual gas-and-electricity power plants, it the internal and external multi-level risks must be further clarified.

Risk Analysis of Multiple Uncertain Factors

The internal composition of the power supply of coupled gas-electricity virtual power plants involves large uncertainties, including the output of distributed renewable energy, load demand, market electricity price, and carbon emission price, which lead to certain risks in the bidding optimization of the virtual gas-electricity power plants, as described below:

Risk of output fluctuation in distributed renewable energy; Wind and photovoltaic power are affected by the climate and environment, resulting in randomness in their output. In the process of the bidding optimization of virtual gas power plants, the output of distributed wind and photovoltaic power strongly impacts the system benefit objective function during the bidding optimization of coupled gas-power virtual power plants. In the bidding modeling of virtual power plants, if the uncertainty in the output of the above distributed energy is not considered in the formulation of control variables, the declared and actual power will deviate, so power supply income will be difficult to guarantee. In extreme adverse circumstances, this may lead to a poor objective function and wide deviation from the formulated bidding strategy.

Risk of load demand uncertainty; In the bidding optimization process of coupled gas-electricity virtual power plants, the supply situation is adjusted in real time according to the user demand for various electricity, heat, and gas loads; the energy supply and consumption systems are coordinated and optimized. The dynamic change in the terminal load includes two processes: random uncertainty and regular change, where random uncertainty in the terminal load refers to the randomness of the operation of energy-consuming equipment being affected by changes in climate conditions and the dynamic adjustment of energy price, which are difficult to predict. Therefore, in the bidding optimization of virtual gas-and-electricity power plants, if the uncertainty in the load demand is not considered in the formulation of control variables, the economic benefits of virtual power plant will be lost.

Risk of market price uncertainty; According to the output capacity of a future supply system and the prediction of external energy price, a coupled gas-electricity virtual power plant formulates a bidding strategy with the maximum economic benefit as the goal, participates in market bidding, and submits a bidding curve. In the bidding model of coupled gas-electricity virtual power plants, because the virtual power plant participates in market bidding as the receiver of the market price, from the aspects of income and cost, when the market price is less than expected or punishment is received due to processing deviation, the income of virtual gas-electricity power plants decreases and their costs increase, resulting in serious risks to the operation of virtual power plants. Therefore, during the bidding operation of virtual gas-and-electricity power plants, financial risk that is caused by power generation deviation in the real-time market is borne.

Risk of price uncertainty of carbon emission rights; In the bidding optimization process of virtual gas power plants, the output of gas-fired boilers and other equipment and the purchase of power from the public grid increase carbon dioxide emissions. According to China's carbon emission policy, when a power generation system exceeds the specified carbon emission limit, corresponding economic penalties are given to increase the operation cost. When the carbon emission is lower than the quota, the excess carbon emission quota is sold in the carbon-trading market to improve operational efficiency. Therefore, due to the influence of energy price, supply and demand of carbon emission rights, technological progress, and other factors, predictions re uncertain, resulting in certain risks to the low-carbon economic operation of a system during the market bidding of coupled gas-electricity virtual power plants.

Risk Analysis of Including Electric Vehicles

Because large uncertainties exist in the number and capacity of electric vehicles that can be charged and discharged, as well as in the enthusiasm to participate in charge and discharge, the risks to the system caused by these uncertainties must be considered when virtual gas-electric power plants participate in bidding optimization in the power market. Electric vehicles generally have dual attributes: they operate in coordination with other multienergy conversion equipment as controllable load or power supply under different scenarios and provide regulation services to virtual power plants by controlling the deviation between the actual and planned charge discharge power. Therefore, in the bidding optimization process of coupled gas-electricity virtual power plants, the following risks exist:

Because the number and capacity of electric vehicles participating in the bidding of virtual gas-electric power plants are difficult to predict, obtaining income through electric vehicle charging alone is uncertain;

Because a regulated reserve may be required in the actual operation process, which results in the output being impossible to predict in advance, the income of the FM service in the objective function is at risk;

The coupled gas-electric virtual power plant provides charging services for aggregated electric vehicles. When the output of the energy supply system is insufficient, electricity should be purchased from the external market to meet the charging demand, hindering the accurate calculation of the power purchase cost due to the fluctuation in external electricity price. The purchased power is closely related to the number of charged electric vehicles, so the number of schedulable electric vehicles may change due to various reasons, further increasing the operation risk of virtual gas-electric power plant.

Risk Analysis of Comprehensive Demand Response

In the bidding optimization considering integrated demand response (IDR), multifunctional users in coupled gas-electric virtual power plants become important response resources. Through the implementation of the comprehensive demand response, various users change their energy demand and use interruptible, transferable, and adjustable loads to change the energy load curve. According to different response principles, the energy load curve is divided into price based demand response resources and incentive based demand response resources, as follows:

The purpose of price-based demand response is to independently adjust the load according to price changes because the independent adjustment of user load is markedly affected by external factors such as user energy consumption habits, family income level, operation conditions of energy-consuming equipment, and climatic conditions. Therefore, the actual response of users presents a normal or partial distribution centered on the theoretical response, which further shows that the change in price demand response is uncertain and uncontrollable.

Incentive-based demand response is an interruptible load operation according to the signed demand response agreement and the requirements in power grid instructions. Due to client load regulation technology and economic considerations, the user load regulation according to instructions is inaccurate, so over- and under-response may occur. When the incentive obtained by the demand response is less than the loss caused by load adjustment, default will occur for economic reasons, and the unreliability of the user response will increase.

When considering the comprehensive demand response during bidding optimization, regardless of the response technology adopted, users are guided to change their energy consumption habits and load curves. However, based on the uncontrollable price demand response and the uncertainty in incentive response reliability, a more comprehensive demand response output is required to account for the higher degree of uncertainty and the increased risk of the bidding strategy for virtual gas-power plants.

Design of Risk Evaluation Index System Of Coupled Gas-Electric Virtual Power Plant

Based on multiple perspectives of their characteristics, we analyzed the bidding risk of virtual gas-power plants following the principle of risk index selection. We designed a risk evaluation index system for virtual coupled gas-power plants from five dimensions: external policy, participant, coupling technology, bidding transaction, and credit management risks.

The factors influencing the production process of the bidding and management of coupled gas-electric virtual power plant may different. To comprehensively evaluate information from multiple angles, based on the analysis of the results in the previous section, we constructed a complete risk evaluation index system for coupled gas-electric virtual power plants, including five first-class risk indices: external policy, participants, coupling technology, bidding transaction, and credit management, as shown in Table 1.

Table 1 shows that the designed index system for evaluating the bidding risk of coupled gas-electric virtual power plants designed involves 5 primary indicators, 10 secondary indicators, and 29 tertiary indicators, which are explained as follows:

Risk indicators of participants. The risk evaluation index for participants includes four three-level indicators. The concentration of the electricity market reflects the fair competition environment of the market. The more concentrated the market, the more the market tends to monopolize, and the higher the risk caused by market participants. In addition, to reflect the uncertainty produced by the market transactions of distributed energy resources and energy users in the operation of the power grid and energy market, the market participation rate of distributed energy resources and user participation rate are included in the scope of risk considered for market participants.

$$\alpha = \frac{W_{WT} + W_{PV} + ... + W_{ES}}{W} \times 100\% \tag{1}$$

where α is the acceptance of distributed resources; W_{WT}, W_{PV}, ..., W_{ES} indicate the installed capacity of distributed energy; Q_i is the total installed capacity of all energy.

The market participation rate of users is expressed by the ratio of the number of users participating in market transactions to the number of admitted users,

Table 1. Risk index system.

1st indices-A	2ed indices-B	3rd indices-C	Attribute
External policy risk A_1	Top level policy B_1	Macrocontrol policy C_1	Qualitative
		Relevant industry policies C_2	Qualitative
	Related industries B_2	30•60 scheme C_3	Qualitative
		Electricity transaction rules C_4	Qualitative
Participant risk A_2	Market monopoly B_3	Generation market concentration C_5	Qualitative
		Sales market concentration C_6	Qualitative
	System access B_4	Distributed resource acceptance C_7	Ration
		User participation rate C_8	Ration
Coupling technology risk A_3	Operational risk B_5	Coupling equipment reliability C_9	Ration
		Peak valley difference of coupled operation C_{10}	Ration
		Renewable energy consumption C_{11}	Ration
	Technical risk B_6	Conversion technology maturity C_{12}	Ration
		Energy supply-demand ratio C_{13}	Ration
		Charge discharge efficiency C_{14}	Ration
Bidding transaction risk A_4	Market risk B_7	Fuel price volatility C_{15}	Ration
		Carbon emission price volatility C_{16}	Ration
		Electric elasticity coefficient C_{17}	Ration
		Renewable energy output error C_{18}	Ration
	Economic risks B_8	Benefit-cost ratio C_{19}	Ration
		Abandonment cost C_{20}	Ration
		Operation and maintenance cost C_{21}	Ration
		Energy storage cost C_{22}	Ration
		Loss of energy sales revenue C_{23}	Ration
Information management risk A_5	Manage risk B_9	Transaction breach rate C_{24}	Ration
		Execution deviation rate C_{25}	Ration
		User arrears rate C_{26}	Ration
	User comfort B_{10}	Unplanned outage rate C_{27}	Ration
		Market information disclosure C_{28}	Qualitative
		Credit rating system C_{29}	Qualitative

reflecting the proportion of users participating in the comprehensive demand response market, which is calculated as follows:

$$\delta = \frac{H_b}{H_a} \times 100\% \tag{2}$$

where δ is the market participation rate of users, H_b is the number of users participating in market transactions, and H_a is the total number of users with market access.

Coupling technical risk indicators. The risk assessment index of coupling technology includes six three-level indices in terms of operation and technology. The reliability of coupled operation equipment is a quantitative index that measures the reliability of multienergy coupling conversion equipment in virtual gas-electric power plants, which is expressed as the ratio of available hours of coupling equipment to hours in a statistical period. The higher the availability factor, the higher the reliability of the coupling equipment. The availability factor (AF) can be expressed as:

$$\text{AF} = \text{available hours} / (\text{available hours} + \text{planned outage hours} + \text{unplanned outage hours}) \tag{3}$$

The peak valley difference of coupled operation directly reflects the coupled conversion capacity of the energy conversion equipment in coupled gas-electric virtual power plants at the peaks and valleys of energy load, which is expressed by the output difference of the virtual power plant between load peaks and valleys. The larger the coupling peak valley difference, the stronger the coupling regulation capacity of a virtual gas-electric power plant.

The renewable energy consumption rate distributed resource acceptance is expressed as the proportion of distributed energy consumption to the total energy consumption, reflecting the acceptance of distributed energy by the main energy network. The specific calculation formula is as follows:

$$\beta = \frac{Q_{WT} + Q_{PV} + ... + Q_{HP}}{Q_i} \times 100\% \tag{4}$$

where β represents the maturity of energy conversion technology in virtual gas-electric power plants; Q_{WT}, Q_{PV}, ..., Q_{HP} represent the total energy input to the conversion equipment; Q_i is the available energy output by the energy conversion equipment.

The maturity of P2G and other energy conversion technologies is expressed as the conversion efficiency of various energy conversion equipment in coupled gas-electric virtual power plants, which reflects if technology meets the expected objectives of the project, which is calculated as:

$$\eta = \frac{E_{\text{out}}}{E_{in}} \times 100\% \tag{5}$$

where η represents the maturity of energy conversion technology in virtual gas-electric power plants; E_{in} is the total energy input to the conversion equipment; E_{out} is the available energy output by the energy conversion equipment.

The energy supply-demand ratio is expressed as the ratio of the total demand and total supply of various types of energy in the region, such as electricity, heat, cooling, and gas. The magnitude of this ratio directly explains the energy consumption of a region in the current period.

The charging and discharging efficiency of an energy storage system is related to the service life and cost of energy storage equipment, which is expressed as the ratio of energy stored by energy storage elements to input energy.

Bidding transaction risk index. The risk evaluation index of bidding transaction includes 10 three-level indicators of two aspects: market and economy. The market risk consists of four indicators such as the price volatility of natural gas and other fuels, and the economic risk consists of six indicators regarding the income of virtual gas-and-electricity power plants.

Market risk indicators. The price volatility of natural gas and other fuels is expressed by the standard deviation of the rise and fall in fuel price in a certain time period. This quantitative index measures the degree of fluctuation in various fuel prices for virtual gas-and-electricity power plants, providing a measure of the uncertainty in asset returns, which is used to reflect the risk level of virtual power plant assets. The higher the volatility, the stronger the uncertainty in the yield of the virtual power plant. The specific calculation formula is as follows:

$$HV = \sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 / n} \tag{6}$$

where HV represents the fluctuation rate of the fuel price for virtual gas-electric power plants, x_i is the fuel price at each time point in a certain period, and $\bar{x}$ is the average fuel price in a certain period.

The volatility in the carbon emission price is expressed by the standard deviation of the rise and fall in the carbon emission price in a certain time period. The higher the volatility, the more intense the volatility of the carbon emission price, resulting in the increase in the carbon income risk of virtual gas-and-electricity power plants.

The elasticity coefficient of power consumption is expressed as the ratio of the average annual growth rate of total power consumption in a certain period to the average annual GDP growth rate o in the same period. This index reflects the potential space for using renewable energy power to promote economic development and the demand for renewable energy power under the power supply structure with the aim of using new energy in the future. The calculation formula is as follows:

$$\mathrm{e} = \frac{\Delta E}{\Delta Y} \times 100\% \tag{7}$$

where ΔE is the average annual growth rate in total power consumption in a certain period, and ΔY is the average annual growth rate in GDP in the same period.

The prediction error of renewable energy output is calculated by subtracting the predicted value from the actual value of renewable energy output in virtual gas-electric power plants, which is the gap between the prediction and the real result of the development of and change in the predicted object.

Economic risk index. The benefit-cost ratio is an important index that reflects the profitability of virtual gas-electric power plants, which is expressed as the ratio of the present value of the total income to the present value of the total cost during the operation life of a coupled gas-electric virtual power plant. The calculation formula is as follows:

$$F_{NPV} = \sum_{t=0}^{T} \frac{(f_{in})_t}{(1+i_0)} \tag{8}$$

$$C_{NPV} = \sum_{t=0}^{T} \frac{(c_{out})_t}{(1+i_0)} \tag{9}$$

$$\lambda = \frac{F_{NPV}}{C_{NPV}} \times 100\% \tag{10}$$

where λ represents the income cost ratio of the project; F_{NPV} is the present value of total income; C_{NPV} is the present value of total cost; T is the number of periods from construction to operation; i_0 is the benchmark rate of return.

The renewable energy abandonment cost is a quawntitative index reflecting the abandonment loss of virtual gas-power plants. It mainly considers the on-grid price of wind and photovoltaic power, the output of wind and photovoltaic power under certain regulation strategies, and the actual output of wind and photovoltaic power, which is calculated as:

$$C = P_{re} \times (W_s - W_t) \tag{11}$$

where C represents the cost of renewable energy abandonment; P_{re} represents the on-grid price; W_s is actual output; W_t is the output under certain control requirements.

The operation and maintenance costs of renewable energy do not separately consider energy storage, which is required for wind, photovoltaic, and other renewable energy, and is determined by the output actually involved in dispatching and their respective linear cost coefficients of operation and maintenance.

Energy storage costs include the operation and maintenance costs, the power purchase and sales costs (battery), and the energy loss cost under the storage and discharge efficiency (battery) of the energy storage system.

The loss of energy sales revenue refers to the cost of purchasing energy from the external energy market when a coupled gas-electric virtual power plant cannot meet the energy needs of end users.

Credit management risk indicators. The credit management risk evaluation index consists of six three-level indices from the management and two additional aspects.

Manage risk. The contract breaking rate of a trading system refers to the possibility that, according to the trading agreement reached between the virtual gas-and-electricity power plant and various distributed resource subjects, relevant obligations are not met in a certain future time period. As one of the basic indicators reflecting the degree of credit risk, this rate is expressed as the ratio of the number of times the contract is broken by the virtual gas-and-electricity power plant to the total number of agreed transactions.

The regulation implementation deviation rate reflects the output risk of virtual gas-and-electricity power plants participating in market transactions. The higher the implementation deviation rate, the higher the degree and risk of the system output deviating from the declared or expected value. The specific calculation formula is as follows:

$$D_A = \sqrt{\frac{1}{N}\sum_{t=1}^{T}\left(\frac{P_t^{'}-P_t}{C_{ap}}\right)^2} \times 100\% \tag{12}$$

where D_A is the implementation deviation rate; P'_t is the declared expected output at time t; P_t is the actual output of the virtual power plant at time t; N is the total number of assessment periods; C_{ap} is the startup capacity of the virtual power plant.

The user arrearage rate is expressed as the ratio of the arrearage amount to the total main business income, which reflects the financial management risk of gas and power projects. The higher the arrearage rate, the higher the management risk.

Other risks. The unplanned outage rate of important information systems reflects the operational stability of the information infrastructure. The vulnerability of the information infrastructure and external environmental threats (hacker attacks, poor operation and maintenance, etc.) pose information security risks.

The quality of market information disclosure reflects the average timeliness, accuracy, and completeness of market information disclosure as well as the openness and transparency of the market.

The credit rating system supervises and manages the credit rating of market participants according to relevant laws, regulations, and regulatory responsibilities, thereby reflecting the market credit level.

Pretreatment of risk assessment indicators. Each evaluation index contained in the risk evaluation index system for coupled gas-electric virtual power plants involves different index types and dimensional units. Therefore, before risk assessment, each evaluation index needed to be preprocessed to create a consistent and dimensionless evaluation index, as follows:

1) Consistency processing of indicator types

The proposed risk evaluation index of coupled gas-electric virtual power plants includes 29 evaluation indices. The indices are divided into forward, reverse, and interval indices. The larger the positive index value, the lower the risk in terms of renewable energy use rate, comprehensive energy saving rate, internal rate of return, and other evaluation indicators. The larger the reverse index value, the higher the risk in terms of investment payback period, noise level, among other evaluation indices. The closer the interval index with a segmentation attribute to the middle of the interval, the better. Therefore, all evaluation indices need to be consistent before evaluating the risk of coupled gas-electric virtual power plants. The specific calculation formula is as follows:

For the treatment of positive evaluation indicators, we used:

$$x_{ij}^{*} = \max\left\{x_{ij}\right\} - x_{ij} \tag{13}$$

For the processing of reverse evaluation indicators, the positive indicators were transformed into reverse indicators through the above formula.

For the forward processing of interval indicators, we used:

$$x_{ij}^{*} = \max\left|x_{ij} - x_{ijmid}\right| - \left|x_{ij} - x_{ijmid}\right| \tag{14}$$

where x_{ij} and x_{ij}^{*} represent the index value before and after the evaluation index consistency processing, respectively; x_{ijmid} represents the median value of the interval index.

2) Dimensionless evaluation index

After the risk evaluation indices of coupled gas-electric virtual power plants are consistent, because each evaluation index has different dimensions and types, they cannot be directly compared, so all evaluation indices required further processing to ensure dimensionless. Dimensionless treatment methods include the linear dimensionless tempering and nonlinear dimensionless methods. For the designed risk evaluation index system, the linear dimensionless treatment method was used. In this study, the indices were made dimensionless using the extreme value processing method, which is calculated as:

$$x_{ij}^{*} = \frac{x_{ij} - x_{ij}^{\min}}{x_{ij}^{\max} - x_{ij}^{\min}} \tag{15}$$

where $x_{ij}^{\min}$ and $x_{ij}^{\max}$ are the minimum and maximum values after considering the consistent treatment of various risk assessment indicators, respectively.

Improved Cloud Model Risk Assessment Model Based on Entropy Weight Method Order Relationship

As information is easily affected by subjective factors, we used combined weighting to combine the entropy weight and order relation methods, avoiding the shortcomings of both when used alone. On this basis, we considered the fuzziness and randomness of the risk evaluation process for multiple scenarios of virtual gas-and-electricity power plants. We constructed an improved cloud model risk assessment model based on the entropy weight order relation, which is described as:

Entropy Weight Order Relation Weighting Method

In the weighting mechanism for the importance of evaluation indicators, the hierarchical weight decision-making method is mainly adopted, but this method does not fully use the objective information in data or the subjective factors of artificial weighting are large. First, we used the entropy and order relation weight methods to calculate the weight of each three-level index and. We comprehensively weighted and optimized the subjective weight obtained by the order relation weighting method and the objective weight obtained by the entropy weight method. We then solved the optimal combination coefficient, and we obtained the combination weight considering the advantages of the subjective and objective weights. Thus, we developed an index combination weighting method based on the entropy weight order relation, which combines and optimizes the subjective and objective weights, so that the index weight considers the advantages of both the subjective and objective weight, producing an index weight that is closer to the actual value.

Entropy weight method. According to information theory, information is the measure of system order, and entropy is the measure of system disorder. In Zeng and Liu study , the entropy weight method is an objective weighting method used to determine an index weight based on the data-difference-driven principle: the larger the difference in an index, the larger the amount of information contained in the index and the large the role it plays [16]. So, its entropy value is small and the weight is large, and vice versa. The specific calculation steps are as follows:

Construct judgment matrix. If m samples are evaluated by n evaluation indices, the corresponding index value is $r_{ij}\,(i = 1, 2, 3, ..., m; j = 1, 2, 3, ..., n)$:

$$R = \begin{pmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{pmatrix} \tag{16}$$

Where $R = (r_{ij})_{m\times n}$ represents the risk evaluation value of the jth expert for the ith index.

Index preprocessing. First, preprocess each index r_{ij}; that is, process the proportion of the risk index of the coupled gas-electric virtual power plant for the similar indices and calculate the proportion of the ith risk under the jth index.

$$P_{ij} = \frac{(1+\hat{r}_{ij})}{\sum_{i=1}(1+\hat{r}_{ij})} \tag{17}$$

Where i = 1, 2, ..., m, j = 1, 2, …, n.

Calculate the entropy of the jth index Q_j

$$Q_j = -\frac{1}{\ln m}\sum_{i=1}^{m} P_{ij}\ln P_{ij} \tag{18}$$

Calculate the weight coefficient of the j-th index v_j

$$v_j = \frac{(1-Q_j)}{m-\sum_{j=1}^{n} Q_j} \tag{19}$$

Finally, the objective weight vector of the index is:

$$V = (v_1, v_2, ..., v_n)^T \tag{20}$$

Comprehensive weighting method. The comprehensive weighting of indicators reflects not only the subjective judgment of experts but also the objective value of data, which integrates the advantages of subjective and objective weights. Qu et al. pointed out that in the weighted linear method and the mixed method of addition and multiplication, the determination of the synthesized coefficient includes artificial subjective tendency [17]; so, we adopted the multiplication synthesis method based on the principle of minimum information entropy in this study.

Determine the comprehensive weight W_i.

$$W_i = \frac{w_i v_j}{\sum_{i=1}^{m} w_i v_j} \tag{21}$$

Minimum information entropy principle. To ensure the comprehensive weight W_i reflects the subjective weight obtained by the order relation analysis method and the objective weight obtained by the entropy weight method as much as possible, according to the principle of minimum entropy weight, calculate:

$$\min E = \sum_{i=1}^{m} W_i (\ln \frac{W_i}{w_i}) + \sum_{i=1}^{m} W_i (\ln \frac{W_j}{v_j}) \tag{22}$$

Perform Lagrange multiplier optimization:

$$W_i = (w_i v_j)^{1/2} / \sum_{i=1}^{m} (w_i v_j)^{1/2} \tag{23}$$

$$\sum_{i=1}^{m} W_i = 1,\ W_i \geqslant 0,\ i = 1, 2, \ldots, m,\ i = j \tag{24}$$

where Wi is the comprehensive weight of index i; w_i is the subjective weight of the ith index calculated by the order relation method; v_j is the objective weight of the jth index calculated according to the entropy weight method.

Cloud model algorithm. Brito et al. shown that in the real world, everything has qualitative characteristics that are fuzzy and random, so are often difficult to quantify with accurate numbers [18]. In this study, the cloud model comprehensively considers the fuzziness and randomness of indicators through a specific calculation process, enabling a transformation from qualitative to quantitative. Finally, the results are visually represented through a cloud map, and the randomness of the cloud model when a qualitative concept is transformed into a quantitative concept is consistent with the objective law of things. Cloud models have been proven to be universal in fields of application such as risk assessment and data mining.

Normal cloud and cloud drop. Cloud models can reflect the overall characteristics of things. During evaluation, cloud models can represent the advantages and disadvantages of a specific item according to selected evaluation criteria. Clouds are formed by the aggregation of cloud droplets, which reflect the fuzziness of each qualitative concept of an item. In the real world, everything has a wide range of normal distribution laws, so we used a normal cloud to analyze the laws in the cloud model. Fig. 2 shows the level 5 standard normal cloud model of an evaluation object.

Each cloud has expected value (Ex), entropy (En), and hyper entropy (He), where Ex is the central value of the whole cloud, which is the most representative qualitative point; En is the dispersion degree of cloud droplets and represents the uncertainty of the mean value. The larger the entropy, the wider the distribution range of cloud droplets and the wider the cloud. He is the entropy of entropy, indicating the dispersion degree of entropy. In a cloud map, the specific representation is the thickness of cloud. The larger the hyper entropy, the

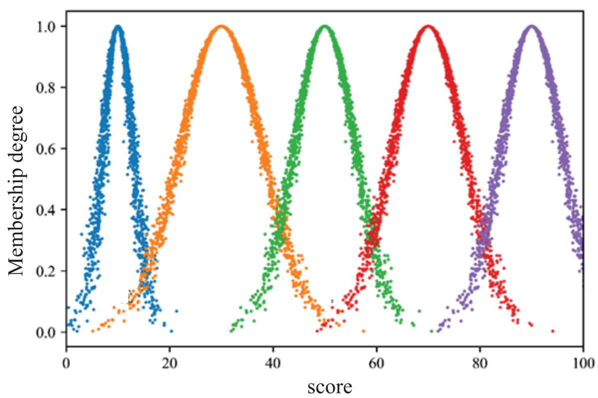

Fig. 2. Standard cloud model of an evaluated object.

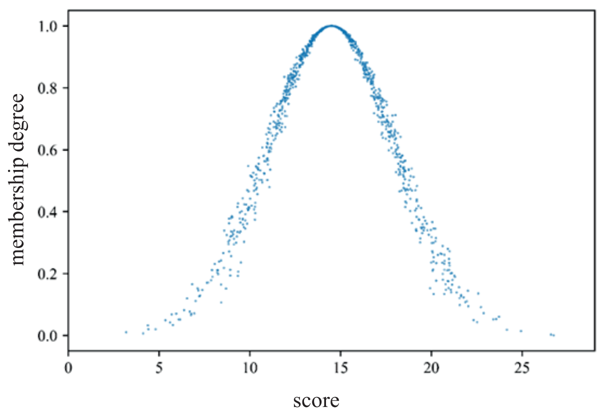

Fig. 3. Membership cloud of adolescent age.

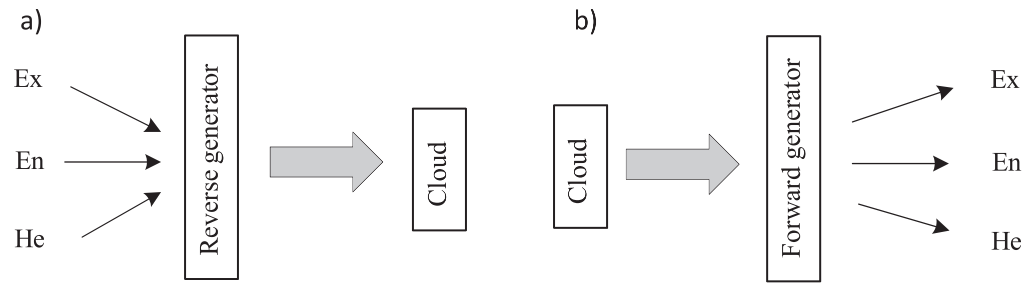

Fig. 4. Cloud generator: a) Reverse generator, b) Forward generator.

thicker the cloud. As an example, Fig. 3 shows a cloud diagram of the age of teenagers, demonstrating that the cloud droplets at 14.5 are the most dense, which means that when the teenagers are 14.5 years old, they are more likely to be "teenagers". The farther the droplets are away from 14.5, the less likely they are "teenagers", and the cloud droplet shape is more dispersed.

Forward and reverse cloud generators. Cloud generators includes forward and reverse cloud generators. These are algorithms responsible for performing the mutual transformation between qualitative concepts and quantitative data in cloud models. The cloud and eigenvalue are mapped to each other. The eigenvalue generates the cloud through the forward generator, and the cloud can obtain three eigenvalues through the reverse generator. The cloud generator converts qualitative to quantitative evaluation information, as shown in Fig. 4.

Forward cloud generator algorithm steps:
Input: three characteristic values Ex, En, He
Output: cloud drops (x_i, μ_i)
a) Generate normal random number $\overline{\mu}_i$, $\overline{\mu}_i$~N (En, He)
b) Generate normal random number x_i, x_i~N (Ex, $\overline{\mu}_i$)
c) Calculate the membership degree subject to normal distribution N (Ex, En):

$$\mu_i = e^{-\frac{(x_i - Ex)^2}{2\overline{\mu}^2}} \tag{25}$$

d) Repeat steps (a) to (c) until m cloud droplets are generated to form normal clouds.

4) Three characteristic check-in calculation methods of reverse cloud generator

Assuming that there are N samples, x_i represents the ith sample, and represents the arithmetic mean of the samples. Then, Ex is

$$\mu_i = e^{-\frac{(x_i - Ex)^2}{2\overline{\mu}^2}} \tag{26}$$

En is

$$En = \sqrt{\frac{\pi}{2}} * \frac{1}{N}\sum_{i=1}^{N}\left|x_i - Ex'\right| \tag{27}$$

and He' is

$$He' = \sqrt{S^2 - En'^2} \tag{28}$$

Where S^2 is the sample variance, $S^2 = \frac{1}{N-1}\sum_{i=1}^{m}(x_i - \overline{X})^2$.

When the evaluation standard is the interval number, the following reverse cloud generation algorithm can be adopted:

$$Ex = (C_{min} + C_{\max}) / 2 \tag{29}$$

$$En = (C_{\max} - C_{min}) / 6 \tag{30}$$

$$He = k \tag{31}$$

Risk Assessment Calculation Process

Virtual cloud theory. A virtual cloud converts the eigenvalues of the base cloud into a new set of eigenvalues through an algorithm to produce a reference (such as a comprehensive evaluation of an object). The cloud represented by this new set of eigenvalues is a virtual cloud. Wang and Zhang pointed out that in the comprehensive evaluation method based on a cloud model, the virtual cloud is mainly divided into a floating cloud and a comprehensive cloud [19]. Floating clouds can integrate multiple independent concepts into a broader concept. Integrated clouds can integrate multiple interrelated concepts into a broader concept.

Main steps of risk assessment of coupled gas-electric virtual power plant based on cloud model.

1) Build the evaluation index system;

2) Invite domain experts to confirm the level of each secondary index in the virtual power plant evaluation system;

3) Through the cloud generator, the evaluation levels of each secondary index obtained in the previous step are transformed into cloud model language;

4) Build the corresponding virtual cloud to synthesize the secondary index comments;

5) Build the corresponding virtual cloud to synthesize the primary indicators;

6) Obtain the final evaluation result through cloud transformation.

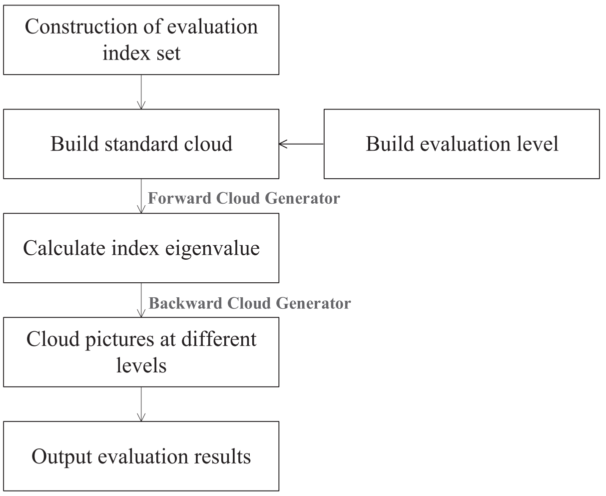

Fig. 5. Flow chart of cloud model evaluation.

Index virtual cloud construction. The overall risk of a coupled gas-electric virtual power plant comprehensively considers each three-level index, which show correlation. The comprehensive cloud method can be used to calculate the three eigenvalues:

$$Ex = \frac{\sum_{i=1}^{m} Ex_i * En_i * \omega_i}{\sum_{i=1}^{m} En_i * \omega_i} \tag{32}$$

$$En = n\sum_{i=1}^{m} En_i * \omega \tag{33}$$

$$He = \frac{\sum_{i=1}^{m} He_i * En_i * \omega_i}{\sum_{i=1}^{m} En_i * \omega_i} \tag{34}$$

Where: Ex_i is the expectation of each three-level index, En_i is the entropy of each three-level index, He_i is the super entropy of each three-level index, and ω_i is the weight of each three-level index.

Results and Discussion

To analyze the effect of multiple uncertainties, electric vehicle characteristics, and the comprehensive demand response characteristics on the risk assessment of coupled gas-electric virtual power plants from multiple angles, we analyzed the risk assessment and set scenarios using Sections 3, 4, and 5 as the data sources, as follows:

Scenario 1: Based on the study of the bidding optimization of virtual gas-and-electricity power plants under multiple uncertainties in Section 3, we considered the bidding risk of these power plants under multiple uncertainties;

Table 2. Judgment matrix of first-level indicators.

Expert	Primary Index				
	External policy risk	Participant risk	Coupling technology risk	Bidding transaction risk	Credit risks
1	2	4	3	3	1
2	2	3	4	2	2
3	2	5	5	4	2
4	3	4	5	3	3
5	3	5	5	4	2
6	2	3	3	3	2
7	1	3	4	2	2
8	2	6	3	3	1
9	2	5	3	2	1
10	3	5	4	2	3
11	2	4	3	4	2
12	2	4	5	2	3
13	1	4	6	2	2
14	2	3	3	3	1
15	3	5	4	3	2

Table 2. Continued.

16	2	4	3	2	2
17	2	6	4	3	2
18	2	4	4	3	3
19	3	3	5	2	1
20	4	4	4	2	2
21	2	5	4	4	2
22	2	5	3	2	1
23	3	4	4	1	3
24	4	4	3	3	2
25	2	3	2	2	2

Scenario 2: Based on the study on bidding optimization of virtual gas-electric power plants under electric vehicle characteristics in Section 4, we considered the bidding risk of these plants for various electric vehicle characteristics;

Scenario 3: We considered the bidding optimization study of virtual gas-electric power plants in terms of comprehensive demand response according to Section 5;

Scenario 4: We simultaneously considered the impact of the first three scenarios on the bidding risk of virtual gas-and-electricity power plants.

In addition, to avoid the distortion of the risk evaluation results, we used the improved cloud model evaluation and fuzzy analytic hierarchy process to evaluate the risk.

Analysis of Risk Assessment Results Based on Improved Cloud Model

Evaluation Index Weight Calculation

Determination of objective weight of evaluation index by entropy weight method. We used the entropy weight order relation method to comprehensively weight the evaluation index system of the coupled gas-electric virtual power plant.

a) Construct judgment matrix

In this study, we used a six-item Likert scale [20] to express the impact of external policy, participant, coupling technology, bidding transaction, and credit management risks on coupled gas-electricity virtual power plants. We interviewed 25 experts engaged in power systems, integrated energy systems, and virtual power plants; these experts also filled in a scoring form. After collection, we statistically analyzed the data to summarize the degree of impact of the risk assessment indicators of coupled gas-electric virtual power plants, as shown in Table 2.

b) Standardize the data

We normalized the above matrix to obtain the matrix P as:

$$P_{ij} = \begin{pmatrix}
0.164399 & 0.186299 & 0.151911 & 0.217643 & 0.096674 \\
0.164399 & 0.139724 & 0.202548 & 0.145095 & 0.193347 \\
0.164399 & 0.232873 & 0.253185 & 0.290190 & 0.193347 \\
0.246598 & 0.186299 & 0.253185 & 0.217643 & 0.290021 \\
0.246598 & 0.232873 & 0.253185 & 0.290190 & 0.193347 \\
0.164399 & 0.139724 & 0.151911 & 0.217643 & 0.193347 \\
0.082199 & 0.139724 & 0.202548 & 0.145095 & 0.193347 \\
0.164399 & 0.279448 & 0.151911 & 0.217643 & 0.096674 \\
0.164399 & 0.232873 & 0.151911 & 0.145095 & 0.096674 \\
0.246598 & 0.232873 & 0.202548 & 0.145095 & 0.290021 \\
0.164399 & 0.186299 & 0.151911 & 0.290190 & 0.193347 \\
0.164399 & 0.186299 & 0.253185 & 0.145095 & 0.290021 \\
0.082199 & 0.186299 & 0.303822 & 0.145095 & 0.193347 \\
0.164399 & 0.139724 & 0.151911 & 0.217643 & 0.096674 \\
0.246598 & 0.232873 & 0.202548 & 0.217643 & 0.193347 \\
0.164399 & 0.186299 & 0.151911 & 0.145095 & 0.193347 \\
0.164399 & 0.279448 & 0.202548 & 0.217643 & 0.193347 \\
0.164399 & 0.186299 & 0.202548 & 0.217643 & 0.290021 \\
0.246598 & 0.139724 & 0.253185 & 0.145095 & 0.096674 \\
0.328798 & 0.186299 & 0.202548 & 0.145095 & 0.193347 \\
0.164399 & 0.232873 & 0.202548 & 0.290190 & 0.193347 \\
0.164399 & 0.232873 & 0.151911 & 0.145095 & 0.096674 \\
0.246598 & 0.186299 & 0.202548 & 0.072548 & 0.290021 \\
0.328798 & 0.186299 & 0.151911 & 0.217643 & 0.193347 \\
0.164399 & 0.139724 & 0.101274 & 0.145095 & 0.193347
\end{pmatrix}$$

c) Calculate the entropy of each index

According to the formula for calculating entropy, the entropy vector of each index was obtained as follows:

$$e_i = \left(0.9767 \quad 0.9642 \quad 0.9691 \quad 0.9748 \quad 0.9804\right)^T$$

d) Calculate the weight of each index

According to the weight calculation formula, the weight vector was obtained as follows as shown in Table 3:

$$v_i = \left(0.0921 \quad 0.3172 \quad 0.2804 \quad 0.2325 \quad 0.0778\right)^T$$

Table 3. Weight of first-level indicators.

Index	External policy risk	Participant risk	Coupling technology risk	Bidding transaction risk	Credit risks
Weight	0.0921	0.3172	0.2804	0.2325	0.0778

Table 4. Weight of third-level indicators (entropy weight method).

Index	Weight	Index	Weight
C_1	0.0478	C_{16}	0.0376
C_2	0.0421	C_{17}	0.0294
C_3	0.0463	C_{18}	0.0438
C_4	0.043	C_{19}	0.0352
C_5	0.0452	C_{20}	0.0376
C_6	0.0410	C_{21}	0.0294
C_7	0.0457	C_{22}	0.0301
C_8	0.0424	C_{23}	0.0267
C_9	0.0472	C_{24}	0.0273
C_{10}	0.0418	C_{25}	0.0304
C_{11}	0.0424	C_{26}	0.0292
C_{12}	0.0383	C_{27}	0.0261
C_{13}	0.0336	C_{28}	0.0270
C_{14}	0.0438	C_{29}	0.0263
C_{15}	0.0352	-	-

Table 7. Weight of third-level indicators (order relation method).

Index	Weight	Index	Weight
C_1	0.0296	C_{16}	0.0283
C_2	0.0192	C_{17}	0.0301
C_3	0.0174	C_{18}	0.0294
C_4	0.0187	C_{19}	0.0401
C_5	0.0454	C_{20}	0.0392
C_6	0.0382	C_{21}	0.0339
C_7	0.0421	C_{22}	0.0342
C_8	0.0397	C_{23}	0.0341
C_9	0.0442	C_{24}	0.0298
C_{10}	0.0464	C_{25}	0.0325
C_{11}	0.0428	C_{26}	0.0322
C_{12}	0.0406	C_{27}	0.0354
C_{13}	0.0422	C_{28}	0.0328
C_{14}	0.0378	C_{29}	0.0313
C_{15}	0.0324		

Similarly, according to the above steps, the weight vector of the second level index relative to the first level index and the weight vector of the third level index relative to the second level index can be calculated as shown in Table 4..

Determining Subjective Weight of Evaluation Index by Order Relation Method

Definite order relation. In this study, we invited 25 experts involved in power systems, integrated energy systems, and virtual power plants to rank the established indices according to their importance, and finally determine a unique evaluation index order relationship.

After several rounds of discussion by the 25 experts, we obtained the primary evaluation index for the proposed risk evaluation index of coupled gas-electric virtual power plants. The specific results ranked according to importance were as follows:

$$x_2 \geq x_3 \geq x_4 \geq x_1 \geq x_5$$

Table 5. Weight ranking of first-level indicators (order relation method).

$\omega^*{}_5$	$\omega^*{}_4$	$\omega^*{}_3$	$\omega^*{}_2$	$\omega^*{}_1$
$(1+7.3152)^{-1} = 0.1203$	$\omega^*{}_5 r_5 = 0.1443$	$\omega^*{}_4 r_4 = 0.2020$	$\omega^*{}_3 r_3 = 0.2424$	$\omega^*{}_2 r_2 = 0.2909$

Table 6. Weight coefficient of first-level indicators (order relation method).

$\omega_1 = \omega^*{}_4$	$\omega_2 = \omega^*{}_1$	$\omega_3 = \omega^*{}_2$	$\omega_4 = \omega^*{}_3$	$\omega_5 = \omega^*{}_5$
0.1443	0.2909	0.2424	0.2020	0.1203

$$x^*_1 \geq x^*_2 \geq x^*_3 \geq x^*_4 \geq x^*_5$$

Quantitative analysis of the importance of each index. The order relationship is assigned according to the importance of the index:

$$r_2 = \frac{\omega_1^*}{\omega_2^*} = 1.2 \; r_3 = \frac{\omega_2^*}{\omega_3^*} = 1.2 \; r_4 = \frac{\omega_3^*}{\omega_4^*} = 1.4 \; r_5 = \frac{\omega_4^*}{\omega_5^*} = 1.2$$

Then:

$$\begin{aligned} & r_2r_3r_4r_5 = 2.4192 \\ & r_3r_4r_5 = 2.016 \\ & r_4r_5 = 1.68 \\ & r_5 = 1.2 \\ & r_2r_3r_4r_5 + r_3r_4r_5 + r_4r_5 + r_5 = 7.3152 \end{aligned}$$

Calculate subjective weight. According to the calculation of the order relation analysis method, the weight ranking of each first-level evaluation index for the risk evaluation of the power plants according to the weight was as shown in Table 5.

According to the above calculation results, the obtained weight coefficients of the primary indicators $\{x_1, x_2, ..., x_5\}$ of the risk assessment of the coupled gas-electricity virtual power plant are shown in Table 6.

According to the above methods and steps and by analogy, we calculated the weight of the secondary and tertiary indicators. We then obtained the judgment matrix of the various indicators of risk assessment of coupled virtual power plants as shown in Table 7.

Comprehensive Weight

According to the above comprehensive weighting method and combined with the subjective and objective weight results obtained in the above calculation process, we finally obtained the subjective and objective comprehensive weights, as shown in Table 8.

Risk Assessment Results Based on Improved Cloud Model

Determination of evaluation grade. We invited experts to score 29 three-level indicators from five aspects: external policy, participant, coupling technology, bidding transaction, and credit management risks. For the scoring, we adopted a percentage system. We set the evaluation grade standard for each index, as shown in Table 9.

We calculated the characteristic values of the cloud model for the risk assessment standard of virtual gas-electric power plants according to the level ranges divided in Table 10, and the results were excellent (100, 10/3, 0.5), good (85, 5/3, 0.5), medium (75, 5/3, 0.5), poor (65, 5/3, 0.5), and bad (0, 20, 0.5). Based on this, we constructed a cloud chart of the risk assessment standard of virtual power plants, as shown in Fig. 6.

Fig. 6 shows that the risk assessment standard cloud of virtual gas-and-electricity power plants was divided into five levels: excellent, good, medium, poor, and bad. We used the half-cloud method to map the excellent and poor levels.

Cloud model evaluation results. According to the above comprehensive cloud computing method, we calculated the characteristic values of the risk assessment of virtual power plants under four scenarios, as shown in Table 10.

Table 8. Weight of third-level indicators of risk evaluation for coupled gas-electric coupling VPPs.

1st-level indices	2nd-level indices	3rd-level indices	Weight		
			Order	Entropy	Comprehensive
External policy risk	Top level policy	Macro-control policy	0.0296	0.0206	0.024
		Relevant industry policies	0.0192	0.0172	0.018
	Related industries	30•60 scheme	0.0174	0.0201	0.019
		Electricity transaction rules	0.0187	0.0152	0.016
Participant risk	Market monopoly	Generation market concentration	0.0454	0.0478	0.047
		Sales market concentration	0.0382	0.0421	0.041
	System access	Distributed resource acceptance	0.0421	0.0463	0.045
		User participation rate	0.0397	0.0430	0.042
Coupling technology risk	Operational risk	Coupling equipment reliability	0.0442	0.0452	0.045
		Peak valley difference of coupled operation	0.0464	0.0410	0.043
		Renewable energy consumption	0.0428	0.0457	0.045
	Technical risk	Conversion technology maturity	0.0406	0.0424	0.042
		Energy supply-demand ratio	0.0422	0.0472	0.045
		Charge discharge efficiency	0.0378	0.0418	0.040

Table 8. Continued.

Bidding transaction risk	Market risk	Fuel price volatility	0.0324	0.0424	0.039
		Carbon emission price volatility	0.0283	0.0383	0.035
		Electric elasticity coefficient	0.0301	0.0336	0.032
		Renewable energy output error	0.0294	0.0438	0.039
	Economic risk	Benefit cost ratio	0.0401	0.0352	0.037
		Abandonment cost	0.0392	0.0376	0.038
		Operation and maintenance cost	0.0339	0.0294	0.031
		Energy storage cost	0.0342	0.0301	0.032
		Loss of energy sales revenue	0.0341	0.0267	0.029
Information management risk	Manage risk	Transaction breach rate	0.0298	0.0273	0.028
		Execution deviation rate	0.0325	0.0304	0.031
		User arrears rate	0.0322	0.0292	0.030
	User comfort	Unplanned outage rate	0.0354	0.0261	0.029
		Market information disclosure	0.0328	0.0270	0.029
		Credit rating system	0.0313	0.0263	0.028

Table 9. Division of grades of risk evaluation for coupled gas-electric virtual power plants.

Tertiary indicators	Evaluation grade standard				
	(100,90]	(90,80]	(80,70]	(70,60]	<60
C_i	Excellent	Good	Medium	Poor	Bad

Table 10. Integrated cloud eigenvalues for each scenario.

Scenario	Ex	En	He
1	86.662	1.585	0.5
2	85.913	1.752	0.5
3	87.048	1.741	0.5
4	92.147	1.049	0.5

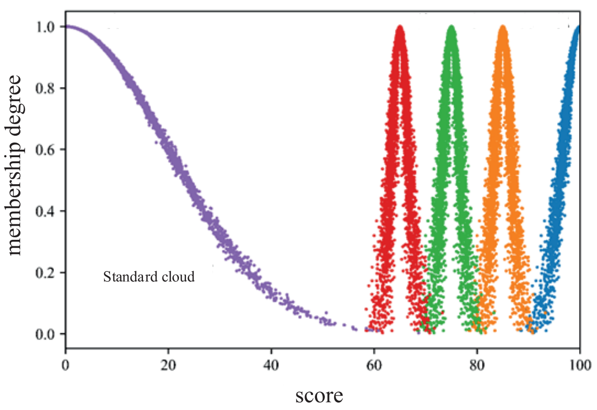

Fig. 6. Comprehensive evaluation standard cloud atlas of coupled gas-electric virtual power plants.

The expected eigenvalues of Ex, En, and He in Table 11 accurately reflect the central value, fuzziness, and randomness of the risk of virtual gas-and-electricity power plants under the four scenarios. According to these obtained eigenvalues, we separately constructed the risk assessment cloud diagrams of the virtual power plant under Scenarios 1-4, which more clearly and intuitively displayed the comprehensive evaluation results, as shown in Fig. 7.

Cloud eigenvalue calculation of indicators. According to the score, we calculated the cloud characteristic values of the three-level indicators as shown in Table 11.

We then used the three eigenvalues of each first-level indicator under the four as cloud charts, as shown in Fig. 8.

In Fig. 7, the black cloud chart is the standard cloud for the risk assessment of virtual gas-and-electricity power plants, and the red cloud chart is the evaluation results of the cloud model under each scenario. The risk assessment cloud levels of Scenarios 1, 2, and 3 are in the range of good to medium. Among the four scenarios, Scenario 4 obtained the best comprehensive assessment result, with the risk assessment level being between excellent and good, and the eigenvalues were (86.662, 1.585, 0.5), which belong to the comprehensive risk rating of excellent to good. Combined with the cloud chart of the primary index evaluation under the four scenarios in Figure 8, the participants and

Table 11. Cloud eigenvalues of third-level indicators for each scenario.

Evaluating indicator	Scenario 1	Scenario 2	Scenario 3	Scenario 4
C_1	(84.00, 1.33, 0.5)	(80.50, 0.83, 0.5)	(80.50, 0.50, 0.5)	(94.50, 1.50, 0.5)
C_2	(94.00, 1.33, 0.5)	(93.50, 1.83, 0.5)	(94.00, 1.33, 0.5)	(94.50, 1.50, 0.5)
C_3	(91.00, 1.00, 0.5)	(93.00, 1.33, 0.5)	(90.00, 0.67, 0.5)	(93.50, 1.83, 0.5)
C_4	(84.00, 2.00, 0.5)	(86.50, 2.17, 0.5)	(88.00, 2.00, 0.5)	(88.50, 0.50, 0.5)
C_5	(91.50, 1.17, 0.5)	(82.00, 1.67, 0.5)	(82.50, 1.17, 0.5)	(92.50, 1.83, 0.5)
C_6	(82.50, 1.83, 0.5)	(81.00, 2.00, 0.5)	(89.50, 0.83, 0.5)	(93.50, 1.83, 0.5)
C_7	(88.00, 2.33, 0.5)	(88.00, 2.33, 0.5)	(88.00, 2.33, 0.5)	(96.00, 0.33, 0.5)
C_8	(80.50, 1.17, 0.5)	(86.50, 2.50, 0.5)	(86.50, 2.50, 0.5)	(88.00, 1.33, 0.5)
C_9	(81.50, 0.83, 0.5)	(86.50, 2.83, 0.5)	(81.00, 1.00, 0.5)	(91.50, 2.50, 0.5)
C_{10}	(88.00, 2.00, 0.5)	(83.50, 1.50, 0.5)	(91.00, 2.33, 0.5)	(90.00, 1.33, 0.5)
C_{11}	(80.00, 1.33, 0.5)	(88.50, 2.17, 0.5)	(85.50, 3.17, 0.5)	(88.00, 1.33, 0.5)
C_{12}	(93.00, 1.67, 0.5)	(80.00, 1.33, 0.5)	(85.50, 0.83, 0.5)	(91.50, 1.17, 0.5)
C_{13}	(91.00, 1.33, 0.5)	(82.00, 1.33, 0.5)	(90.50, 1.50, 0.5)	(91.50, 2.50, 0.5)
C_{14}	(85.00, 1.33, 0.5)	(86.50, 1.83, 0.5)	(87.50, 2.50, 0.5)	(90.50, 0.50, 0.5)
C_{15}	(84.50, 1.83, 0.5)	(87.00, 2.67, 0.5)	(94.50, 1.50, 0.5)	(92.50, 0.83, 0.5)
C_{16}	(87.50, 3.17, 0.5)	(94.50, 1.50, 0.5)	(81.50, 1.50, 0.5)	(98.00, 0.33, 0.5)
C_{17}	(90.50, 2.17, 0.5)	(90.00, 0.67, 0.5)	(85.00, 2.33, 0.5)	(91.00, 0.33, 0.5)
C_{18}	(81.50, 1.83, 0.5)	(83.50, 1.83, 0.5)	(91.50, 1.17, 0.5)	(92.50, 1.83, 0.5)
C_{19}	(89.00, 2.00, 0.5)	(86.50, 2.83, 0.5)	(92.50, 2.17, 0.5)	(95.50, 0.17, 0.5)
C_{20}	(90.00, 1.33, 0.5)	(91.00, 1.00, 0.5)	(81.50, 1.50, 0.5)	(94.50, 0.17, 0.5)
C_{21}	(83.00, 2.00, 0.5)	(85.00, 0.33, 0.5)	(89.00, 2.67, 0.5)	(93.50, 1.50, 0.5)
C_{22}	(82.50, 1.17, 0.5)	(88.50, 0.50, 0.5)	(84.00, 1.67, 0.5)	(92.00, 2.00, 0.5)
C_{23}	(88.00, 2.00, 0.5)	(88.00, 2.33, 0.5)	(81.00, 1.00, 0.5)	(96.50, 0.83, 0.5)
C_{24}	(82.00, 1.33, 0.5)	(84.00, 1.67, 0.5)	(91.00, 2.33, 0.5)	(89.00, 1.00, 0.5)
C_{25}	(91.50, 1.83, 0.5)	(83.00, 1.67, 0.5)	(88.00, 2.33, 0.5)	(94.00, 1.33, 0.5)
C_{26}	(82.00, 2.33, 0.5)	(84.50, 1.17, 0.5)	(83.00, 2.00, 0.5)	(92.00, 1.00, 0.5)
C_{27}	(95.50, 1.17, 0.5)	(81.50, 1.83, 0.5)	(82.50, 1.17, 0.5)	(96.00, 1.00, 0.5)
C_{28}	(88.00, 0.33, 0.5)	(86.50, 1.83, 0.5)	(88.00, 2.00, 0.5)	(93.50, 1.50, 0.5)
C_{29}	(87.50, 0.50, 0.5)	(86.00, 3.00, 0.5)	(81.00, 1.67, 0.5)	(92.00, 1.00, 0.5)

bidding transaction risks in Scenario 1 are the most prominent; the risk scores for credit management, external policies, and coupling technology in Scenario 2 are low; and the main risks in Scenario 3 are coupling technology, bidding transaction, and credit management. In Scenario 4, the cloud charts of all primary indicators are in the good and excellent range, but the risk scores for coupling technology, participants, and bidding transactions are relatively low, indicating certain risks. Therefore, the cloud eigenvalues of the three-level indicators in Figs 7-9 show that, subject to the impact of the operation characteristics of the coupled gas-electricity virtual power plant and its participation in market transactions, the cloud results of the comprehensive risk assessment of virtual gas-electricity power plants . based on the improved cloud model risk assessment method, indicate that the main risks are participant and coupling technology risk. Bidding transaction risk involves three aspects. When considering uncertainty only, we must focus on the risk management of participants and bidding transactions. When considering the participation of electric vehicles only, due to the large differences in electric vehicle user habits and personal credit, the focus should be improving credit management risk. When considering the comprehensive demand response only, the

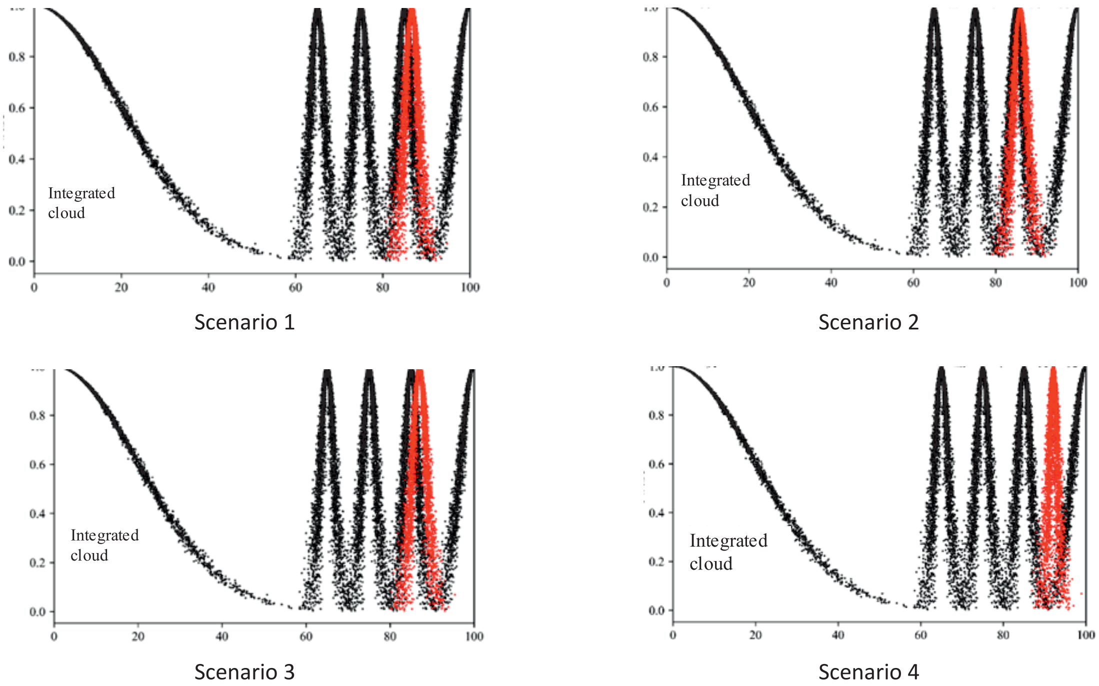

Fig. 7. Risk evaluation standard cloud atlas for each gas-electric VPP scenario.

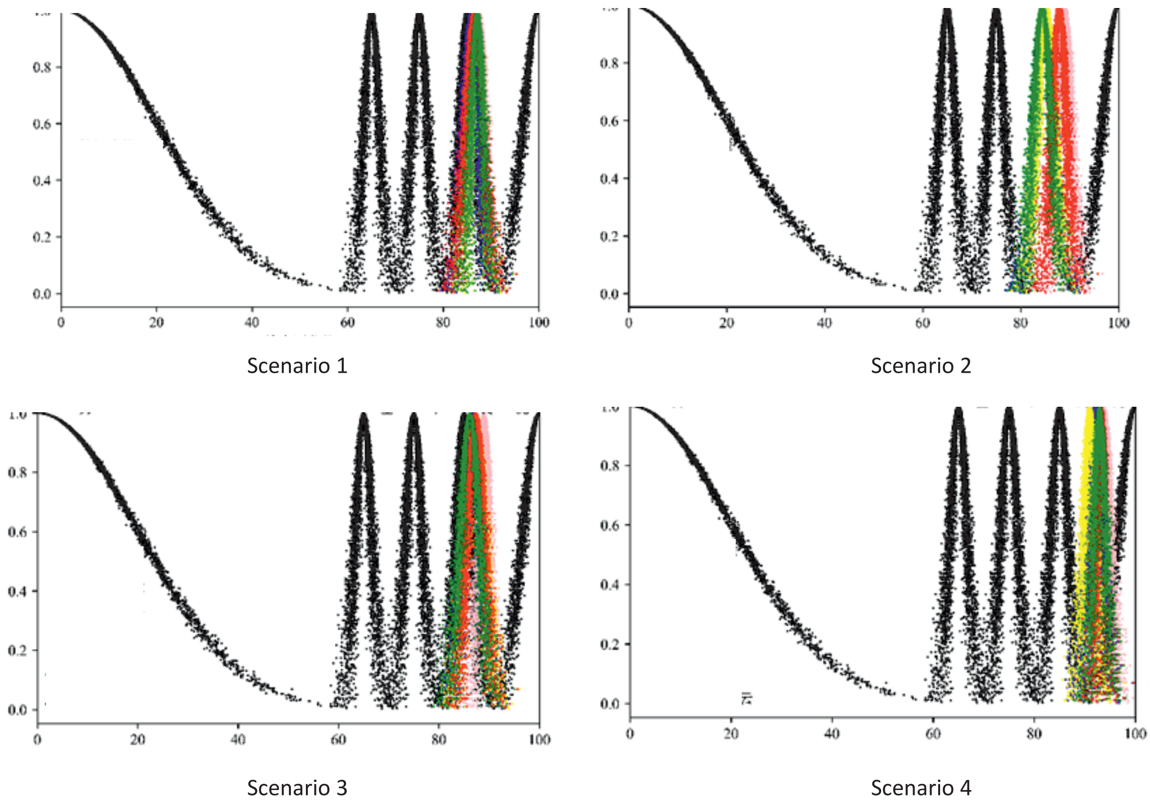

Fig. 8. Risk evaluation cloud atlas of first-level indicators for each gas-electric VPP scenario.

implementation of multienergy supply and multiload coupling conversion technology is crucial to improve the response willingness and performance ability of users. The coupling technology and credit management should be improved to reduce the level of system risk. When comprehensively considering the risks of multiple uncertainties, electric vehicles, and comprehensive demand response, the evaluation effect of each first-level index cloud is more effective, and the market risks and market acceptance faced by the participants are reduced, which further improves the reliability and stability of the coupled gas-electric virtual power plant participating in the energy and power market.

Conclusion

We analyzed the influence of the characteristics of different factors affecting virtual gas-and-electric power plants on the bidding process from multiple perspectives, and we developed a bidding risk assessment model for these power plants.

1) We constructed a comprehensive and scientific evaluation index system of virtual power plant operation risk. While considering the safety, stability, and economy of the operation of the virtual power plant, we also considered the influence of external factors such as market environment and policies, new security and management risks, and information security. By enriching and improving various indicators, the proposed rating system is both comprehensive and scientific.

2) We developed a cloud model evaluation method based on entropy weight. Considering the fuzziness of the evaluation indicators, we transformed each qualitative indicator to a quantitative indicator through the feedback correction of the traditional cloud model method. Considering the randomness of the indicators, we transmitted the randomness of the evaluation through the cloud generator to reasonably quantitatively evaluate the indicators. We visually displayed the operation risk evaluation results of a virtual power plant through a cloud map.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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