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Information Entropy Algorithm-Empowered Virtual Power Plant Multi-Subject Coupling Operation Risk Transmission Identification and Assessment

Jiangping Liu[1], Jing Wang[1], Song Deng[1] and Jiaxin Zhao[2,*]
[1] Hubei Electric Power Equipment Co., Ltd., Wuhan, Hubei, 430000, China
[2] Beijing TsIntergy Technology Co., Ltd., Beijing, 100080, China
Corresponding authors: (e-mail: 18810113620@163.com).

Abstract This paper constructs the risk identification framework of multi-subject virtual power plant, builds the operation risk assessment index system, and screens out the risk factors of virtual power plant. The entropy weight method and gray correlation theory are connected and jointly applied in the risk identification of multi-subject virtual power plant operation, and the risk assessment model of multi-subject virtual power plant based on entropy weight and gray correlation is established. A case study of multi-body virtual power plant is taken as an example. In the risk assessment index system, the weighting results of the first-level indexes are, in descending order: persistent risk, construction phase, preparation phase, operation phase, and handover phase. During the operation period, in addition to paying comprehensive attention to the risk factors that exist throughout the project cycle, it is also necessary to focus on controlling the risks faced during the construction phase to reduce the chances of risk occurrence. The operational risk level (Ⅰ ~ V) of the multi-body virtual power plant A is evaluated as -6.339, 2.206, -2.155, -11.387, -14.095 respectively, and the operational risk level of the multi-body virtual power plant A is evaluated as Class II (lower risk).

Index Terms entropy weight method, gray correlation, virtual power plant, multi-object coupling, risk assessment

I. Introduction

With the steady progress of the “double carbon” goal, the proportion of renewable energy in China's power system will continue to increase, and the traditional centralized power system is facing more and more challenges [1], [2]. On the one hand, the inherent stochastic, fluctuating and intermittent characteristics of wind and solar power generation pose serious challenges to the balance between supply and demand and stability of the power system [3]. On the other hand, the flexibility of the power system must be continuously improved to adapt to the uncertainty of renewable energy sources and changes in load demand [4]. The virtual power plant (VPP), as an advanced energy management system, can integrate resources such as distributed power sources, energy storage, and loads to achieve unified management and scheduling, thus improving energy utilization and enhancing the flexibility and reliability of the power grid [5]. In addition, multi-subject coupling can also convert electrical energy with other energy forms such as heat and cold energy, and synergistically optimize them through advanced control technology and information and communication technology to achieve higher comprehensive energy utilization [6].

Along with the challenges and opportunities there are naturally risks that cannot be ignored. VPP itself is also a double-edged sword, on the one hand it provides a tool for solving the realities of development, on the other hand the realities of the development of the problem will also bring the risk of loss to the VPP itself [7], [8]. On the issue of power market reform, since the release of the reform document, the effect of power market-oriented reform is obvious and rapid progress, but the market environment is bound to change accompanied by risk, how to effectively control the risks in the market reform has long been the center of attention of the various market players [9], [10]. Compared with traditional power plants, virtual power plants (VPPs) are characterized by diverse and environmentally friendly resources, collaborative operations, and a wider range of competition, etc., and their operational risks also show more complex characteristics such as the inevitability of risks brought by virtual characteristics, the contingency of risks in specific spatial and temporal forms, the potentiality and reality of risk objects, and the controllability and uncontrollability of operational risks [11]-[14]. Therefore, VPP needs to be more careful to recognize the risks brought about by changes in the market environment, and the operational risks it faces are more complex and urgent than those of conventional power plants.

Various operational risk identification activities in the VPP system are mainly the process of systematically classifying and analyzing various potential and obscure uncertainties in the operation process to reveal potential risks to the best of its ability [15], [16]. If risks are not accurately identified, it is impossible to know what risks are present in the operation of the virtual power plant and what risks may arise [17]. Effective and timely control of the "chances" of the emergence of risks can be a good way to reduce the number of situations that originate from the risks of the operation of the virtual power plant. Risk assessment is the process of analyzing and determining the risk of VPP operation, applying scientific methods to correctly and objectively assess the risk of VPP operation, and providing theoretical basis and methods for operation managers [18].

In this paper, after the basic research on multi-subject coupled virtual power plant, we construct the HHM framework and the risk dynamic identification framework of multi-subject virtual power plant risk identification, identify and screen the risk factors, form the risk identification list of multi-subject virtual power plant, and construct the risk assessment index system of multi-subject virtual power plant. The risk assessment model of multi-subject virtual power plant is established by the combination of entropy weight method and gray correlation theory. Through the risk assessment model, the case analysis is carried out with multi-body virtual power plant A as the research object. The weights, classical domains and section domains of risk assessment indicators are determined by entropy weight-gray correlation. Finally, the risk level in the operation of multi-body virtual power plant A is assessed.

II. Risk identification of multi-agent virtual power plants

II. A. Virtual power plant

Virtual Power Plant (VPP), as a kind of intelligent management technology for DER (distributed energy resources) [19], [20], aggregates independent DERs into a virtual whole, internally respects the pursuit of individual interests of DERs, and realizes the complementarity and coordination of each DER; externally, it formulates bidding strategies and participates in the trading of the electricity market as a whole.

The resources aggregated by VPP are diversified, including clean energy such as wind power and photovoltaic and controllable distributed power sources to participate in the trading of the electricity market, and flexible resources such as energy storage and flexible loads to provide energy balancing, rotating standby, frequency regulation, and other auxiliary services for the power grid. Therefore, the VPP that aggregates multiple DERs can participate in the trading of multiple power markets such as electric energy, peaking, frequency regulation, etc., which improves the market competitiveness of the VPP as a whole and of each DER, and obtains more economic benefits.

VPP achieves coordinated management and efficient integration of multiple DERs through internal coordination and optimization. Under the traditional centralized management mode, the central control unit completes the internal coordination and optimization of the VPP and formulates the power plans of internal members, and its core objective is to smooth out the power volatility of uncontrollable distributed power sources through the coordinated control of the VPP on the internal controllable distributed power sources and members of the energy storage, and explore the optimal power plan of the members, so as to improve the overall economic efficiency of the VPP.

The structure of the virtual power plant (VPP) is shown in Figure 1, where the VPP operator acts as a manager and aggregates wind power, photovoltaic (PV), controllable distributed power generation (CDG), energy storage, and flexible loads into a virtual whole, and each member of the VPP has a different function, and coordinates and cooperates with each other in order to enable the whole to effectively participate in the market transactions and obtain more economic benefits.

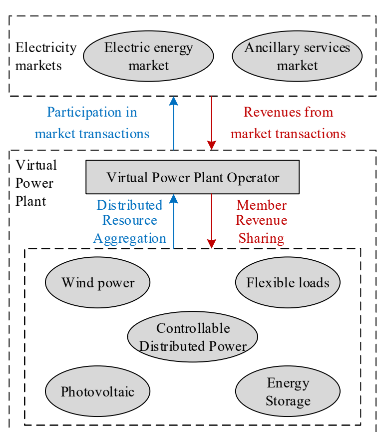

Figure 1: The Structure of virtual power plant

Functions of the VPP operator: as a manager, it has the characteristics of bilateral interaction of externally participating in the trading of the electricity market and internally coordinating and cooperating with each member.When the VPP operator participates in the electricity market externally, it accomplishes the acquisition of market information, the formulation of bidding plans, etc., and obtains the maximum market revenue.The VPP operator internally coordinates and cooperates with the members, realizing the coordination and interaction of the DERs to ensure the economic benefit of each members' economic benefits.

Functions of CDG: Common CDGs include gas units, cogeneration units, etc., which can respond quickly to scheduling commands, and can make power adjustments within a certain range, which can ensure the power balance of the VPP and provide backup.

Function of uncontrollable distributed power supply: common uncontrollable distributed power supplies are wind power generator sets and photovoltaic generator sets, which are greatly affected by natural weather and other factors, difficult to control, and have strong uncertainty of power output. In order to deal with the power uncertainty of uncontrollable distributed power sources, VPP needs to call internal CDG and flexibility resources to reserve backup to enhance the overall reliability and economy.

Functions of flexibility resource energy storage and flexible load: energy storage works in charging mode, which is equivalent to a load; it works in discharging mode, which is equivalent to a power source, and is able to formulate appropriate charging and discharging behaviors according to the needs. Flexible loads are able to perform load curtailment and load increase, thus adjusting the behavior of electricity consumption. Flexible resources can play a role in VPP by effectively transferring loads to realize peak shaving and valley filling, and participate in auxiliary services.

II. B. Virtual power plant risk identification

II. B. 1) Constructing a HHM framework for risk identification

The Multi-Agency Virtual Power Plant (VPP) project adopts the model of 25% government investment + operation subsidy. Under this model, the main stakeholders are government departments, social investors, the general public and other stakeholders, and the main operational phases of the project include planning, survey, design, financing, construction, operation and transfer. Stakeholders and project operation phases are the main core key points to control the project, which can be used as two perspectives for risk identification of this project. In addition, in risk identification, risk can be subdivided into social risk loss, economic risk loss and environmental risk loss according to the type of risk loss, which can basically cover the comprehensive risk loss.

Based on this, the article divides the perspective of risk identification of multi-body virtual power plants into three aspects: stakeholders, project operation stage and risk loss type. For the stakeholder perspective, the risk identification level under this perspective is categorized into four levels because it includes government departments, social investors, the public and other stakeholders. For the project operation phase perspective, the risk identification level under this perspective is categorized into six levels because it includes six aspects: planning, investigation, design, financing, construction, operation and handover. For the risk-loss perspective, the risk identification level under this perspective is divided into three levels because it includes three aspects: social risk loss, economic risk loss and environmental risk loss. Based on the identified risk identification perspectives and risk identification levels, the HHM framework for risk identification of multi-subject virtual power plants is determined as shown in Figure 2.

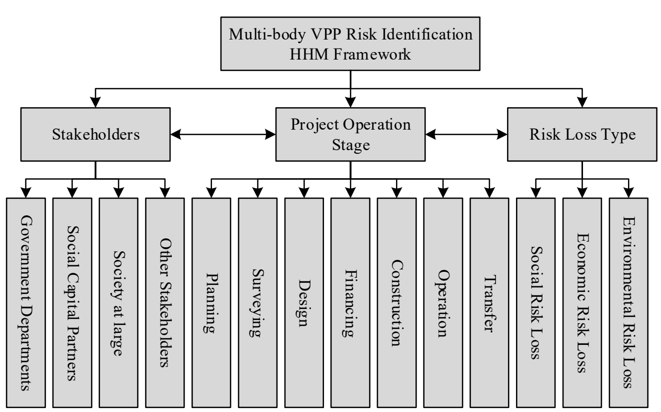

Figure 2: Risk identification HHM framework of multi-body VPP

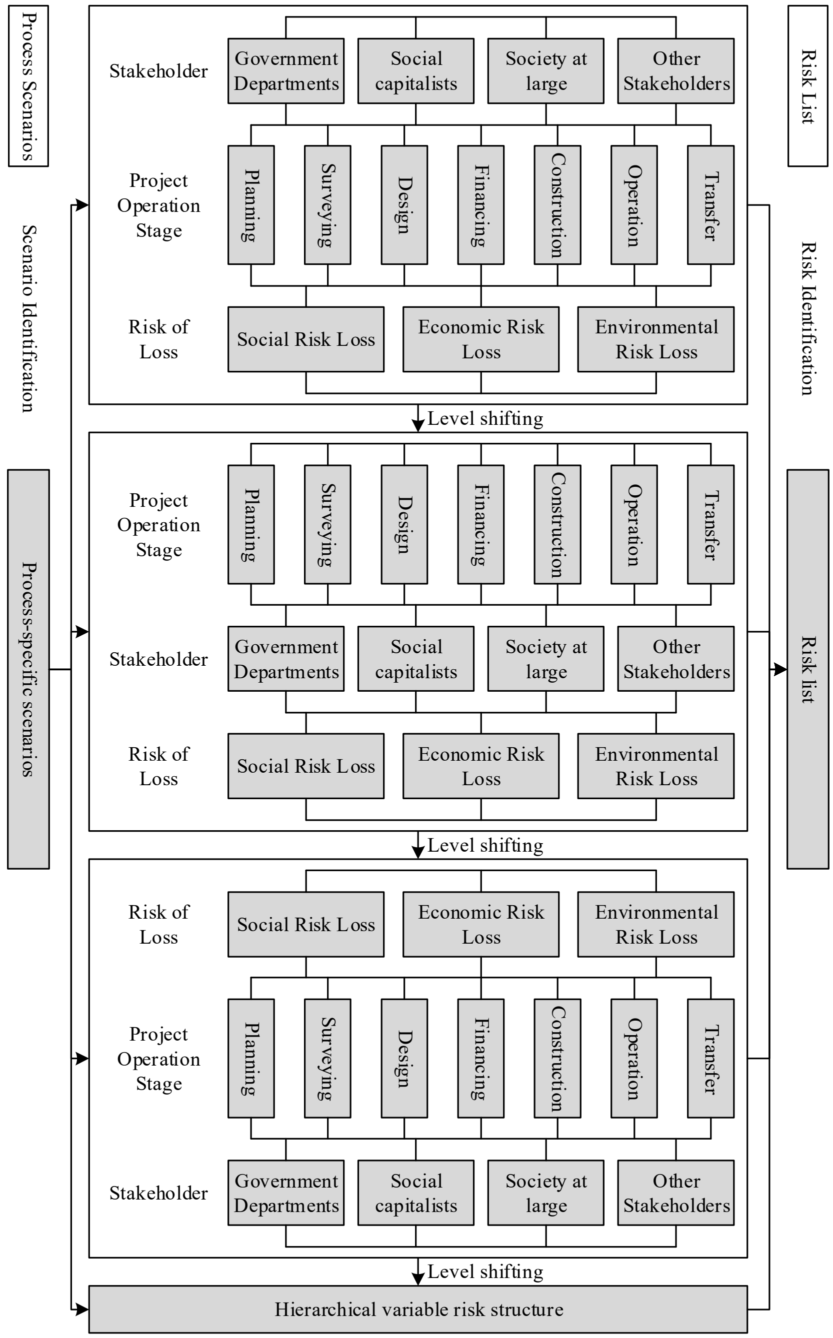

Figure 3: Risk identification dynamic framework of multi-body VPP

II. B. 2) Developing a dynamic risk identification framework

In the HHM framework for risk identification, the stakeholder perspective, the project operation stage perspective, and the risk loss perspective are in parallel. Based on the specific scenarios and characteristics of risk identification in multi-agency virtual power plants, the dynamic framework of project risk identification is constructed with the stakeholder perspective, the project operation stage perspective, and the risk loss perspective. Firstly, government departments, social capitalists, the public and other stakeholders are selected as the first level of the stakeholder perspective, planning, survey, design, financing, construction, operation and transfer are selected as the second level of the project operation stage perspective, and social risk loss, economic risk loss and environmental risk loss are selected as the third level of the risk loss type perspective.

When the risk identification of the scenario is finished, the risk identification levels are rearranged. Planning, investigation, design, financing, construction, operation and transfer from the perspective of project operation stage are selected as the first level, governmental departments, social capitalists, the public and other stakeholders from the perspective of stakeholders are selected as the second level, and social risk loss, economic risk loss and environmental risk loss from the perspective of risk loss type are selected as the third level.

When the risk identification of the scenario is finished, the risk identification levels are ranked again. The social risk loss, economic risk loss and environmental risk loss from the perspective of risk loss type are selected as the first level, the planning, survey, design, financing, construction, operation and handover from the perspective of project operation stage are selected as the second level, and the governmental departments, social capitalists, the public and other stakeholders from the perspective of stakeholders are selected as the third level. And so on by analogy until all the risks are identified. The dynamic framework for risk identification of multi-stakeholder virtual power plants is shown in Figure 3.

II. B. 3) Formation of a risk identification checklist

Based on the constructed dynamic framework for risk identification of multi-agency virtual power plants, the article identifies a total of 65 risk factors under each risk identification scenario. However, considering the time, technology, economic and other constraints in the project risk management work, it is impossible to track, manage and control all the risk factors. Therefore, it is necessary to filter the 65 risk factors identified, so as to filter and eliminate the risk of a lower probability of occurrence of risk, after the occurrence of a smaller degree of impact of the risk.

By filtering the risk factors of the multi-agency virtual power plant, the risk factors are identified and categorized to form a risk evaluation index system as shown in Table 1.

Table 1: Multi-body VPP risk evaluation index system

	Primary index	Secondary index
Multi-body VPP risk	Preparation stage (A)	Project approval delay risk (A1)
		Financing risk (A2)
		Design risk (A3)
		Public opposition risk (A4)
		Risk of demolition of land expropriation (A5)
		Risk of bidding process (A6)
		Risk of major social events (A7)
	Construction stage (B)	Project change risk (B1)
		Project quality risk (B2)
		Project accomplishment risk (B3)
		Cost overrun risk (B4)
		New technical risk (B5)
		Management decision risk (B6)
		Technical risk (B7)
		Risk of materials, resources, equipment and other supplies (B8)
	Operation stage (C)	Risk of change in market demand (C1)
		Competition risk of homogeneous project (C2)
		Charging standard risk (C3)
		Operating cost overrun risk (C4)
		Risk of operating management system (C5)
	Transition stage (D)	Risk of not reaching transition condition (D1)
	Persistent risk (E)	Contract file risk (E1)
		Policy risk (E2)
		Risk of laws and rules (E3)
		Inflation risk (E4)
		Government credit risk (E5)
		Government corruption risk (E6)
		Third party delay/default risk (E7)
		Risk of responsibility misallocation (E8)

III. Risk assessment modeling of multi-agent virtual power plants

III. A. Entropy weight method

Information entropy inherits the basic properties of thermodynamic entropy [21], but by distinguishing it from the entropy defined in thermodynamics, which is now applied in many social fields such as computers, economic management and engineering risk evaluation.

According to the principle of information theory, the entropy of a system is defined as when the system is in a number of different states, assuming that the probability of occurrence of each state $P_i\left(i=1,2,\cdots m\right)$:

$$e=-\sum_{i=1}^{m}p_i\times\ln p_i \tag{1}$$

Clearly, when $p_i=\frac{1}{m}(=1,2,\cdots m)$, the entropy takes its maximum value when the probability of various states occurring is the same:

$$e_{\max}=\ln m \tag{2}$$

From the formula, it can be seen that if the entropy value of an indicator e is smaller, it means that the degree of variation of the indicator value is larger, and it plays a larger role in the comprehensive evaluation, and its weight is also larger. If the entropy value of an indicator e is larger, it means that the degree of variation of the indicator value is smaller, the role in the comprehensive evaluation is smaller, and its weight is also smaller.

III. B. Gray correlation

III. B. 1) Concepts

Gray correlation is a part of gray theory [22], which is based on the sample data of each factor and describes the connection between factors through gray correlation. The quantitative model of gray correlation analysis is defined on the basis of four axioms of gray correlation the four axioms of gray correlation are normality, wholeness, even pair symmetry, and proximity.

(1) Normality:

$$0<\gamma\left(X_0,X_i\right)\le 1,\gamma\left(X_0,X_i\right)=1\Leftrightarrow X_0=X_i \tag{3}$$

(2) Holistic:

$$\begin{gathered}\text{For } X_i,X_j\in X=\left\{X_s\mid s=0,1,2,\ldots,m,m\ge 2\right\}\\ \text{There is } \gamma\left(X_i,X_j\right)\ne\gamma\left(X_j,X_i\right)(i\ne j)\end{gathered} \tag{4}$$

(3) Even pair symmetry:

$$\begin{gathered}\text{For any } X_i,X_j\in X\\ \text{There are } \gamma\left(X_i,X_j\right)=\gamma\left(X_j,X_i\right)\Leftrightarrow\left\{X_i,X_j\right\}\end{gathered} \tag{5}$$

(4) Proximity:

$$\left|x_0(k)-x_i(k)\right|\text{Smaller, }\gamma\left(x_0(k),x_i(k)\right)\text{Larger} \tag{6}$$

where the real $\gamma\left(X_0,X_i\right)$ is the gray correlation of X_0 with X_i and $\gamma\left(x_0(k),x_i(k)\right)$ is the gray correlation coefficient of X_i with X_0 at k the gray correlation coefficient.

III. B. 2) Common analyses

In this paper, three gray correlation methods commonly used today will be described and compared.

(1) Dunn's correlation method

Dunn's correlation is a measure of gray correlation based on the perspective of similarity.

Let the reference sequence be $X_0=\left\{x_0(k),k=1,2,\ldots,n\right\}$, and the compared sequence be $X_i=\left\{x_i(k),k=1,2,\ldots,n\right\}$, and $\left(i=1,2,\ldots,m\right)$. Then the gray correlation $\gamma\left(X_0,X_i\right)$ between X_0 and X_i is defined as:

$$\gamma\left(X_0,X_i\right)=\frac{1}{n}\sum_{k=1}^{n}\gamma\left(x_0(k),x_i(k)\right) \tag{7}$$

Among them:

$$\gamma\left(x_0(k),x_i(k)\right)=\frac{\min\limits_i\min\limits_k\left|x_0(k)-x_i(k)\right|+\rho\max\limits_i\max\limits_k\left|x_0(k)-x_i(k)\right|}{\left|x_0(k)-x_i(k)\right|+\rho_i\max\limits_i\max\limits_k\left|x_0(k)-x_i(k)\right|} \tag{8}$$

ρ is the discrimination coefficient, and $\rho \in [0,1]$, generally take 0.5. All m sequences gray correlation $\gamma(X_0, X_i)$ from the largest to the smallest order to get the correlation sequential set, and use this to judge the sequence X_i and X_0 the magnitude of the degree of correlation. The correlation method is to use the displacement difference $\left(\left|\Delta x_{0i} = x_0(k) - x_i(k)\right|\right)$ reflecting the similarity of the development process or the magnitude between the two sequences.

(2) Absolute correlation degree

The steps of absolute correlation calculation are as follows:

Step1: The original sequences $X_0 = \{x_0(k), k = 1, 2, \ldots, n\}$ and $X_i = \{x_i(k), k = 1, 2, \ldots, n\}$ are initialized:

$$Y_0 = \left\{ y_0(k) = \frac{x_0(k)}{x_0(1)}, k = 1, 2, \ldots, n \right\} \tag{9}$$

$$Y_i = \left\{ y_i(k) = \frac{x_i(k)}{x_i(1)}, k = 1, 2, \ldots, n \right\} \tag{10}$$

Step2: Calculate the absolute correlation between x_0 and x_i as:

$$r(X_0, X_i) = \frac{1}{n-1} \sum_{k=1}^{n-1} \frac{1}{1 + \left| \alpha^{(1)}\left(y_0(k+1)\right) - \alpha^{(1)}\left(y_i(k+1)\right) \right|} \tag{11}$$

Among them:

$$\alpha^{(1)}\left(y_0(k+1)\right) = y_0(k+1) - y_0(k) k = 1, 2, \ldots, n; i = 1, 2, \ldots, m \tag{12}$$

$$\alpha^{(1)}\left(y_i(k+1)\right) = y_i(k+1) - y_i(k) k = 1, 2, \ldots, n; i = 1, 2, \ldots, m \tag{13}$$

If the calculated γ is closer to 0 then the weaker the correlation between the factors, and vice versa, the stronger the correlation.

Absolute correlation has symmetry, comparability and uniqueness, which in essence utilizes the first order skewness $\left|\Delta x_i(k) - \Delta x_0(k)\right| \Delta x_i(k) = x_i(k) - x_i(k-1)$, $\Delta x_0(k) = x_0(k) - x_0(k-1)$ reflecting the similarity of the trend of the two sequential trends or the shape of the curves is more suitable for the application of the research on the analysis of correlation between multiple factors. Absolute correlation method does not have proximity and normality, and cannot scientifically define its critical value.

(3) T type correlation

For discrete time series, the so-called proximity of the relative change potentials of the two curves refers to the magnitude of the normalized increment of the original variables between the two time series at each corresponding time period $\Delta t_k = t_k - t_{k-1} \left(k = 2, 3, \cdots, n\right)$, and if in the case of Δt_k, the larger the difference between the increments, the smaller the correlation coefficient between the two time series in the Δt_k; the smaller the difference between the increments, the larger the correlation coefficient.

The correlation of two time series is defined as the weighted average of the correlation coefficients between Δt_k in each time period, with weights of Δt_k. It is calculated as follows:

$$\zeta(k) = \begin{cases} \operatorname{sgn}\left(\Delta y_1(k) \Delta y_2(k)\right) \dfrac{\min\left(\left|\Delta y_1(k)\right|, \left|\Delta y_2(k)\right|\right)}{\max\left(\left|\Delta y_1(k)\right|, \left|\Delta y_2(k)\right|\right)} \\ 0 \ Which \ \Delta y_1(k) \Delta y_2(k) = 0 \end{cases} \tag{14}$$

$$r(X_1, X_2) = \frac{1}{n-1} \sum_{k=2}^{n} \zeta(k) \tag{15}$$

Among them:

$$\Delta y_i(k) = y_i(k) - y_i(k-1) = \left(x_i(k) - x_i(k-1)\right) / D_i \tag{16}$$

$$D_i = \frac{\sum_{k=2}^{n} \left|\left(x_i(k)\right| - x_i(k-1)\right)}{n-1} \left(i = 2, 3, \cdots, n\right) \tag{17}$$

Among these three methods, Dunn's correlation method is relatively mature, effective and small in calculation, so Dunn's correlation will be chosen in this paper to analyze each risk factor of multi-subject virtual power plant.

III. C. Entropy-weighted gray correlation-based risk assessment model

III. C. 1) Entropy weighting method to determine the weight of each risk indicator

The risk indicator evaluation analysis in this paper is a multi-object virtual power plant risk evaluation model constructed on the theoretical basis of entropy weight method and gray correlation degree.

(1) Determination of evaluation index series

The data obtained by taking the risk indicators as a reference sequence and assigning values to each indicator through expert scoring is the original data, i.e., the comparison sequence:

$$Y=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{ij} \end{bmatrix}_{i\times j} \tag{18}$$

where r_{ij} denotes the result of the j expert's score on the i risk indicator.

(2) Standardized processing of data

There are two types of standardized processing, cost type and benefit type.

The cost type (the smaller the better) formula is expressed as:

$$Y_{ij}=\frac{r_{ij}-\min\left(r_i\right)}{\max\left(r_i\right)-\min\left(r_i\right)} \tag{19}$$

The efficiency-based (bigger is better) formula is expressed as:

$$Y_{ij}=\frac{\max\left(r_{ij}\right)-r_i}{\max\left(r_i\right)-\min\left(r_i\right)} \tag{20}$$

(3) Determine the entropy value e_i:

$$e_j=-\ln(m)^{-1}\sum_{i=1}^{m}P_{ij}\times\ln P_{ij} \tag{21}$$

$$P_{ij}=\frac{Y_{ij}}{\sum_{i=1}^{m}Y_{ij}} \tag{22}$$

(4) Calculate the weight w_j of each indicator by information entropy:

$$w_j=\frac{1-e_j}{\sum_{j=1}^{n}\left(1-e_j\right)} \tag{23}$$

III. C. 2) Comprehensive gray correlation evaluation method

(1) Determine the ideal indicator series

Let $Y_0=(y_1,y_2...y_j)$ is the ideal indicator series, i.e. the reference sequence. Since the larger the score, the larger the risk coefficient when judging the risk indicators, the reference sequence film and television the smallest value among the indicators.

(2) Indicator normalization

Generally speaking, the evaluation indicators have different scales and orders of magnitude, so it is not possible to directly compare the indicators. In order to ensure the reliability of the results, the original indicators need to be dimensionless. The raw data can be transformed into dimensionless values according to formula (20).

(3) Find the difference sequence, the maximum difference and the minimum difference according to $\Delta_{0i}(k)=\left|y_0'(k)-x_i'(k)\right|$, $i=1,2,\cdots,m$ Calculate the absolute value of the reference sequence and each of the remaining comparison sequences to form the following absolute value Matrix: $\left(\Delta_{01},\Delta_{02},\cdots,\Delta_{0n}\right)$. Also find the largest number (maximum difference) and the smallest number (minimum difference) in the difference matrix and denote them as $\Delta_{\max}$ and $\Delta_{\min}$ respectively.

(4) Calculate the correlation coefficient

The correlation coefficient indicates the degree of geometric difference between the curves, and the magnitude of the difference between the curves is used to measure the degree of correlation between the factors:

$$\zeta_{0i}(k)=\frac{\Delta_{\min}+\rho\Delta_{\max}}{\Delta_{0i}(k)+\rho\Delta_{\max}} \tag{24}$$

where ρ is the discrimination coefficient, ρ takes values within $[0,1]$, generally 0.5, yielding a correlation matrix of: $\zeta_{0i} = (\zeta_{01}, \zeta_{02}, \cdots, \zeta_{0i})$.

(5) Calculate the correlation degree

Based on the weight of each risk factor determined by the entropy weighting method $w_i = (w_1 \quad w_2 \quad \cdots \quad w_n)^{\mathrm{T}}$ and the correlation matrix derived in step 4, the degree of correlation is found γ_{0i}:

$$\gamma_{0i} = \sum_{i=1}^{n} \zeta_{0i} w_i \tag{25}$$

γ_{0i} is the relative ideal evaluation benchmark correlation of each evaluation index.

(6) Sorting by correlation

Compare the size of the correlation degree of each factor and sort it from the largest to the smallest.

The gray correlation of the multi-indicator evaluation object is calculated through the above steps, and then the correlation of each comparative sequence with the reference sequence is sorted from the largest to the smallest, and the smaller the correlation, the smaller the average distance between the comparative sequence and the reference sequence, and the smaller the risk coefficient thereof.

Table 2: Feature weight, entropy redundancy and index weight calculation results

Index	Entropy	Entropy redundancy	Weight
Project approval delay risk (A1)	0.9922	0.0097	0.0367
Financing risk (A2)	0.9912	0.0083	0.0265
Design risk (A3)	0.9915	0.0066	0.0275
Public opposition risk (A4)	0.9912	0.0075	0.0275
Risk of demolition of land expropriation (A5)	0.9929	0.0081	0.0259
Risk of bidding process (A6)	0.9907	0.0061	0.0385
Risk of major social events (A7)	0.9938	0.0069	0.0384
Project change risk (B1)	0.9909	0.0106	0.0435
Project quality risk (B2)	0.9919	0.0055	0.0285
Project accomplishment risk (B3)	0.9916	0.0089	0.0315
Cost overrun risk (B4)	0.9941	0.0086	0.0332
New technical risk (B5)	0.9939	0.0065	0.0372
Management decision risk (B6)	0.9905	0.0067	0.0418
Technical risk (B7)	0.9895	0.0056	0.0366
Risk of materials, resources, equipment and other supplies (B8)	0.9935	0.0069	0.0245
Risk of change in market demand (C1)	0.9909	0.0103	0.0377
Competition risk of homogeneous project (C2)	0.9898	0.0062	0.0354
Charging standard risk (C3)	0.9909	0.0076	0.0226
Operating cost overrun risk (C4)	0.9925	0.0105	0.0388
Risk of operating management system (C5)	0.9928	0.0094	0.0415
Risk of not reaching transition condition (D1)	0.9905	0.0104	0.0385
Contract file risk (E1)	0.9915	0.0077	0.0468
Policy risk (E2)	0.9899	0.0058	0.0285
Risk of laws and rules (E3)	0.9926	0.0067	0.0436
Inflation risk (E4)	0.9943	0.0055	0.0364
Government credit risk (E5)	0.9899	0.0096	0.0299
Government corruption risk (E6)	0.9924	0.0066	0.0324
Third party delay/default risk (E7)	0.9939	0.0082	0.0417
Risk of responsibility misallocation (E8)	0.9899	0.0104	0.0284

IV. Case Studies

In this paper, the multi-agent virtual power plant A project is selected as a case study for analysis.

IV. A. Determination of weights

Adopting the risk assessment model of multi-subject virtual power plant established in this paper, according to the data obtained from this volume, we use EXCEL to calculate the characteristic weight, entropy redundancy and indicator weight of each indicator, and the calculation results are shown in Table 2.

Based on the additivity of entropy and gray correlation, the weights and correlations of risk assessment indicators are calculated as shown in Table 3. The results of the weights in the first-level indicators are, in descending order, the persistent risk (0.2877), the construction phase (0.2768), the preparation phase (0.2210), the operation phase (0.1760), and the handover phase (0.0385). This indicates that the persistent risk factor has the greatest impact on project risk, the construction phase is greater, the preparation phase is next, the operation phase is average, and the handover phase is the smallest.

Table 3: Risk assessment index weight and correlation summary

Primary index	Weight	Correlation	Secondary index	Single weight	Total weight	Correlation	Rank
A	0.2210	0.823	A1	0.1661	0.0367	0.3649	29
			A2	0.1199	0.0265	0.7547	3
			A3	0.1244	0.0275	0.8158	2
			A4	0.1244	0.0275	0.6951	6
			A5	0.1172	0.0259	0.6979	4
			A6	0.1742	0.0385	0.6975	5
			A7	0.1738	0.0384	0.5054	20
B	0.2768	0.668	B1	0.1572	0.0435	0.6397	10
			B2	0.1030	0.0285	0.6584	9
			B3	0.1138	0.0315	0.5232	18
			B4	0.1199	0.0332	0.6351	11
			B5	0.1345	0.0372	0.3858	27
			B6	0.1510	0.0418	0.5851	15
			B7	0.1322	0.0366	0.5242	17
			B8	0.0885	0.0245	0.4096	22
C	0.1760	0.893	C1	0.2142	0.0377	0.3978	24
			C2	0.2011	0.0354	0.6601	8
			C3	0.1284	0.0226	0.6108	14
			C4	0.2205	0.0388	0.3936	25
			C5	0.2358	0.0415	0.5188	19
D	0.0385	0.635	D1	0.0385	0.0385	0.3844	28
E	0.2877	0.732	E1	0.1627	0.0468	0.6293	12
			E2	0.0991	0.0285	0.4287	21
			E3	0.1516	0.0436	0.6841	7
			E4	0.1265	0.0364	0.4039	23
			E5	0.1039	0.0299	0.5649	16
			E6	0.1126	0.0324	0.8204	1
			E7	0.1449	0.0417	0.3904	26
			E8	0.0987	0.0284	0.6274	13

IV. B. Determination of classical and sectional domains

According to the multi-subject virtual power plant operation risk evaluation index system, the classic domain of the index system is determined by financial statistics, government filed data and evaluation methods and parameters as a reference to get the section domains of each dimension of risk evaluation, and the classic domains and section domains of the multi-subject virtual power plant operation risk indexes are shown in Table 4.

Table 4: Classical domain and section of risk indicators for multi-body VPP

Index	Level 1	Level 2	Level 3	Level 4	Level 5	Section
A1	<0,1.5>	<1.5,2.5>	<2.5,3.5>	<3.5,4.5>	<4.5,6>	<0,6>
A2	<1,1.5>	<0.9,1>	<0.8,0.9>	<0.7,0.8>	<0.4,0.7>	<0.4,1.5>
A3	<8,10>	<7,8>	<5,7>	<3,5>	<0,3>	<0,10>
A4	<0,1.5>	<1.5,2.5>	<2.5,3.5>	<3.5,4.5>	<4.5,6>	<0,6>
A5	<0,1.5>	<1.5,2.5>	<2.5,3.5>	<3.5,4.5>	<4.5,6>	<0,6>
A6	<5,6>	<4,5>	<3,4>	<2,3>	<0,2>	<0,6>
A7	<0,1.5>	<1.5,2.5>	<2.5,3.5>	<3.5,4.5>	<4.5,6>	<0,6>
B1	<0,5>	<5,6>	<6,7>	<7,8>	<8,10>	<0,10>
B2	<1.5,1.6>	<1.4,1.5>	<1.3,1.2>	<1.1,1.2>	<1,1.1>	<0.9,1.1>
B3	<1.5,1.6>	<1.4,1.5>	<1.3,1.2>	<1.1,1.2>	<1,1.1>	<0.9,1.1>
B4	<1,1.1>	<1.1,1.2>	<1.2,1.3>	<1.3,1.4>	<1.4,1.5>	<.5,1.6>
B5	<8,10>	<6,8>	<4,6>	<2,4>	<0,2>	<0,10>
B6	<8,10>	<6,8>	<4,6>	<2,4>	<0,2>	<0,10>
B7	<8,10>	<6,8>	<4,6>	<2,4>	<0,2>	<0,10>
B8	<5,6>	<4,5>	<3,4>	<2,3>	<0,2>	<0,6>
C1	<0.5,0.8>	<0.8,1.0>	<1.1,1.2>	<1.2,1.3>	<1.3,1.5>	<0.5,1.5>
C2	<0,1.5>	<1.5,2.5>	<2.5,3.5>	<3.5,4.5>	<4.5,6>	<0,6>
C3	<8,10>	<6,8>	<4,6>	<2,4>	<0,2>	<0,10>
C4	<1,1.1>	<1.1,1.2>	<1.2,1.3>	<1.3,1.4>	<1.4,1.5>	<.5,1.6>
C5	<1,1.2>	<0.8,1>	<0.6,0.8>	<0.4,0.6>	<0.2,0.4>	<0.2,1.2>
D1	<0,1.5>	<1.5,2.5>	<2.5,3.5>	<3.5,4.5>	<4.5,6>	<0,6>
E1	<8,10>	<6,8>	<4,6>	<2,4>	<0,2>	<0,10>
E2	<8,10>	<6,8>	<4,6>	<2,4>	<0,2>	<0,10>
E3	<8,10>	<6,8>	<4,6>	<2,4>	<0,2>	<0,10>
E4	<0,0.5>	<0.5,0.8>	<0.8,1>	<1,1.2>	<1.2,1.4>	<0,1.4>
E5	<8,10>	<7,8>	<5,7>	<3,5>	<0,3>	<0,10>
E6	<1.5,5>	<5,6>	<6,7>	<7,8>	<8,10>	<1.5,10>
E7	<1.5,5>	<5,6>	<6,7>	<7,8>	<8,10>	<1.5,10>
E8	<1.5,5>	<5,6>	<6,7>	<7,8>	<8,10>	<1.5,10>

IV. C. Risk level determination and assessment

In order to calculate the results of the risk assessment, it is necessary to determine the risk level of the operation of the multi-body virtual power plant of Project A. According to the expert's suggestion, this paper divides the risk from low to high into five levels, and the risk level division is shown in Table 5.

Table 5: Classification of operation risk levels for multi-body VPP

Risk level	Risk description	Risk acceptability	Range	Risk control strategy
Ⅰ	Extremely low risk	Controllable	(0,2]	The risk is in control
Ⅱ	Relatively low risk	Acceptable	(2,4]	Take measures to reduce risk
Ⅲ	Normal risk	Preventable acceptance	(4,6]	Take measures to prevent risk
Ⅳ	Relatively high risk	Hard to accept	(6,8]	There are still higher risks to develop safeguards
Ⅴ	Extremely high risk	Unacceptable	(8,10]	The project should be stopped immediately

Following the multi-object virtual power plant risk assessment process, professionals in the field of electric power as well as relevant technical managers were convened to score the operational risk evaluation index system of Project A, and the average score was adopted as the metric value of the assessment object. Based on the weight data determined by the entropy weighting method described in Table 2, the following calculation results were obtained as shown in Table 6.

In response to the calculation results in Table 6, the assessment conclusion can be considered that the evaluation value of each risk level of Project A's multi-subject virtual power plant operation is -6.339 (Ⅰ), 2.206 (Ⅱ), -2.155

(Ⅲ), -11.387 (Ⅳ), and -14.095 (Ⅴ), then it is determined that the risk level of Project A's multi-subject virtual power plant operation is evaluated as Level II, which is a lower risk.

Table 6: Evaluation correlation data

Index	Correlation	Ⅰ	Ⅱ	Ⅲ	Ⅳ	Ⅴ
A1	4.6	-0.192	-0.222	0.196	-0.266	-0.331
A2	4.3	-0.377	-0.242	0.192	-0.258	-0.087
A3	5.1	-0.095	-0.224	0.558	-0.126	-0.412
A4	4.7	-0.182	-0.137	0.189	-0.564	-0.312
A5	4.4	-0.104	-0.288	0.087	-0.298	-0.221
A6	4.8	-0.198	-0.128	0.525	-0.568	-0.483
A7	5.2	-0.358	-0.078	0.201	-0.469	-0.831
A		-0.128	0.111	0.166	-0.385	-0.444
B1	4.4	-0.090	0.069	-0.178	-0.058	-0.688
B2	4.0	0.346	0.247	-0.476	-0.263	-0.229
B3	3.7	-0.326	0.256	0.068	-0.134	-0.356
B4	4.5	-0.121	0.091	0.496	-0.279	-0.815
B5	4.2	-0.103	-0.193	-0.133	-0.114	-0.784
B6	4.6	-0.067	0.185	0.371	-0.157	-0.339
B7	3.8	-0.189	0.195	-0.173	-0.672	-0.781
B8	3.6	-0.068	0.215	-0.656	-0.486	-0.114
B		-0.239	0.094	0.486	-0.241	-0.614
C1	2.5	0.268	-0.166	-0.108	-0.126	-0.623
C2	1.8	-0.377	0.034	0.157	-0.573	-0.758
C3	2.9	-0.063	0.127	-0.159	-0.127	-0.459
C4	4.1	-0.355	0.018	-0.252	-0.288	-0.561
C5	2.6	-0.386	0.246	0.468	-0.049	-0.417
C		-0.369	0.220	-0.485	-0.262	-0.126
D1	3.6	-0.366	0.285	-0.404	-0.377	-0.253
D		-0.366	0.285	0.701	-0.129	-0.121
E1	3.4	-0.191	0.123	-0.497	-0.499	-0.714
E2	3.2	-0.183	0.151	-0.236	-0.392	-0.172
E3	3.5	-0.269	0.050	-0.466	-0.189	-0.308
E4	2.9	-0.201	0.188	-0.177	-0.428	-0.196
E5	3.7	-0.216	0.117	-0.523	-0.617	-0.066
E6	3.5	-0.245	0.012	-0.620	-0.495	-0.149
E7	3.3	-0.152	0.198	-0.629	-0.352	-0.575
E8	3.0	-0.113	0.185	-0.545	-0.453	-0.364
E		-0.264	0.182	-0.299	-0.693	-0.392
Integrated correlation		-6.339	2.206	-2.155	-11.387	-14.095

V. Conclusion

Through the study of multi-object virtual power plant, construct the dynamic identification framework of risk identification to identify the risks in the operation process of virtual power plant, and screen out the list of operational risks, and construct the multi-object virtual power plant operational risk assessment index system. The risk assessment model is established by entropy weight-gray correlation method.

The weight results in the first-level indexes are, in descending order: persistent risk, construction phase, preparation phase, operation phase, and handover phase, and their weights are 0.2877, 0.2768, 0.2210, 0.1760, and 0.0385, respectively, which indicates that the persistent risk factors during the operation period have the greatest impact on the risk of multi-body virtual power plants, and the relevant departments should pay attention to them. The case study of multi-subject virtual power plant A, its operational risk Ⅰ, Ⅱ, Ⅲ, Ⅳ, Ⅴ grade evaluation value were -6.339, 2.206, -2.155, -11.387, -14.095, multi-subject virtual power plant A's operational risk level is assessed as Ⅱ, is a lower risk.

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