Research on risk assessment method of energy system based on data mining

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Abstract: In order to overcome the problem of data index confusion and index weight ambiguity in the traditional energy system risk assessment process, this paper proposes an energy system risk assessment method based on data mining. This method USES data mining technology and quantitative index processing method to select risk assessment index of energy system, construct risk assessment index system of energy system, determine the weight of risk assessment index of energy system, and build risk assessment model of energy system on this basis. The experimental results show that the weighing accuracy and evaluation accuracy of the proposed method are above 90%, and the skewness coefficient is always close to 0. The method has a high degree of rationality in energy risk index selection, high precision in index weight and high accuracy in evaluation results, which can effectively guarantee the safety of urban energy system.

Keywords: data mining; energy system; indicator system; risk assessment.

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1 Introduction

The basis of human existence is energy, which is also the economic lifeline of the country. Nowadays, the world is facing the problem of ensuring the sustainable supply of energy for human society while reducing environmental pollution (Dong et al., 2018). Many countries are facing the dual challenges of environment and resources, and have planned the integrated energy system in the future development strategy. As the same as heating, power supply, cooling and gas supply at present, people's basic requirements for the comprehensive energy system are economy, reliability and safety (Wang and Sun, 2017). The risk level of energy system can be reflected by quantitative or qualitative indicators through risk assessment to guide the production practice activities of integrated energy system, such as maintenance, operation, etc. (Wang, 2016). With the continuous improvement of economic and social development, people's demand for the reliability of energy supply is directly connected with the comprehensive energy system in physics, such as heat, electricity, cold and gas. In the above context, it is particularly important to ensure the reliability of the energy system, making the risk assessment method for energy system become a research hotspot (Hasanipanah et al., 2016). The current risk assessment method of energy system has the problems of low rationality of indicator, low accuracy of indicator weight and low accuracy of assessment results, so it is necessary to study the risk assessment method of energy system (Liu et al., 2016).

Xing et al. (2016) put forward the risk assessment method of energy system based on risk field. This method analyses the mechanism of risk receptor and risk field formation on the basis of risk field theory, identifies the risk source with the example of energy system, and establishes the environmental risk field with the combination of set pair analysis method and the result of risk source identification, so as to realise the risk assessment of energy system through risk field. The risk assessment results obtained by this method are inconsistent with the actual situation, mainly because there is no accurate acquisition of assessment indicators in the method. Ma et al. (2017) put forward a risk assessment method for energy system based on entropy weight method and AHP. This method obtains the risk assessment indicator of energy system through field investigation, constructs the risk assessment indicator system, introduces the objective preference coefficient and the subjective preference coefficient on the basis of entropy weight method and AHP to carry on the linear weighting processing to the corresponding weight of the risk assessment indicator, so as to obtain the comprehensive weight, and construct the risk assessment indicator system. In order to realise the risk assessment of energy system, the fuzzy comprehensive assessment model of energy system risk is established, and the rationality of the indicator selected by this method is relatively low. Sheng et al. (2018) put forward the risk assessment method of energy system based on load duration curve. By comprehensively considering the economy and safety of energy system equipment operation, new indicators such as safety risk penalty factor, average load rate and maximum transportable load are put forward. The impact of safety risk penalty factor by load duration curve is analysed, and according to the analysis results, the risk assessment of energy system is realised through the risk assessment model. The weight error of the assessment indicator calculated by this method is large, and the accuracy of the indicator weight is low. Chen et al. (2016) put forward the risk assessment method of energy system based on Bayesian network. This method combines fault tree and expert experience to build Bayesian network structure. The causal relationship between risk accidents and causes is analysed through Bayesian network structure, and the probability of risk occurrence in energy system is calculated through fuzzy comprehensive assessment method. Through the Dirichlet model and risk registration form, the risk assessment of the energy system is realised. The error of the assessment results obtained by this method is large, and the assessment accuracy is low (Valenzuela et al., 2018).

In order to solve the problems in the above methods, a risk assessment method for energy system based on data mining is proposed. The method of data mining is used to obtain the risk assessment index reasonably and to strengthen the organisation of the risk data index of energy system. The weight of risk assessment index of energy system is determined by means of tomographic analysis to improve the accuracy of index weight.

2 Application of data mining technology

2.1 *Energy system risk assessment index data selection*

The risk assessment method of energy system based on data mining selects the risk assessment indicator of energy system through the qualitative indicator processing method and the quantitative indicator processing method, and constructs the risk assessment indicator system of energy system.

2.1.1 *Qualitative indicator processing method*

It is the essence of normalisation to get the membership degree corresponding to fuzzy comment on the membership function of each assessment result (Long and Zhang, 2016).

Let $U = \{u_1, u_2, u_3, u_4\}$ represent the risk assessment indicator set of energy system, $V = \{v_1, v_2, v_3, v_4\}$ represent the fuzzy assessment set, including better, good, general, bad and worse. The assessment results include poor, excellent, medium and good, which are represented by $W = \{w_1, w_2, w_3, w_4\}$.

Let u_R represent the risk assessment indicator of energy system, $X_R^*(w_k)$ represent the membership function of the risk assessment indicator of energy system u_R in each comment result w_k. The mining is based on the overall indicators, and the expression is as follows:

$$X_R^*(w_k) = \frac{\sum_{m=1}^{7} \min\left(v_{j^m}, w_{k^m}\right)}{\sum_{m=1}^{7} \max\left(v_{j^m}, w_{k^m}\right)}, k = 1, 2, 3, 4 \tag{1}$$

Let $X_R(w_k)$ represent the mining level corresponding to the assessment result set of fuzzy comments. The calculation formula is as follows through the normalisation of membership function $X_R^*(w_k)$:

$$X_R(w_k) = \frac{X_a^*(w_k)}{\sum_{k=1}^{4} X_a^*(w_k)} \tag{2}$$

$$E_a(w_k) = \{e(w_1), e(w_2), e(w_3), e(w_4)\} \tag{3}$$

Let $E_a(w_k)$ represent the utility value corresponding to the assessment result set, and take the value in the interval [0,1]. The calculation formula is as follows:

The assessment value of a risk assessment indicator of energy system can be calculated by the utility value, i.e. the initial fuzzy membership function value Y_a of the qualitative indicator of energy system risk assessment. The calculation formula is as follows:

$$Y_a = \sum_{k=1}^{4} X_a(w_k) \times E_a(w_k) \tag{4}$$

2.1.2 Quantitative indicator processing method

The risk assessment method of energy system based on data mining uses range transformation to standardise the treatment of quantitative assessment indicators. On the basis of transformation, the data as small as possible or as large as possible are obtained.

If the risk assessment indicator of energy system belongs to the type of the greater the better, there is the following formula:

$$y_{ij} = \frac{x_{ij} - x_{\min}(j)}{x_{\max}(j) - x_{\min}(j)} \tag{5}$$

If the risk assessment indicator of energy system belongs to the type of the smaller the better, the re-mining results are as follows:

$$y_{ij} = \frac{x_{\max}(j) - x_{ij}}{x_{\max}(j) - x_{\min}(j)} \tag{6}$$

In the formula, y_{ij} describes the data obtained through range transformation; x_{ij} describes the original data; $x_{\min}(j)$ describes the minimum value corresponding to risk assessment indicator j of energy system; $x_{\max}(j)$ describes the maximum value corresponding to risk assessment indicator j of energy system.

2.2 Risk assessment indicator system of energy system

The risk assessment method of energy system based on data mining divides energy system into power system, wind system and water supply system. The assessment indicators of power system, wind system and water supply system are selected respectively, to construct the risk assessment indicator system of energy system.

2.2.1 Risk assessment indicators of electrical system

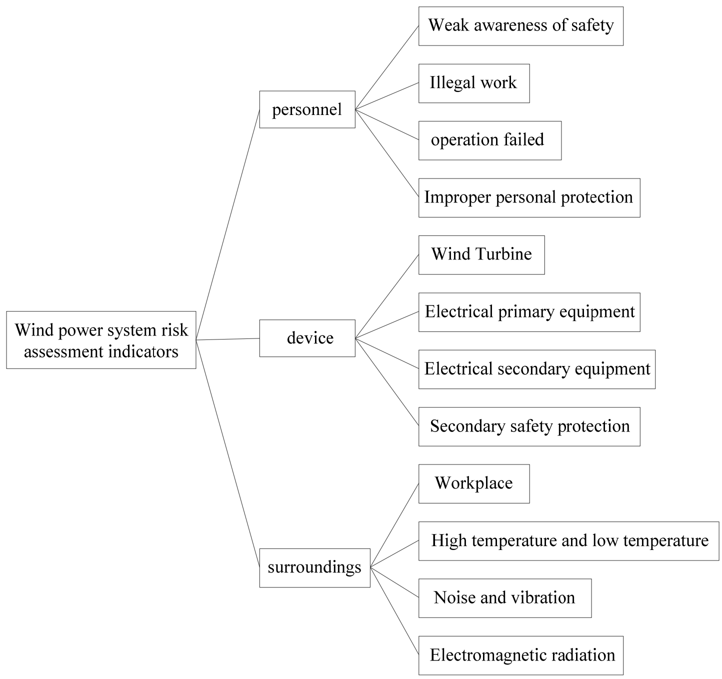
The risk assessment method of energy system based on data mining divides the risk assessment indicator system of electrical system into four levels, among which the first level includes safety management risk, personnel risk, environmental risk and inherent risk; the second level includes electricity supervision, operators, training management, other personnel, management system, electrical circuit, natural environment, social environment and electrical equipment (Abdollahzadehmoradi et al., 2019; George-Williams et al., 2018). The indicator system of electrical system risk assessment constructed by the risk assessment method of energy system based on data mining is as follows:

Figure 1 Risk assessment indicators of electrical system

2.2.2 Risk assessment indicators of wind system

The risk assessment method of energy system based on data mining constructs the risk assessment indicator system of wind system in three aspects of personnel, equipment and environment, as shown in Figure 2.

Figure 2 Risk assessment indicators of wind system



2.2.3 Risk assessment indicators of water supply system

According to the risk assessment method of energy system based on data mining, the risk assessment indicators of water supply system are divided into four primary assessment indicators, namely, secondary water supply system, raw water system, water transmission and distribution system and water production system. The risk assessment indicator system of water supply system is constructed as follows:

3 Energy system risk assessment model construction

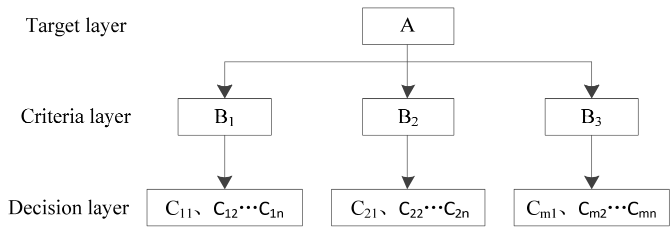
3.1 Risk assessment model weight acquisition

(1) *Hierarchical structure model*:

The risk assessment method of energy system based on data mining determines the weight of risk assessment indicator of energy system through the method of tomographic analysis, makes decision-making problems in hierarchy and organisation, and constructs the hierarchical structure model. Generally, the hierarchical structure is divided into decision-making level, quasi level and target level. All relevant factors are sorted according to the order from target to decision (Chen et al., 2016; Sarshar et al., 2017), and the hierarchy chart is obtained as follows:

Figure 3 Risk assessment indicators of water supply system

Figure 4 Hierarchy chart



(2) *Judgment matrix*:

For a risk assessment indicator of energy system of the previous level, the importance of the risk assessment indicator of energy system and the related indicators of this level is compared, and the judgment matrix is constructed according to the comparison results:

$$A = \delta_{ij} n \times n = \begin{bmatrix} \delta_{11} & \delta_{12} & \cdots & \delta_{1n} \\ \delta_{21} & \delta_{22} & \cdots & \delta_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \delta_{n1} & \delta_{n2} & \cdots & \delta_{nn} \end{bmatrix} \tag{7}$$

In the formula, δ_{ij} represents the importance scale value of factors B_i and B_j relative to A, and its calculation formula is as follows:

$$\delta_{ij} = \frac{B_i}{B_j} \tag{8}$$

(3) *Consistency inspection*:

In order to ensure the consistency of expert thinking when judging the importance of risk assessment indicators for energy system, the judgment matrix is constructed by the following consistency test:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{9}$$

Generally, $CI > 0$, $\lambda_{\max} > n$, and the consistency increases with the decrease of *CI* value. When *CI* value is 0, it indicates complete consistency.

The process of determining the weight of risk assessment indicator for energy system based on data mining is as follows:

(1) *Establishment of judgment matrix B*:

$$B = \begin{bmatrix} \delta_{11} & \delta_{12} & \cdots & \delta_{1n} \\ \delta_{21} & \delta_{22} & \cdots & \delta_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \delta_{n1} & \delta_{n2} & \cdots & \delta_{nn} \end{bmatrix} \tag{10}$$

(2) *The Eigenvalue and Eigenvector are calculated, and the judgment matrix is normalised by the following formula*:

$$\overline{\delta_{ij}} = \frac{\delta_{ij}}{\sum_{i=1}^{n} \delta_{ij}} \left(i = 1, 2, \cdots, n \right) \tag{11}$$

Judgment matrix is summed by column:

1 *The first column*:

$$s_1 = \sum_{i=1}^{n} \delta_{i1} = \delta_{11} + \delta_{21} + \cdots + \delta_{n1} \left(i = 1, 2, \cdots, n \right) \tag{12}$$

2 *The second column*:

$$s_2 = \sum_{i=1}^{n} \delta_{i2} = \delta_{12} + \delta_{22} + \cdots + \delta_{n2} \left(i = 1, 2, \cdots, n \right) \tag{13}$$

3 *The n-th column*:

$$s_n = \sum_{i=1}^{n} \delta_{in} = \delta_{1n} + \delta_{2n} + \cdots + \delta_{nn} \left(i = 1, 2, \cdots, n \right) \tag{14}$$

Normalising elements:

$$\begin{cases} \overline{\delta_{11}} = \dfrac{\delta_{12}}{\sum_{i=1}^{n} \delta_{i1}} \\ \overline{\delta_{12}} = \dfrac{\delta_{12}}{\sum_{i=1}^{n} \delta_{i2}} \\ \quad \vdots \\ \overline{\delta_{1n}} = \dfrac{\delta_{1n}}{\sum_{i=1}^{n} \delta_{in}} \end{cases} \tag{15}$$

$$\begin{cases} \overline{\delta_{21}} = \dfrac{\delta_{21}}{\sum_{i=1}^{n} \delta_{in}} \\ \overline{\delta_{22}} = \dfrac{\delta_{22}}{\sum_{i=1}^{n} \delta_{in}} \\ \quad \vdots \\ \overline{\delta_{2n}} = \dfrac{\delta_{2n}}{\sum_{i=1}^{n} \delta_{in}} \end{cases} \tag{16}$$

$$\begin{cases} \overline{\delta_{n1}} = \dfrac{\delta_{n1}}{\sum_{i=1}^{n} \delta_{in}} \\ \overline{\delta_{n2}} = \dfrac{\delta_{n2}}{\sum_{i=1}^{n} \delta_{in}} \\ \quad \vdots \\ \overline{\delta_{nn}} = \dfrac{\delta_{nn}}{\sum_{i=1}^{n} \delta_{in}} \end{cases} \tag{17}$$

Through the above process, the matrix B is obtained

$$\overline{B} = \begin{bmatrix} \overline{\delta_{11}} & \overline{\delta_{12}} & \cdots & \overline{\delta_{1n}} \\ \overline{\delta_{21}} & \overline{\delta_{22}} & \cdots & \overline{\delta_{2n}} \\ \cdots & \cdots & \cdots & \cdots \\ \overline{\delta_{n1}} & \overline{\delta_{n2}} & \cdots & \overline{\delta_{nn}} \end{bmatrix} \tag{18}$$

The vector $\overline{W}$ is obtained by adding the judgment matrix $\overline{B}$, which is expressed as follows:

$$\overline{W} = \sum_{j=1}^{n} \overline{\delta_{ij}} \left(i = 1, 2, \cdots, n \right) \tag{19}$$

The vector $\overline{W}$ is normalised to obtain the matrix W:

$$W = \left[w_1, w_2, \cdots, w_n \right]^T \tag{20}$$

$$w_i = \frac{\overline{w_i}}{\sum_{j=1}^{n} \overline{w_i}} \tag{21}$$

The Eigenvector is the matrix W calculated by formula (20).

Let $\lambda_{\max}$ represent the maximum Eigenvalue, and its calculation formula is as follows:

$$\lambda_{\max} = \sum_{1}^{n} \frac{\left(BW \right)_i}{nW_i} \tag{22}$$

where $(BW)_i$ describes the i-th element corresponding to vector BW, and W_i represents the i-th element existing in vector W.

The risk assessment method of energy system based on data mining revises the weight of risk assessment indicator of energy system by entropy weight method. The specific process is as follows:

(1) Normalise the items existing in matrix B to obtain the standard matrix $\overline{B}$

$$\overline{B} = \begin{bmatrix} \overline{\delta_{11}} & \overline{\delta_{12}} & \cdots & \overline{\delta_{1n}} \\ \overline{\delta_{21}} & \overline{\delta_{22}} & \cdots & \overline{\delta_{2n}} \\ \cdots & \cdots & \cdots & \cdots \\ \overline{\delta_{n1}} & \overline{\delta_{n2}} & \cdots & \overline{\delta_{nn}} \end{bmatrix} \tag{23}$$

(2) Let E_j represent the information entropy corresponding to the risk assessment indicator of energy system, and its calculation formula is as follows:

$$E_j = -k\sum_{i=1}^{n}\overline{\delta_{ij}}\left(i, j = 1, 2, \cdots, n\right) \tag{24}$$

$$k = \frac{1}{\ln n} \tag{25}$$

(3) Let w_j represent the entropy weight corresponding to the risk assessment indicator of energy system, and its calculation formula is as follows:

$$w_j = \frac{1 - E_j}{n - \sum_{j=1}^{n} E_j} \tag{26}$$

(4) According to the calculated entropy weight, the final weight corresponding to the risk assessment indicator of energy system is obtained

$$\omega_j^{'} = \frac{\omega_j w_j}{\sum_{j=1}^{n}\omega_j w_j} \tag{27}$$

3.2 Risk assessment of energy system under weight acquisition

The risk assessment method of energy system based on data mining introduces the concept of 'Distance' between risk level and risk assessment indicator (Wang et al., 2016). The risk assessment indicator system of energy system constructed by the risk assessment method of energy system based on data mining contains many risk assessment indicators. The points in the multi-dimensional coordinate system represent the risk assessment indicators. The relationship between risk level and risk assessment indicators is described by the distance between points in the coordinate system (Wang and Li, 2018; Wu, 2017).

Let d_{ij} represent the absolute value distance, and its calculation formula is as follows:

$$d_{ij} = \sum_{k=1}^{m}\left|x_{ik} - x_{jk}\right| \tag{28}$$

Let d_{ij}^{*} represent the Euclidean distance, and its calculation formula is as follows:

$$d_{ij}^{*} = \left[\sum_{k=1}^{m}\left(x_{ik} - x_{jk}\right)^2\right]^{\frac{1}{2}} \tag{29}$$

According to the standard Eigenvalues of known risk assessment indicators of c levels or states, the sample set is identified, and the matrix Y of standard Eigenvalues of $m \times c$ level risk assessment indicators is obtained

$$Y = \left(y_{ih}\right) \tag{30}$$

In the formula, y_{ih} describes the standard characteristic value corresponding to the level or status of risk assessment indicator i when h is selected.

According to the increase and decrease of indicator standard Eigenvalues, the risk assessment indicators of energy system are divided into two categories, i.e. increasing type and decreasing type (Li et al., 2018; Dobrota et al., 2016), and the membership functions corresponding to the increasing type and decreasing type of risk assessment indicators of energy system are as follows:

$$r_{ij} = \begin{cases} 0 & x_{ij} \leq y_{ic} \\ \dfrac{x_{ij} - y_{ic}}{y_{i1} - y_{ic}} & y_{i1} > x_{ij} > y_{ic} \\ 1 & x_{ij} \geq y_{ic} \end{cases} \tag{31}$$

$$s_{ij} = \begin{cases} 0 & x_{ij} \leq y_{ic} \\ \dfrac{y_{ih} - y_{ic}}{y_{i1} - y_{ic}} & y_{i1} > y_{ih} > y_{ic} \\ 1 & y_{ih} \geq y_{i1} \end{cases} \tag{32}$$

The standard Eigenvalue matrix and the risk assessment indicator can be transformed into the relative membership matrix of the standard Eigenvalue and the selected risk assessment indicator through the relative membership function:

$$R = \left(r_{ij}\right) \tag{33}$$

$$S = \left(s_{ih}\right) \tag{34}$$

The row vectors $\left(s_{11}, s_{12}, \cdots, s_{1c}\right)$, $\left(s_{21}, s_{22}, \cdots, s_{2c}\right)$, $\left(s_{m1}, s_{m2}, \cdots, s_{mc}\right)$ of the matrix S are compared with the membership degree $r_{1j}, r_{2j}, \cdots, r_{mj}$ corresponding to m risk assessment indicators. According to the comparison results, the lower level value a_j and the upper level value b_j are obtained (Qu et al., 2018; Bui et al., 2016).

Let u_{hj} represent the membership degree of sample j when it belongs to level h. Combined with the calculated risk assessment indicator weight of energy system ω (Ji et al., 2016; Ma et al., 2016), the difference between the level h and the sample j is described by the weighted generalised Euclidean weight distance D_{hj}

$$D_{hj} = u_{hj} d_{hj} = u_{hj} \sqrt{\sum_{i=1}^{m} \left[\omega_i \left(r_{ij} - s_{ih}\right)\right]^2} \tag{35}$$

The objective function is established to solve the optimal relative membership of class h sample j for A.

$$\min\left\{F\left(u_{hj}\right)=\sum_{h=a_j}^{b_j}D_{hj}^2\right\} \tag{36}$$

Set constraints:

$$\sum_{h=a_j}^{b_j}u_{hj}=1, 0\le u_{hj}\le 1, \sum_{i=1}^{m}\omega_i=1, \omega_i>0 \tag{37}$$

The objective function is solved to obtain the risk assessment model of energy system (Yan et al., 2016; Ford et al., 2017):

$$\begin{cases} & 0 & n<a_j \; or \; h>b_j \\ u_{hj}= & \dfrac{1}{\sum_{k=1_j}^{b_j}\left\{\dfrac{\sum_{i=1}^{m}\left[\omega_i\left(r_{ij}-s_{ih}\right)\right]^p}{\sum_{i=1}^{m}\left[\omega_i\left(r_{ij}-s_{ik}\right)\right]^p}\right\}^{\frac{2}{p}}} & a_j\le h\le b_j, d_{hj}\ne 0 \\ & 1 & d_{hj}=0 \end{cases} \tag{38}$$

where p represents the distance parameter.

4 Experiment and discussion

In order to verify the overall effectiveness of the risk assessment method for energy system based on data mining, it is necessary to test the risk assessment method for energy system based on data mining, and test the risk assessment method for energy system based on data mining in Matlab platform.

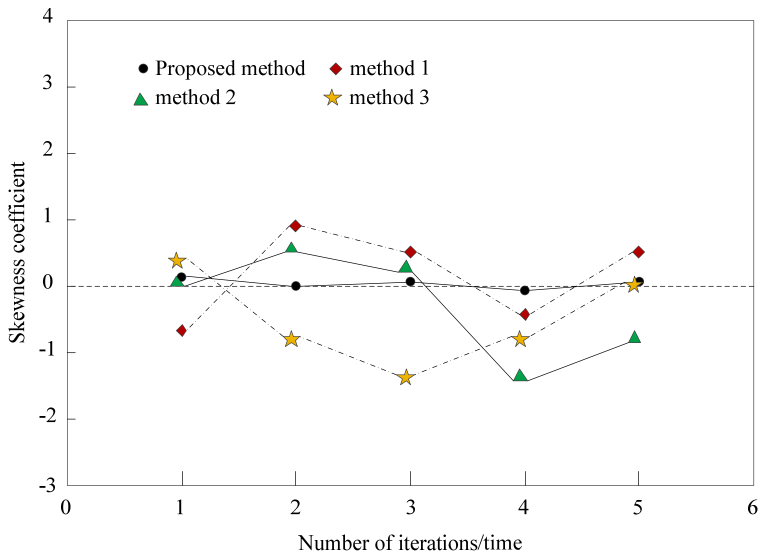
The experiment is divided into three parts. The assessment indicators of the effectiveness of different methods are bias coefficient, weight accuracy and assessment accuracy. Three traditional methods are used as the experimental control group, which are risk assessment method of energy system based on risk field, risk assessment method of energy system based on entropy weight method and AHP, and risk assessment method of energy system based on load duration curve. The results are as follows.

4.1 Comparison of skewness coefficients of different methods

By the coefficient of skewness testing reasonable risk assessment index of the degree, the coefficient of skewness is close to zero, the higher the risk assessment index of the reasonable degree, the energy system risk assessment method based on data mining (proposed method) is put forward, based on the field of energy system risk assessment method (method 1), the energy system based on entropy weight method and AHP risk assessment method (method 2) and energy system risk assessment method based on the load duration curve method (3) were tested in different number of iterations, the skewness coefficient comparison, numerical method is close to zero to prove that the higher the degree of evaluation index is reasonable.

The index skewness coefficients of the four different methods are shown in Figure 5.

Figure 5 Skewness coefficient of four different methods



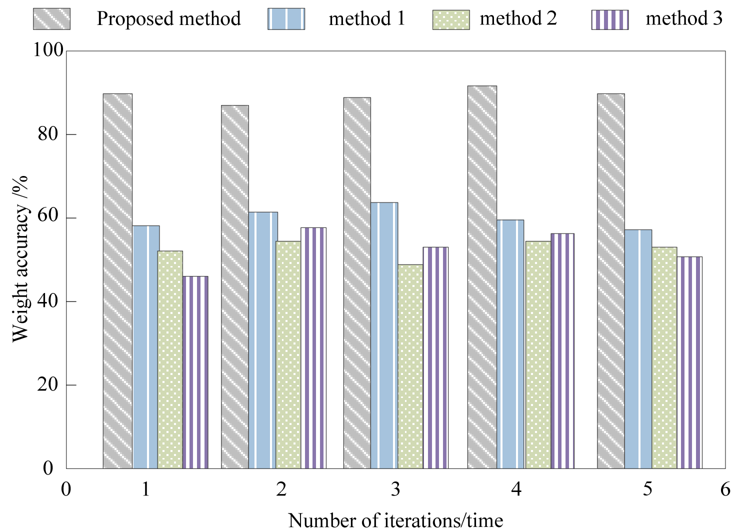
It can be seen from the analysis of Figure 5 that the skewness coefficient of the comparative research method and the other three traditional methods is the closest to zero, which is because the method processes the risk assessment indicator through the qualitative indicator processing method and the quantitative indicator processing method, improving the rationality of the assessment indicator.

4.2 Comparison of weight accuracy of different methods

The test was carried out in different iteration times, and the accuracy of index weight was compared with the four methods. The higher the value, the higher the accuracy of method weight. The test results are as shown in Figure 6.

Analysis of Figure 6 shows that the weight accuracy of the research method is significantly higher than that of the traditional method. This is because the risk assessment method for energy system based on data mining modifies the weight of the risk assessment indicator of energy system, and improves the accuracy of the weight of the risk assessment method for energy system based on data mining.

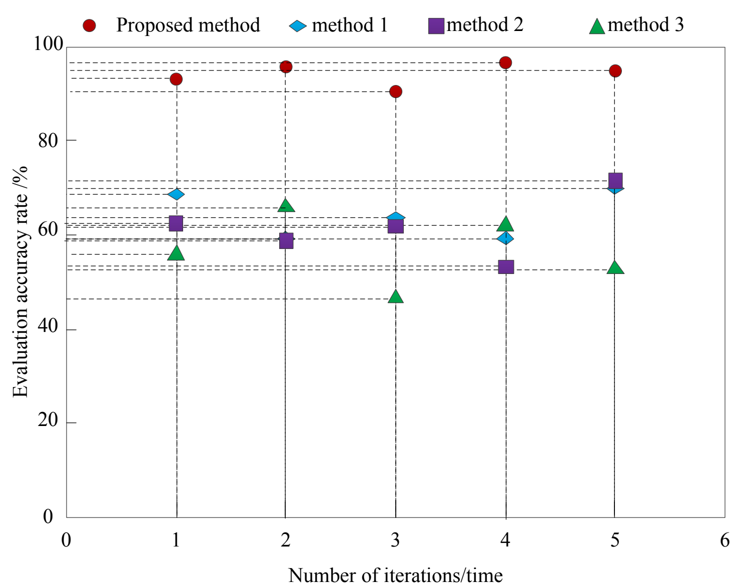
Figure 6 Weight accuracy of different methods



4.3 Comparison of assessment accuracy of different methods

The test was carried out in different iterations, and the evaluation accuracy of the four different methods was compared. The higher the value, the higher the accuracy of the method. The test results are as shown in Figure 7.

Figure 7 Assessment accuracy of different methods



According to the analysis of Figure 7, the accuracy rate of risk assessment method for energy system based on data mining in multiple iterations is higher than that of traditional methods. This is because the research method of this paper introduces the concept of 'Distance' between risk level and risk assessment indicator to assess the risk of energy system, which improves the accuracy of assessment results.

5 Conclusions

The important infrastructure to ensure the normal development and operation of the city is the energy system, but the vulnerability of the energy system itself, natural disasters, accident disasters and other emergencies will seriously threaten the safety of the city. Through risk analysis, we can master the state of the energy system in the operation process, realise risk management, reduce and control the occurrence of risks, and ensure the safety of the city's energy system.

At present, the risk assessment method of energy system has the problems of disordered data index and unclear index weight, which leads to the security hidden trouble of urban resource system. The use of data mining technology can effectively solve this problem. An energy system risk assessment method based on data mining is proposed, which can effectively improve the accuracy of risk index acquisition. The use of chromatography analysis can accurately calculate the weight of risk assessment indicators, accurately complete the risk assessment of the energy system, and provide a guarantee for the safe operation of the energy system. Experimental results show that both the weighing accuracy and evaluation accuracy of the proposed method are above 90%, 30% higher than the traditional method, and the deflection coefficient is always close to 0.The precision of the risk assessment of the energy system and the accuracy of the assessment results have been significantly improved to realise the risk management of the energy system and effectively guarantee the safety of the city's energy system. As a strong basis, it proves that the research method has stronger applicability and provides a reliable basis for the research in related fields.

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