Research Article

Power-Sensitive Early Warning Data Conversion Method Combined with Multiobjective Differential Evolution Algorithm

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Aiming at the problems of economy, security, and reliability of power system operation, the multiobjective gap evolutionary algorithm is introduced into power-sensitive early warning data conversion. A power-sensitive early warning data conversion (PSEWDC) method based on multiobjective gap evolutionary algorithm (MOGEA) is proposed. According to the type of equipment with problems in the operation of the power system and the rapid diagnosis of defects and problems, the method quickly locates the problems and analyzes the causes, replaces and rearranges the original data by using the substitution data method to eliminate the nonlinear autocorrelation, and then, according to the convergence of the long-range correlation index, identifies the abnormal values that have no impact on the overall fluctuation of the original sequence, judges that the current sequence reaches the critical point of extreme events, and provides a reference threshold for real-time risk early warning. Finally, the example analysis shows that this method can finally determine the risk early warning threshold of power peak and valley load by analyzing the convergence of long-range correlation index, so as to avoid the blindness of subjective experience, provide a theoretical basis for power load risk early warning research, effectively solve the problems of subjectivity, lack of dynamics, and lack of theoretical basis for setting risk threshold in traditional power risk early warning research, and have an intelligent insight into the security situation of power big data.

1. Introduction

Even though people continue to improve the stability of electrical energy, due to the impact of many factors such as operation, maintenance, and insulation degradation in the power system [1, 2], failures often occur during use. In order to be able to early warning and troubleshooting quickly, so that the power system can operate stably and improve the reliability and continuity of power operation, it is necessary to improve the high-quality power-sensitive early warning performance. In the power-sensitive early warning data conversion, a lot of data analysis that can reflect the operation of power-sensitive early warning has been accumulated. These data can show the historical problems of power-sensitive early warning and the corresponding solutions [3, 4]. For a long time, this data analysis has not been used effectively and is usually stored in the data system. The historical case studies that can be used for reference can help maintainers quickly grasp the operation and overhaul of power-sensitive early warning and quickly improve the maintenance level of maintainers. It is of great significance for the effective diagnosis of power-sensitive early warning in the later period [5]. Most power-sensitive early warnings often use fusion sensors such as lidar technology, mileage recording, and inertial measurement unit technology to achieve early warning. Different from the traditional GPS early warning method, this sensor-based early warning is not disturbed by the environment, and no worry about the weakening of satellite signals occurs, and can effectively achieve specific early warning in power-sensitive early warning data. The specific power-sensitive early warning usually includes two methods: one is to realize specific early warning based on basic image processing, and the other is to effectively convert sensitive early warning data for multiple
sensors. In addition, it should be noted that different methods require different sensors, such as RFID, WIFI, and pedometer sensors, but these sensors will also be interfered and differentiated due to different materials, equipment production, technology, and structure, which often leads to instability of data collection. The pedometer of the mileage program mainly relies on the installation of the specific motor to realize the coding work and does not need the external information of the sensor to realize the specific early warning, but this method often has systematic and random errors, which will cause the estimation accuracy of the pose to become lower and lower. The early warning of inertial measurement unit technology needs to realize early warning after the specific intelligent machine moves, but the precision of the early warning in this way is not enough, and deviations often occur. Relatively speaking, the precision of lidar early warning is high, but it requires a clearer environment. If the information of the laser is blocked to a certain extent, the scanned information will not match the corresponding map information, thus leading to inaccurate early warning. By setting up real-time early warning and real-time monitoring on the basis of the multiobjective gap evolution algorithm, various data information in the multiobjective gap evolution algorithm can be perceived. Multiple sensor terminals are used to achieve monitoring and management, to complete real-time monitoring and management of power-sensitive early warning data. Since the nodes corresponding to the distributed power-sensitive early warning data flow have the characteristics of high mobility and relatively large network scale, higher requirements are also put forward for the reliability, stability, and security of the real-time early warning and real-time monitoring system. Compared with the traditional method, the early warning and real-time monitoring system based on the multiobjective gap evolution algorithm needs to analyze the extracted multisource data information and can complete the early warning of the multiobjective gap evolution algorithm. The equipment structure is simple, and the cost is low. Its simple structure, low cost, and convenient maintenance have gradually become the trend of real-time early warning and real-time monitoring for intelligent maintenance have gradually become the trend of real-time early warning and real-time monitoring systems. The economic cost optimization is achieved while satisfying safety and stability.

2. Multiobjective Gap Evolution Algorithm

The multiobjective gap evolution algorithm is one of the heuristic random sensitive algorithms. The distinguishing feature of this technology is that it has the characteristics of simple operation, easy to understand, good convergence of the algorithm, and high accuracy. To use this algorithm, it is necessary to determine the sensitive data, sort the order of the optimal fitness of individuals, and introduce the variable input value of fuzzy inference into each sensitive link. The variable output of sensitive data in this paper can be represented by a Gaussian linear function, and then the corresponding optimal fitness value of the i-th individual can complete a linear mapping between the minimum and maximum dependencies, which can be expressed as

\[
u_i = U_{\max} - (sizepop - Indexxfitnessgbest(i)) * \frac{U_{\max} - U_{\min}}{sizepop - 1},\]

\[
u_{ij} = u_i + (1 - u_i) * \text{rand}(j = 1, 2, 3, \ldots, D).\]

From the expression, the corresponding membership function of the i-th individual can be known, and the membership corresponding to the individual with the best fitness value can be obtained according to the formula. The determined data are

\[a_{ij} = \delta_{ij} \sqrt{-\log (u_{ij})}.\]

According to the above expression \(a_{ij}\), the i-th individual can use the sensitive data of \(\delta_{ij}\) in the j-dimensional sensitive space. Then, the obtained Gaussian membership function parameters are expressed as

\[\delta_{ij} = H(t) * |z_{best} - 5 * \text{rands}(1, 10)|,\]

\[H(t) = \frac{\text{max gen} - t}{\text{max gen}}.\]

According to expression (5), it can be known that \(z_{best}\) represents the global optimal sensitivity; \(\text{rands}(1, 10)\) represents a randomly selected value in the interval [1, 10]; and \(H(t)\) represents the function that changes constantly under the weighting function of the t-th iteration and in the meantime satisfies the maximum number of iterations and the number of real-time iterations that can be obtained at maxgen = 100.

In the process of determining the global sensitive direction, it is necessary to combine the optimal situation of the individual and the overall optimal situation to clarify the
The identification of the weight vector of the multi-objective gap evolution algorithm analysis is directly related to the size of the data set. In order to ensure the fairness and validity of the evaluation results, the Gaussian distribution is discretized in this study. In this method, the degree of freedom value is placed where the weighting value is relatively small, effectively eliminating the adverse effects of other factors on the evaluation process.

The set \( \mu \) is the mathematical expectation of \((1, 2, \ldots, n)\) given the weight vector \( w = (1/n, 1/n, \ldots, 1/n) \); \( \sigma \) is the standard deviation of \( \mu \), and \((1, 2, \ldots, n)\) in the weight vector \( w \), so we have

\[
\mu_n = \frac{1}{n(n+1)} - \frac{n+1}{2}, \quad \sigma_n = \sqrt{\frac{n}{2}} \sum_{i=1}^{n} \left( i - \mu_n \right)^2.
\]

To evaluate \( n \) information systems, the set of evaluation groups is \( D = (d_1, d_2, \ldots, d_m) \), where \( d_k \) \((k = 1, 2, \ldots, m)\) represents the K-th evaluator. The subjective judgment given in the form of evaluation is as follows: the utility value is \( u^{(k)} = (u_{1}^{(k)}, u_{2}^{(k)}, \ldots, u_{n}^{(k)}) \), the evaluation value of the active defense analysis language is \( S = (s_0, s_1, \ldots, s_F) \), and the complementary judgment matrix of the active defense analysis is \( P^{(k)} = (p_{ij}^{(k)})_{m \times n} \); therefore, the information that matches these judgments becomes the utility value.

The multiobjective gap evolutionary algorithm is one of the evolutionary heuristic algorithms. The algorithm mainly uses the differential method to complete the evolution of the species population, improve the search speed, and enhance the convergence [10, 11]. Figure 1 shows the power-sensitive early warning data conversion process of the multiobjective gap evolution algorithm [12].

According to the corresponding multiobjective gap evolution algorithm, if the power-sensitive early warning data can be accurately calculated, the data posture at a specific moment can be calculated specifically using formula (15):

\[
x_{k+1} = f(x_k, u_{k+1}) + w_{k+1}.
\]

The estimated value of the specific motion model data of the power-sensitive early warning can be calculated using formula (16):

\[
\hat{x}_{k+1} = \hat{x}_k + \begin{pmatrix} \cos \theta_k & \sin \theta_k & 0 \\ -\sin \theta_k & \cos \theta_k & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} V_{Odo,x} & V_{Odo,y} & \omega_{Odo} \end{pmatrix} dt.
\]

The covariance matrix of the a priori estimate of the predicted state vector can be specifically calculated using formula (17):

\[
P_{k+1} = \mathbb{V} f_x P_k f_x^T + \mathbb{V} f_w Q_{k+1} \mathbb{V} f_w^T.
\]

On the basis of formula (17), changes can be made, as shown in formulas (18) and (19):
\[ f_x = \begin{pmatrix} 1 & \cos \theta_k & -\sin \theta_k \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \sin \theta_k \\ \cos \theta_k \\ 0 \end{pmatrix} \begin{pmatrix} dt \\ dt \sin \theta_k \\ dt \cos \theta_k \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} dt \],

\[ f_w = \begin{pmatrix} \cos \theta_k & \sin \theta_k \end{pmatrix} \begin{pmatrix} dt \\ dt \sin \theta_k \\ dt \cos \theta_k \end{pmatrix} \begin{pmatrix} \sin \theta_k \\ \cos \theta_k \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \begin{pmatrix} \sin \theta_k \\ \cos \theta_k \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} dt \].

On the basis of formulas (18) and (19), make changes, as shown in formula (20):

\[ Q_{k+1} = \begin{pmatrix} 0.01 & 0 & 0 \\ 0 & 0.01 & 0 \\ 0 & 0 & 1 \end{pmatrix} \].

At time \( k + 1 \), the conversion model of power-sensitive early warning data can be specifically calculated using formula (21):

\[ z_{k+1} = \begin{pmatrix} X_{k+1} \\ Y_{k+1} \\ \theta_{k+1} \end{pmatrix} + v_{k+1}, \]

where \( z_{k+1} \) is the system observation amount at time \( k + 1 \), and \( v_{k+1} \) is the observation noise at time \( k + 1 \).

The conversion expression for calculating power-sensitive early warning data is shown in (22):

\[ K_{k+1} = P_k^{-1} \begin{pmatrix} \nabla h_T & \nabla h_z \end{pmatrix} \begin{pmatrix} \nabla h_x P_k^{-1} \nabla h_x^T + R_k \end{pmatrix}^{-1}. \]

On the basis of formula (22), accuracy or noise evaluation can be carried out through experimental statistics, as shown in formula (23):

\[ R_{k+1} = \begin{pmatrix} \sigma_X & 0 & 0 \\ 0 & \sigma_X & 0 \\ 0 & 0 & \sigma_\theta \end{pmatrix}. \]

The conversion of power-sensitive early warning data can be specifically calculated using formula (24):
wV_/he posterior of the state variable can be specifically calculated using formula (25):

$$K_{k+1} = \begin{pmatrix}
\frac{P_{k+1,X}}{P_{k+1,X} + \sigma_X} & 0 & 0 \\
0 & \frac{P_{k+1,Y}}{P_{k+1,Y} + \sigma_Y} & 0 \\
0 & 0 & \frac{P_{k+1,\theta}}{P_{k+1,\theta} + \sigma_{\theta}}
\end{pmatrix}.$$  \(24\)

The posterior of the state variable can be specifically calculated using formula (25):

$$\tilde{x}_{k+1} = \tilde{x}_{k+1} + K_{k+1} (z_{k+1} - \tilde{x}_{k+1}).$$  \(25\)

On the basis of formula (26), the specific calculation of the covariance matrix is performed, as shown in formula (26):

$$P_{k+1} = (I_3 - K_{k+1}) P_{k+1},$$  \(26\)

where \(I_3\) is the third-order identity matrix.

3. Power-Sensitive Early Warning Data Conversion Platform

For the problems of data mining and use in the process of power-sensitive early warning data conversion, this paper constructs an early warning data conversion platform based on multiobjective gap evolutionary algorithm. The architecture of the designed early warning data conversion system is shown in Figure 2. It can be divided into data layer, application layer, ontology layer, and business layer. The data layer mainly applies the named entity recognition (NER) method to the collection of data information in the system according to the early warning information of power-sensitive data recorded in the previous system, so as to provide data basis for the established knowledge map. The ontology layer is based on protege ontology structure and uses analysis tools to realize the relationship between entities, so as to build a sensitive data conversion model for power equipment data analysis. Based on the ontology layer, the business layer converts the sensitive early warning data collected by the data accordingly. At the same time, it can effectively supplement the distance between the system’s lost collected data information query and business operation, so as to facilitate the rapid problem location and diagnosis of the application layer.

The process of the “analysis on the root cause of early warning and the status of fault handling” is carried out in the data processing layer. In this paper, the recognition method of the named entity is adopted in the conversion process of electronically sensitive data on early warning. With the target task as the theme, this method can be used to identify the boundaries of the naming process in the power text, while dividing the results of the classification into the sets as defined. At present, the recognition method of the named entity can be classified into rules, dictionaries, and online knowledge base recognition methods. With the continuous
In this paper, the data on system defects are taken as the practical cases for a case study. Although the power data information on early warning lacks naming, it does not comply with the common definition of the entity name with regard to critical information or sensitive data. From the perspective of the analysis on the early warning target, if the power early warning process of “turn off the lights during the operation and restart upon failure” is used to eliminate the early warning faults, it is reasonable to apply the NER method in the input and output features of the system data on early warning. At the same time, the conversion of the power-sensitive data on early warning can be acquired as soon as possible; and “restart upon failure” is an example where no early warning can be issued upon failure, which can be secured by using multiple entities. Hence, the data information on “restart upon failure” in the process of conversion of power-sensitive data can be deemed as an NER target object task; and finally, the extraction of the sensitive data information on its point force can be implemented [16, 17].

The power-sensitive database is a database of basic knowledge that can be retrieved and constructed provided by Google with the complex relationships that are present among the basic knowledge, entities, and concept definition results in the database. On the basis that the conversion of power-sensitive data has been completed, the semantics contained among different types of data can be extracted and the basic data composition of “loss of system data” and “measurement of power-sensitive data” is commonly observed. The data storage methods used traditionally are often stored in the database in accordance with the type of data, and this model is prone to losing the interrelationship among the data stored, which will not be conducive to the application of early warning data. Due to its advantages in terms of knowledge graph, it has been extensively applied.

However, the knowledge mapping of the power-sensitive data on early warning is lack of the relevant knowledge analysis at present, and the process of mapping established in the constructed power-sensitive data can include different data between clusters of complex knowledge to carry out the entity analysis on the corresponding entity data. At the same time, in combination with the basic requirements of the business, analysis can be carried out on the professional expertise and the specific early warning data so as to implement effective mining and analysis of power data on early warning in different application scenarios. The power-sensitive early warning database established in this paper is mainly used in the relevant business scenarios.

The multiobjective gap evolutionary algorithm for power-sensitive early warning used in this paper is mainly based on the data information obtained from the feedback of the installed maintenance personnel in the field. During this process, the complexity of the early warning data and the potential value of the data mining information are more likely to be observed, and the objective in the data layer is to extract and normalize the data information on early warning as described above and provide a reference basis for the subsequent early warning database. In this paper, the “phenomenon of defects” in the conversion process of power-sensitive data on early warning is deemed as the NER objective, and the multiobjective gap evolution algorithm in combination with the bidirectional memory network in the long term and the short term is used to extract the features of the power data so as to realize the NER objective and accomplish the relevant task.

In accordance with the long term or the short term, the memory model is mainly used on the basis of the effective combination with the recurrent neural network (RNN). The model data have a special structure with the portal of forgetting, the portal of input, and the portal of output, which can avoid the phenomenon of the gradient disappearance in long sequences based on the traditional model and address and handle the issue effectively. The expressions for the operation of different variables in the basic unit of the LSTM network can be described as follows:

\[
\begin{align*}
  f_t &= \sigma(W_f h_{t-1}; x_t) + b_f, \\
  i_t &= \sigma(W_i h_{t-1}; x_t) + b_i, \\
  o_t &= \sigma(W_o h_{t-1}; x_t) + b_o, \\
  \bar{s}_t &= \tanh(W_s h_{t-1}; x_t) + b_s, \\
  s_t &= f_t \odot s_{t-1} + i_t \odot \bar{s}_t, \\
  h_t &= o_t \odot \tanh(s_t),
\end{align*}
\]

In the above expressions, \( \sigma(\cdot) \) and \( \tanh(\cdot) \) are used to stand for the activation function; \( h_t, s_t, h_{t-1}, \) and \( s_{t-1} \) stand for the output and hidden states of the corresponding cells in the system at moment \( t \) and the moment \( t-1 \), respectively; \( x_t \) stands for the input values of the system at the current moment \( t \); \( f_t \) and \( o_t \) stand for the state of the system portal of forgetting and the portal of output at the moment \( t \) in turn, respectively; \( i_t \) and \( \bar{s}_t \) stand for the states of the system portal of input at the current moment \( t \) in turn; \( W_f, W_i, W_o, W_s \) and \( b_f, b_i, b_o, b_s \) stand for the matrix weights and the bias terms of the corresponding system in turn, respectively; and \( \odot \) stands for the elements multiplied by bit.

4. Analysis of Experiment and Results

In this paper, the multiobjective gap evolution algorithm is applied to the conversion process of power-sensitive data, which can not only provide a basis for the subsequent power system knowledge graph based on the effective analysis of the data evaluation indicators but also provide a basis for the subsequent power system knowledge graph. It has laid a solid foundation for the information reading and standardized processing of power system data. According to the data information of previous tests, it can be concluded that the system adopted in this paper can significantly improve...
the conversion performance of power-sensitive early warning data. Telemetry is not considered: when the number of components in the connection graph is less than \( K \), the connection graph is considered to be inactive and needs to be processed further. Otherwise, the connection graph is active and considered not to be computed by a multi-objective gap evolution algorithm. Here, \( K \) is determined according to the number of components contained in the blackout area formed by active component protection and operating experience. Taking into account the telemetry, it is judged whether it is in a working state according to whether the active element has voltage, whether it has current, and whether it has power transmission capability. If there is no active element for such an action in the connection graph, the connection graph is considered to be inactive and needs to be processed further. Otherwise, the connection graph is active, and it is considered that it does not need to be calculated by the multiobjective gap evolution algorithm.

With the continuous development of computer science technology and multi-Internet network technology, many problems have also appeared in the development of power-sensitive early warning data. During the development process of Internet networks in China and other countries, security incidents in different industries can be mainly divided into the following three categories: loopholes in the security system itself, the security risks caused by the violation of the system from the outside, and the security risks caused by the system being upgraded and updated independently. Under the risk of different types of power-sensitive early warning data, the independency, security, confidentiality, integrity, and detection mechanism of the entire computer operating system or data use and sharing process have huge security risks due to the user’s flaws in the computer operation process due to system security; therefore, it is very important to design a predictive protection system of power-sensitive early warning data. By developing and designing a security protection system that is consistent with current computer and multi-Internet network technologies, the security performance associated with the computer system can be better improved, thus improving the data integrity, confidentiality, and availability. Predictive analysis of power-sensitive early warning data provides a means for sensitive Internet network characteristics in real environments. Predictive analysis of power-sensitive early warning data is also an effective data collection, data decoding, and data analysis process for network equipment. The indicator data is mainly collected from the network and fed back to the monitoring personnel. Power-sensitive early warning data detection and real-time risk early warning are of great significance for power-sensitive early warning data-related resource distribution, traffic planning service level, and security early warning.

Power big data security analysis and early warning define the behavior mode or user access ability according to the user’s behavior habit of using the database. It can realize the intelligent detection of user’s abnormal behavior without setting a fixed threshold in advance. The user behavior is defined by machine learning algorithm. If the user’s real-time behavior mode is quite different from its historical behavior mode, it is considered that the user’s behavior is abnormal. When performing predictive analysis of power-sensitive early warning data, the basic information of big data mapped by network virtualization in the multiobjective gap evolution algorithm environment is described, and the large data packets of network element network virtualization mapped from the source node are transmitted through the network relay node. Multiple network virtualization maps are created to propagate budget analysis, and the budget analysis plan of network virtualization maps is completed. Before planning the network virtualization mapping propagation budget analysis, it is necessary to complete the modeling of the network environment, so as to improve the grasp of the network by the network virtualization mapping.

The network environment modeling in this section selects the multiobjective gap evolution algorithm. The multiobjective gap evolution algorithm is also called the unit solution, that is, the environment located in the big data mapped by the network virtualization is divided into areas or volumes by the unit decomposition method and is divided into several two-dimensional or three-dimensional grids with the same shape; we abstractly explain other elements in the network environment and build a network environment that is easy to understand by big data mapped by network virtualization.

As shown in Figure 3, the simulation operation example in this paper is to improve the power-sensitive early warning model. The thermal power generation unit improves the power-sensitive early warning model to verify the effectiveness of the method proposed in this paper. A wind farm WG with an installed capacity of 100 MW is connected to an energy storage device with a capacity of 100 MWh and a maximum output of 20 MW. The parameters of the thermal power unit are shown in Table 1. The waveform comparison between the set signal and the fitted signal is shown in Figure 4.

The power-sensitive alarm problem of the power system is expressed as a 0–1 integer plan problem, and the following adaptive objective function is used in this paper.

\[
f(s) = w - \sum_{k=1}^{n_s} |r_k - r_k^*(s)| - \sum_{j=1}^{n_s} |c_j - c_j^*(s, r)| - \sum_{i=1}^{n_r} r_i^* c_i.
\]  

Among them, \( n_s \) is the total number of protections, \( n_r \) is the total number of circuit breakers, \( n_{rc} \) is the number of reclosing relay protections, \( s \) is an \( n \)-dimensional vector representing the state of the components in the system, and \( s_i \) is the \( i \)-th element in \( s \), which represents the state of the \( i \)-th element. \( S = 0 \) or \( 1 \), respectively, indicates the normal or fault state of the \( i \)-th component. \( r \) is an \( n_r \)-dimensional vector, representing the actual state of \( n_r \) protections, and the \( k \)-th element \( r_k \) in \( r \) represents the actual state of the \( k \)-th protection. \( r_k^* = 0 \) or \( 1 \), respectively, indicates that the \( k \)-th protection is in a nonoperating or operating state. \( r_k^*(s) \) is an \( n_r \)-dimensional vector, which represents the desired state of \( n_r \) protection, and the \( k \)-th element \( r_k^* \) represents the desired state of the \( k \)-th protection. For example, the \( k \)-th protection should act \( r_k^*(s) = 1 \); otherwise, \( r_k^*(s) = 0 \). The \( r_k^*(s) \) state is determined by the \( s \) state. \( c \) is an \( n_r \)-dimensional
vector that represents the actual state of \( n_c \) circuit breakers, and the \( j \)-th element \( c_j \) in \( c \) represents the actual state of the \( j \)-th circuit breaker. \( c_j = 0 \) or \( 1 \), respectively, indicates the opening or closing state of the \( j \)-th circuit breaker. \( c_j^*(s,r) \) is an \( n_c \)-dimensional vector, which represents the desired state of \( n_c \) circuit breakers, and \( c_j^*(s,r) \) represents the desired state of the \( j \)-th circuit breaker. If it trips, \( c_j^*(s,r) = 0 \); otherwise,
Table 2 shows the results of environmental optimization and various methods. Comparing different optimization objectives, as well as comparing the best compromise and the best economic solution, the total operating cost will increase, but the pollutant emissions will decrease, and the system will run more environmentally friendly. Compared with the best solution for environmental protection, pollutant emissions increase, but the total operating cost is reduced, and the system runs more economically.

It can be seen that the optimal compromise solution has the highest satisfaction and can be used as a multiojective data conversion method for this wind-to-light storage system. In this method, as shown in Figure 5, the output of each type of unit is performed.

5. Conclusions

Power risk early warning is of great significance to ensure the safe and stable operation of power and avoid major safety accidents. It has become a hot issue in theoretical research in recent years. This paper proposes a method to determine the conversion of power-sensitive early warning data. On the basis of verifying the effectiveness of the algorithm, the threshold of extreme load data is determined through example analysis. Starting from the data itself, the subjectivity and risk brought by statistics and manager experience are reduced. With the continuous accumulation of power system monitoring data, the effective utilization of these data has become an urgent problem to be studied. The method provided in this paper provides a way to determine the power load risk threshold based on historical data. At the same time, it can be considered to promote the research in other monitoring data of power system such as temperature and pressure. Through reading power system data information and standardized processing, the power-sensitive early warning data conversion constructed in this paper can be realized quickly and effectively. Finally, the experimental comparative analysis shows that the method proposed in this paper can effectively improve the efficiency of power-sensitive early warning data conversion, making the algorithm more intelligent and more suitable for practical application scenarios.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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