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# COMPREHENSIVE METHOD FOR EVALUATION OF MEDIUM- AND LOW-VOLTAGE DISTRIBUTION NETWORK OPERATING STATE

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*With the development of intelligent distribution networks and access to distributed energy, the solving the problem of timely and accurate determination of the operating state of the distribution network is an urgent task. Based on an improved analysis of the principle components of the network and statements of a self-organizing neural network, this article proposes the method to evaluate the operating state of medium- and low-voltage distribution networks. At the first step, the system of evaluating indices of the network is formed by advanced component analysis. The evaluation system is grounded on four aspects, including safety, reliability, quality and economy. Next, the self-organizing neural network is used to identify and clean up the data regarding the operating state of the distribution network. At the next step, the indicators are modeled at all levels; the entropy method is applied to calculate the total weight of all indicators. Then the value of each indicator is found and the weak links of the distribution network are determined. At the final stage, the comprehensive assessment of the real operation of the distribution network in Guangxi province is carried out. As shown, the method can effectively reduce the effect of abnormal data and subjectivity factor on the results of evaluating the state of the distribution network. That confirms the feasibility and practicability of the proposed method.* References 22, figures 6, tables 6.
***Key words***: distribution network, improved principal component analysis, self-organizing neural network, entropy combination, comprehensive evaluation.

**1. Introduction.** In the recent years, as an important part of smart grid, intelligent distribution network has become a new trend in the development of smart grid [1–3]. However, the defects of different equipment and low automation level in medium- and low-voltage distribution networks are hindered in the development of intelligent distribution network. Moreover, the low- and medium-voltage distribution networks are a key link for the connection between the power system and users, and its operating states affect the national economy [4–6]. Therefore, it is urgent to develop a scientific, effective, fast and accurate evaluation system for the low- and medium-voltage distribution networks.

At present, many evaluation methods have been proposed and studied. The multi-level evaluation index systems for different levels are proposed in [7–9], but without expert experience or ignoring the influence of evaluation indices in distribution network. In [10–13] the AHP-Delphi method is proposed to evaluate the operating state of distribution network or to modify the weights of indices at all levels. However, AHP-Delphi method is too subjective to evaluate the operating state of distribution network objectively. In [14–17], the Monte Carlo method, matter-element extension method, G2-entropy method and other approaches are used to evaluate the operating state of distribution networks. However, the problems of data accuracy and abnormal data in the existing data system are ignored. Moreover, due to the fact that the evaluation results regarding distribution network are easily affected by abnormal data, the evaluation errors may be caused and the wrong control signals may be sent to the distribution network. In a word, the existing studies on the operating state evaluation of medium- and low-voltage distribution networks mostly ignore the following problems: abnormal data of distribution network and subjectivity of evaluation method, which cannot objectively evaluate the real operating state of distribution network.

Therefore, this paper proposes the method for operating state evaluation of medium- and low-voltage distribution networks based on improved analysis of principal components and self-organizing neural network. First of all, the improved principal component analysis method is adopted to extract the indices that can best reflect the operating state of distribution network, and then the AHP index system is constructed. Secondly, the data on the operation of distribution network are cleaned up based on self-organizing neural network. Then the entropy combination weight algorithm is used to calculate the weights of indices. Finally, by calculating the each index, the weak links of distribution network are found. In conclusion, the comprehensive evaluation results of the actual distribution network show that the proposed method can provide the effective technical support and information for the control and management of the medium- and low-voltage distribution networks.

**2. Features of extraction based on improved principal component analysis.** In the evaluation of the operating state of medium- and low-voltage distribution networks, there are many factors that affect the state of distribution network, and there is no unified method to screen the evaluation indices. Most studies establish the evaluation index system of distribution network through research analysis and expert opinions. It is difficult to accurately evaluate the distribution network due to the subjectivity of the method. It is impossible to filter out the overlapping information attributes among evaluation indicators at a certain level, and it is difficult to accurately evaluate the operating state of distribution network.

Therefore this paper proposes an extraction algorithm based on improved principal component analysis to screen evaluation indices. This method can reduce many evaluation indices to several comprehensive indices, make the index system simpler and more reasonable, and extract the index that can best reflect the operating state of distribution network. The steps are as follows:

(1) Selection of a number of evaluation indices of distribution network, quantification of each evaluation index, construction of the evaluation index quantization matrix and elimination of the dimension:

$$x_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}, \tag{1}$$

where $s_j^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)^2$, $\bar{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$, $i$=1,2,3…$n$, $j$=1,2,3…$p$.

According to the covariance principle, the covariance matrix is the correlation coefficient matrix after the standardized transformation of the index.

(2) Then solution of the correlation coefficient matrix, determination of the eigenvalue and eigenvector of the matrix, and sorting of them according to the eigenvalue $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \lambda_p$, the eigenvector corresponding to each eigenvalue $\lambda_i$ is $\alpha_i$.

Then calculation of the cumulative variance contribution rate:

$$\sum_{k=1}^{i}\lambda_k \Big/ \sum_{k=1}^{p}\lambda_k\ . \tag{2}$$

The cumulative variance contribution rate mentioned above reflects the amount of information contained in the linear transformation of variables. When the factor is more important, the cumulative variance contribution rate will be larger.

(3) Special extraction of indices.

Firstly, calculation of the main component load matrix A:

$$A = (\sqrt{\lambda_1}\alpha_1, \sqrt{\lambda_2}\alpha_2, \sqrt{\lambda_3}\alpha_3, \ldots \sqrt{\lambda_m}\alpha_m)\ , \tag{3}$$

where $\lambda_1$, $\lambda_2$, $\lambda_3$...$\lambda_m$ are the eigenvalues of the matrix, $\alpha_1$, $\alpha_2$, $\alpha_3$…$\alpha_m$ are the components of the eigenvector.

Then calculation of the importance degree of each evaluation index: analysis of the selected principal components and calculation of the importance degree of the index in the principal components. The calculation formula of the importance degree H is as follows:

$$H = \sqrt{\lambda_1}\alpha_1 + \sqrt{\lambda_2}\alpha_2 + \sqrt{\lambda_3}\alpha_3 + \ldots\sqrt{\lambda_m}\alpha_m\,. \tag{4}$$

Then normalization of the importance degree of the obtained evaluation index is realized. The higher the importance degree, the stronger the correlation, that is, the more representative of the evaluation index among the numerous evaluation indices. Finally, the key indices of the evaluation of the operating state of the distribution network are obtained.

**3. Data cleaning based on self-organizing neural network.** Medium- and low-voltage distribution networks have complex structure, various equipment and low automation level, so the operation data uploaded by the existing data acquisition system have many defects, such as data collection difficulties, poor accuracy and incomplete data [18]. Therefore, it is urgent to identify and clean abnormal data when evaluating the operating state of low- and medium-voltage distribution networks.

In power system, the methods of data cleaning are numerous, but the traditional data cleaning algorithm is not suitable for distribution network operation evaluation, because the traditional algorithm cannot get the trend of abnormal change of each data and the correlation between the data, which is easy to cause abnormal data is not completely clear. Moreover, because of the large amount of data in the operating state of the distribution network, the outliers belong to the small samples, so the error of the traditional clustering analysis method is also large.

Therefore, this paper proposes a distribution network operation data cleaning algorithm based on self-organizing neural network. Its core theory is deep learning technology [19], which adopts competitive learning to conduct sample training to process high-dimensional data volume and clean distribution network abnormal data more quickly and accurately.

**3.1. Basic principles of self-organizing neural networks.** Self-organizing neural network algorithm refers to the random multiple selection in the sample system, and the mapping of self-organizing neural network by Bootstrap sampling or other sampling methods. The training process is competitive deep learning, the steps are as follows: first, number the sample vector and calculate the Euclidean distance. Then, the weights and the most similar neurons were formed into matching units, and the feature map of the neurons was finally obtained. The closer the distance between the neurons, the higher the similarity, so the more accurate the data. The training process is shown in Fig. 1.

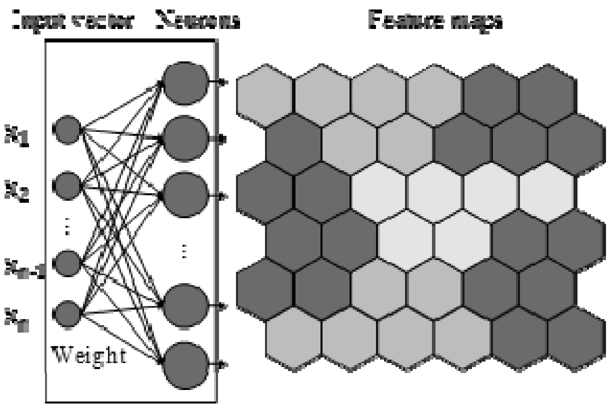


**Fig. 1**

**3.2. Establishment of self-organizing neural network model.** The steps for establishing the model of data cleaning algorithm based on self-organizing neural network described in this paper are as follows:

(1) Normalization of input vector and corresponding vector of neuron:

$$\hat{X} = \frac{X}{\|X\|} = \left( \frac{x_1}{\sqrt{\sum\limits_{j=1}^{n} x_j^2}}, \frac{x_2}{\sqrt{\sum\limits_{j=1}^{n} x_j^2}}, ..., \frac{x_1}{\sqrt{\sum\limits_{j=1}^{n} x_j^2}} \right)^T, \qquad (5)$$

where $j$=1,2,3…$m$, $j$ is the neuron number; $X$ is the input vector.

(2) Whenever any input vector is obtained, compared it with the corresponding vectors of all neurons, the vectors that are most similar to each other are competitive neurons. If the two vectors are similar, their dot product should be maximized as follows:

$$\hat{W}_{j^*}^T \hat{X} = \max_{j\in\{1,2,3,...,m\}} (\hat{W}_j^T \hat{X}). \qquad (6)$$

After transformation of the above equation we get:

$$\left\| \hat{X} - \hat{W}_{j^*}^T \right\| = \min_{j\in\{1,2,3,...,m\}} \left\{ \left\| \hat{X} - \hat{W}_j \right\| \right\}. \qquad (7)$$

Minimum Euclidean distance is equal to:

$$\left\| \hat{X} - \hat{W}_{j^*}^T \right\| = \sqrt{2(1 - W_{j^*}^T \hat{X})}, \qquad (8)$$

where $W_j$ and $W_{j*}$ are the vector of neurons $j$ and $j*$.

(3) When the matching unit is adjusted to the input unit, the amount of matching unit will decrease with distance and time, the weight Ab(s) is obtained by using the following formula:

$$O_j(t+1) = \begin{cases} 1, j = j^* \\ 0, j \neq j^* \end{cases}. \qquad (9)$$

And then the formula for the neuron has the following form:

$$A_b(s+1) = A_b(s) + f(u,b,s)\beta(s)[X(t) - A_b(s)], \qquad (10)$$

where $t$ is the index of the training sample, $X(t)$ is the input vector, $s$ is the step length index, $\beta(s)$ is the learning coefficient of monotonically decreasing, $u$ is the matching unit index of the input vector, $f(u,b,s)$ is the proximity function of the distance between neurons $u$ and $b$ when the step size is $s$. $T$ is the size of the training sample.

**4. Calculation of evaluation index of distribution network operating state.**

**4.1. Modeling of index for evaluation.** The evaluation index system for the operating state of distribution network constructed by the improved principal component analysis method and analytic hierarchy process, and its intermediate layer is: security, reliability, quality and economy. The single index of the index layers is: three phase unbalance, transformer load rate, operation failure rate, reliability of power supply, voltage eligibility rate and line loss rate. For the above six single index of power distribution network operation evaluation, the model is as follows:

(1) Security index.

Three phase unbalances: the amplitude difference of voltage or current in the three phases of the distribution network exceeds the reasonable limit. The smaller the value, the healthier the distribution network is. The formula is as follows:

$$X_1 = \frac{3\max\{P_A, P_B, P_C\} - (P_A + P_B + P_C)}{P_A + P_B + P_C}, \tag{11}$$

where $P_A$, $P_B$, $P_C$ respectively represent the load of three-phase A, B, C at the outlet end of the low-voltage side of the transformer in the distribution network.

The transformer load rate refers to the ratio between the average output power of the distribution network and the rated capacity of the transformer within a certain range. The smaller the load rate within this range, the healthier the distribution network is. The formula is as follows:

$$X_2 = \frac{W_t}{S}, \tag{12}$$

where $W_t$ refers to the power supply load in the distribution network within $t$ time, and $S$ is the transformer capacity.

(2) Reliability index.

Operation failure rate: the average number of failures of the distribution network. The lower the operation failure rate, the healthier the distribution network is. The formula of operation failure rate converted to one year is as follows:

$$X_3 = \lambda_t \cdot \frac{8760h}{t}. \tag{13}$$

where $\lambda_t$ is the rate of failure during the statistical time, 8760h is the number of hours in a year, and $t$ is the number of hours in the statistical time.

Reliability of power supply: The ability of a distribution network to distribute electrical energy to users above the acceptable rate. The higher the reliability of power supply, the healthier the distribution network operation. The formula is as follows:

$$X_4 = (1 - \frac{\bar{t}}{t}) \times 100\%, \tag{14}$$

$$\bar{t} = \frac{\sum W_0 \cdot t_0}{W}, \tag{15}$$

where $\bar{t}$ is the average power consumption time of all users, $W_0$ is the number of users without power; $t_0$ is the blackout time, $W$ is the statistics of all users, $t$ is the total statistical time.

(3) Quality index.

Voltage eligibility rate refers to the rate between the time when the voltage is within the specified limit and the total time. The higher the voltage eligibility rate is, the healthier the distribution network. The formula is as follows:

$$X_5 = (1 - \frac{t_0}{t}) \times 100\%, \tag{16}$$

where $t_0$ is the voltage over-limit time, $t$ is the statistical time.

(4) Economic index.

Line loss rate refers to the percentage of line loss in power supply. The lower the line loss rate, the healthier the distribution network is. The formula is as follows:

$$X_6 = \frac{P_1 - P_2}{P_1} \times 100\%, \tag{17}$$

where $P_1$ is the power supply, $P_2$ is the power sold.

**4.2. Scoring methods for single index.** In this paper, the evaluation function of fuzzy membership degree is used to determine the scoring formula of each single index [20]. Indices can be divided into three categories: positive indices, reverse indices and interval indices.

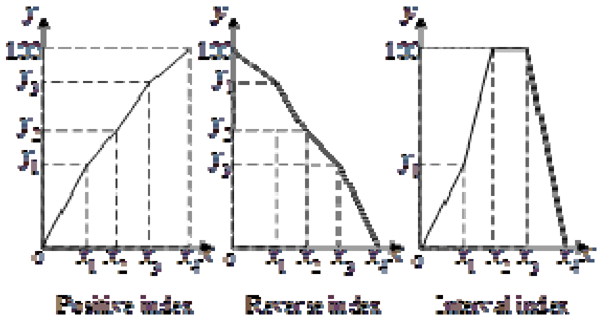


**Fig. 2**

As shown in Fig. 2, the slope of the curve within the interval was determined according to the proportion of index values in each segment, so as to divide the fuzzy membership function graph of each index, and then determine the piecewise function of interval values.

In the Fig. 2 $x$ the single index value, $x_i$ is the factor under investigation and also the segment point of the single index value, $y$ is the evaluation score, $y_i$ is the position of $x_i$ within [0,100] and also the evaluation score corresponding to the index value.

**5. Entropy combination weight method to determine the comprehensive weight.** Assessment the operating state of medium- and low-voltage distribution networks. After constructing the evaluation index system the weight of each index should be determined. At present, there are many methods to determine the weight factor, including analytic hierarchy process, Delphi method, comprehensive weighting method, etc. However, the above methods are more empirical and cannot objectively reflect the importance of each index. This paper proposes an entropy combination weight method to determine the weight of evaluation index. Firstly, on the basis of AHP, the index is positive and dimensionless. Secondly, AHP-Delphi method is used to estimate the importance of each evaluation index and calculate the subjective weight. Then, the entropy weight method is used to measure the information and calculate the objective weight. Finally, the comprehensive weight is optimized by Lagrange multiplier method.

**5.1. AHP-Delphi method to determine the subjective weight.** The calculation process of AHP-Delphi method used to determine the subjective weight of evaluation index is as follows:

(1) Construction of a judgment matrix: $u_i$, $u_j$ ($i$, $j$=1, 2…, $n$) represent factors, while $u_{ij}$ represent the importance of $u_i$ relative to $u_j$, and judgment matrix $P$ is formed through $u_{ij}$ as follows:

$$P=\begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ u_{n1} & u_{n2} & \cdots & u_{nn} \end{bmatrix}. \tag{18}$$

(2) Order of importance: calculation of the largest eigenvalue $\lambda_{\max}$ in $P$ and the corresponding eigenvector $\omega$ as follows:

$$P\omega=\lambda_{\max}\omega . \tag{19}$$

Then the eigenvector $\omega$ is normalized to rank the importance of each evaluation index.

(3) Consistency test: verification of reasonability for the importance ranking as follows:

$$CR=CI/RI , \tag{20}$$

where $CI$=($\lambda_{max}$-$n$)/($n$-1), the values of $RI$ are shown in Table 1, when $CR$<0.1 or $\lambda_{\max}$=$n$, $CI$=0, meet the requirements.

**Table 1**

| n | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| RI | 0 | 0 | 0.58 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 |

**5.2. Entropy weight method to determine the objective weight.** If the AHP-Delphi method adopted in section 5.1 is used to independently determine the weight of the evaluation index, it may lead to subjectivity, and the final evaluation result may be biased due to human factors, while the entropy weight method can effectively make up for the subjectivity of the weight of the index [21–22], the calculation process is as follows:

If there are $m$ units to be evaluated and $n$ evaluation indices, the original data matrix is as follows:

$$X=(x_{ij})_{m\times n} . \tag{21}$$

For one of the evaluation indices the information entropy is equal to:

$$E_j = -\sum_{i=1}^{m} p_{ij} \ln p_{ij} / \ln m , \tag{22}$$

where $p_{ij} = x_{ij} / \sum_{i=1}^{m} x_{ij}$ .

The information value of the evaluation index lies in the difference between the entropy and 1 of the indices. If the difference degree of the evaluation index is defined as $D_j$=1–$E_j$, the entropy weight of the evaluation index is:

$$w_j = D_j / \sum_{j=1}^{n} D_j . \tag{23}$$

**5.3. Determination of comprehensive weight and optimization.** In this paper the entropy combined weight method is used to determine the evaluation index weight of the network operating state. The process is as follows:

(1) The selected state evaluation index is positive and dimensionless, if $X_j$ is the positive index:

$$X_j^* = \frac{X_j - \min(X_j)}{\max(X_j) - \min(X_j)} . \tag{24}$$

If $X_j$ is the reverse index, then

$$X_j^* = \frac{\max(X_j) - X_j}{\max(X_j) - \min(X_j)} . \tag{25}$$

If $X_j$ is the interval index, then

$$X_j^* = \begin{cases} \dfrac{X_j - \min(X_j)}{a - \min(X_j)}, \min(X_j) \le X_j < a \\ 1, \qquad a \le X_j \le b \\ \dfrac{\max(X_j) - X_j}{\max(X_j) - b}, b < X_j \le \max(X_j) \end{cases} . \tag{26}$$

(2) Calculation of the subjective weight of each index according to AHP-Delphi method in section 5.1.

(3) Calculation the objective weight of each index according to the entropy weight method in section 5.2.

(4) Calculation of the comprehensive weight:

$$\overline{\omega} = \left\{ \begin{aligned} & W_1 w_1 / \sum_{j=1}^{n} W_j w_j , \\ & W_2 w_2 / \sum_{j=1}^{n} W_j w_j , \cdots , \\ & W_n w_n / \sum_{j=1}^{n} W_j w_j , \end{aligned} \right\} = (\omega_1, \omega_2, \ldots \omega_n) , \tag{27}$$

$$s.t. \ \sum_{j=1}^{n} \omega_j = 1; \omega_j > 0 . \tag{28}$$

Then the comprehensive weight is optimized by Lagrange multiplier method:

$$\omega_j = (W_j w_j)^{\frac{1}{2}} / \sum_{j=1}^{n} (W_j w_j)^{\frac{1}{2}} . \tag{29}$$

**6. The example analysis.**

**6.1. Development of the evaluation index system.** In the evaluation of the operating state of medium- and low-voltage distribution networks, the excessive number of evaluation indices affects the efficiency and accuracy of the evaluation, and also bring inconvenience to the data cleaning algorithm. Therefore, using the feature extraction algorithm based on improved principal component analysis to extract and delete redundant indices can improve the evaluation efficiency.

Firstly, the several single evaluation indices affecting the operating state of medium- and low-voltage distribution networks are pre-selected as shown in Table 2.

**Table 2**

| Index number | Evaluation index | Index number | Evaluation index |
|---|---|---|---|
| 1 | Three phase unbalances | 9 | Line loss rate |
| 2 | Power supply radius | 10 | Frame power factor |
| 3 | Risk of loss of load | 11 | Linking-up road rate |
| 4 | Reliability of power supply | 12 | Operation failure rate |
| 5 | Voltage eligibility rate | 13 | Harmonics distortion |
| 6 | Distribution transformer Failure rate | 14 | Non-transferable rate |
| 7 | Voltage deviation | 15 | Transformer load rate |
| 8 | Line overload rate | 16 | Rate of economy |

Then, the feature extraction based on improved principal component analysis was carried out for the pre-selected indicators, the quantitative matrix was constructed and the eigenvalue and variance contribution rate were calculated. The principal component load was determined and the importance degree of single index is obtained by formula (4). The results are shown in Fig. 3.

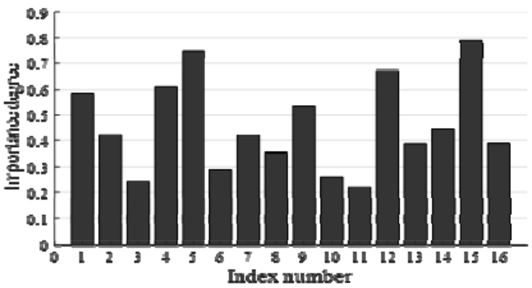


**Fig. 3**

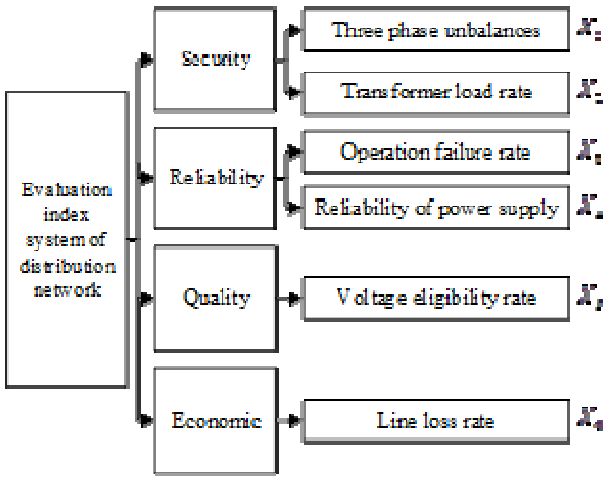


**Fig. 4**

By normalizing the importance degree of each single evaluation index to [0, 1], this paper selects the single evaluation index whose importance degree is greater than 0.5, then obtains six single evaluation indices for the operating state of medium- and low-voltage distribution networks, and develops the AHP index system for them, as shown in Fig. 4.

**6.2. Identification and removal of abnormal data.** In this paper, the distribution network of a region in Guangxi province of China was selected as the evaluation object. Firstly, the field monitoring data is numbered and the input vector is normalized. Then the similarity vector is obtained by calculating the Euclidean distance. After repeated learning and training of the self-organizing neural network, the original data are classified into 36 neurons.

In this work, 3972 groups of real-time monitoring data of distribution network are selected to conduct self-organizing neural network learning and training on the monitoring data. The neuron classification of the monitoring data is shown in Fig. 5 and the Euclidean distance between the neurons is

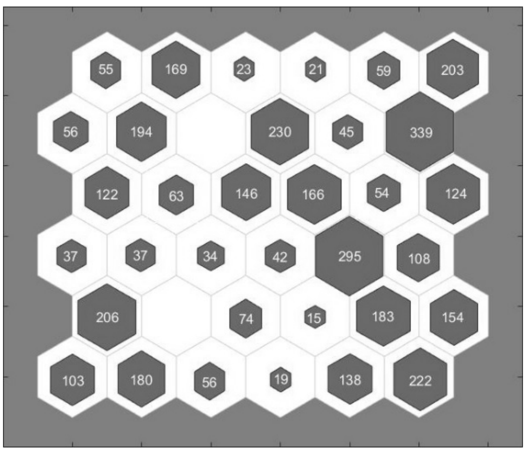

**Fig. 5**

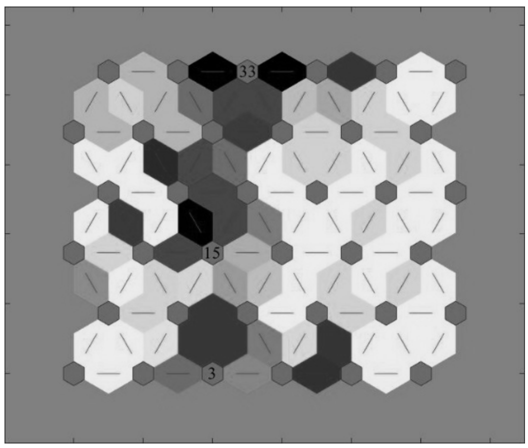

**Fig. 6**

shown in Fig. 6.

According to the neuron classification of monitoring data, shown in Fig. 5, 3972 groups of monitoring data were divided into 34 neurons, and each neuron contained a certain amount of monitoring data. According to the value of the Euclidean distance between neurons, the color of the division between neurons was displayed as white – gray – brown – black, the deeper color represents the Euclidean distance between neighboring neurons. If the Euclidean distance between a neuron and its surroundings is relatively large, the monitoring data of the neuron abnormalities need to be cleaned up. As shown in Fig. 6, the color between neurons no. 3, no. 15 and no. 33 and their neighboring neurons is too dark, it indicates that the Euclidean distance is large. Therefore, the number of abnormal data to be cleaned is shown in Table 3.

**Table 3**

| Category | Neuron no. 3 | Neuron no. 15 | Neuron no. 33 | Clean up the data |
|---|---|---|---|---|
| Amount of data | 56 | 34 | 21 | 111 |

**6.3. Evaluation of actual distribution network operating state.** (1) Determination of the evaluation index weight: calculation of the subjective weight of each separate evaluation index according to the AHP-Delphi method in section 5.1. Then, according to the entropy weight method in section 5.2, the objective weight of each evaluation index was calculated. Finally, according to formula (29), the comprehensive weight of six separate evaluation indices was calculated. The weights of each index are shown in Table 4.

**Table 4**

| Index | Subjective weight | Objective weight | Comprehensive weights |
|---|---|---|---|
| $X_1$ | 0.2106 | 0.0921 | 0.1490 |
| $X_2$ | 0.1326 | 0.3752 | 0.2386 |
| $X_3$ | 0.1242 | 0.2046 | 0.1705 |
| $X_4$ | 0.1536 | 0.0823 | 0.1203 |
| $X_5$ | 0.2435 | 0.1168 | 0.1803 |
| $X_6$ | 0.1354 | 0.1290 | 0.1414 |

After obtaining the weight of each index, the index weight of the intermediate layer of the evaluation index system is calculated, and then the weight factors of the evaluation index system of the medium- and low-voltage distribution network operating state are determined (see Table 5).

**Table 5**

| Intermediate index | Weight | Single index | Weight |
|---|---|---|---|
| Security | 0.3876 | Three phase unbalances | 0.3844 |
| | | Transformer load rate | 0.6155 |
| Reliability | 0.2908 | Operation failure rate | 0.5863 |
| | | Reliability of power supply | 0.4137 |
| Quality | 0.1803 | Voltage eligibility rate | 1 |
| Economy | 0.1414 | Line loss rate | 1 |

(2) Calculation and comparison of evaluation scores: according to the analysis of calculation examples based on the identification and cleaning of abnormal data in the self-organizing neural network in section 6.2. The abnormal data in neurons no. 3, no. 15 and no. 33 should be eliminated. Data from any remaining neuron and data from neuron 33 were selected for evaluation, combined with the single index model, the single index scoring formula and the comprehensive weight, the final result is shown in Table 6.

**Table 6**

| Data source | Security | Reliability | Quality | Economy | Total score |
|---|---|---|---|---|---|
| Neuron 33 | 69.08 | 87.81 | 78.33 | 70.91 | 76.46 |
| Neuron 20 | 66.32 | 83.23 | 61.27 | 75.22 | 71.59 |

As can be seen from Table 6, the overall rating of distribution network operation in Guangxi province is equal to 71.59. The evaluation score of the data in the neuron no. 33 that should be eliminated was higher than that in the neuron no. 20, and the score of quality was much higher than that in the normal data. After investigation and analysis, the voltage eligibility rate in this area is general, especially the low voltage phenomenon is more common, cannot reach a healthy level. It is proved that there is a large deviation when using uncleansed abnormal data to evaluate the status. Then it is proved that the data identification and cleaning based on the data cleaning algorithm of self-organizing neural network can improve the accuracy of distribution network operating state evaluation, and then reflect the actual operating state of distribution network.

**7. Conclusions.** This paper proposes a new operating state evaluation method for distribution networks based on improved principal component analysis and self-organizing neural network, considering the influence of abnormal data on distribution network evaluation, data cleansing by self-organizing neural network algorithm. In addition, the paper presents the improved principal component analysis to construct the evaluation index system, uses the entropy combined weight method to calculate the comprehensive weight of each evaluation index and gives a possibility to evaluate the operating state of distribution networks from the aspects of security, reliability, quality and economy.

By real example, the paper shows that the proposed method is characterized by fast convergence speed and high precision, permits to build the objective and reasonable evaluation index system and can effectively reduce the evaluation error due to abnormal data. The evaluation system and proposed method can provide the effective technical support for control and management of distribution networks.

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**СИСТЕМА КОМПЛЕКСНОЙ ОЦЕНКИ И МЕТОД ОПРЕДЕЛЕНИЯ РАБОЧЕГО СОСТОЯНИЯ РАСПРЕДЕЛИТЕЛЬНОЙ СЕТИ**

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*По мере развития интеллектуальных распределительных сетей и осуществления доступа к распределённой энергетике решение проблемы своевременного и точного определения рабочего состояния распределительной сети становится все более актуальной задачей. На основе усовершенствованного анализа основных компонентов и положений самоорганизующейся нейронной сети в статье предложен метод оценки рабочего состояния распределительных сетей среднего и низкого напряжения. На первом этапе создается система оценочных индексов распределительной сети. Система оценки состояния распределительной сети основана на четырех аспектах, в том числе безопасности, надежности, качества и экономии. Далее используется самоорганизующаяся нейронная сеть для идентификации и очистки данных относительно рабочего состояния распределительной сети. На следующем шаге моделируются индикаторы на всех уровнях, применяется метод энтропии для расчета общего веса каждого индикатора. Затем находится значение всех показателей и определяются слабые звенья в распределительной сети. На заключительном этапе проводится комплексная оценка фактической работы распределительной сети в китайской провинции Guangxi. Показано, что предложенный метод позволяет эффективно уменьшить влияние аномальных данных и фактора субъективности на результаты оценки состояния распределительной сети, что подтверждает целесообразность и осуществимость предложенного метода.* Библ. 22, рис. 6, табл. 6.

***Ключевые слова:*** распределительная сеть, усовершенствованный анализ основных компонентов, самоорганизующаяся нейронная сеть, комбинация энтропии, комплексная оценка.

**СИСТЕМА КОМПЛЕКСНОЇ ОЦІНКИ І МЕТОД ВИЗНАЧЕННЯ РОБОЧОГО СТАНУ РОЗПОДІЛЬНОЇ МЕРЕЖІ**

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*У міру розвитку інтелектуальних розподільчих мереж і здійснення доступу до розподіленої енергетиці рішення проблеми своєчасного та точного визначення робочого стану розподільної мережі стає все більш актуальним завданням. На основі вдосконаленого аналізу основних компонентів та положень нейронної мережі, що самоорганізується, у статті запропоновано метод оцінки робочого стану розподільних мереж середньої та низької напруги. На першому етапі за допомогою вдосконаленого аналізу основних компонентів створюється система оціночних індексів розподільчої мережі. Система оцінки стану розподільної мережі заснована на чотирьох аспектах, у тому числі безпеці, надійності, якості та економії. Далі використовується нейронна мережа, що само-організується, задля ідентифікації та очищення даних щодо робочого стану розподільної мережі. На наступному кроці моделюються індикатори на всіх рівнях, застосовується метод ентропії задля розрахунку загальної ваги кожного індикатора. Потім знаходяться значення всіх показників і визначаються слабкі ланки в розподільній мережі. На заключному етапі проводиться комплексна оцінка фактичної роботи розподільчої мережі в китайській провінції Guangxi. Показано, що запропонований метод дає змогу ефективно зменшити вплив аномальних даних та фактора суб'єктивності на результати оцінки стану розподільної мережі, що підтверджує доцільність і здійсненність запропонованого методу.* Бібл. 22, рис. 6, табл. 6.

***Ключові слова:*** розподільна мережа, аналіз головних компонентів, самоорганізована нейронна мережа, комбінація ентропії, комплексна оцінка.

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