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A Fast Evaluation Method of Power Flow Rationality for Power System Operation Mode Based on Deep Belief Network#

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ABSTRACT

The establishment of power system operation mode plays an important role in the safety, stability, economy and high quality operation of power grid. In order to enable the power grid operation mode staff can more quickly judge the advantages and disadvantages of the power flow of the operation mode according to the mode change and improve the flexibility and efficiency of the mode compilation, a fast evaluation method of the power flow based on the deep belief network is proposed. Firstly, considering the safety and stability guidelines of power system, the method establishes the evaluation index system of power flow state from three aspects of safety, stability and economy. Then the comprehensive evaluation method based on entropy-weight TOPSIS is adopted to comprehensively evaluate the evaluation indexes of multiple operation modes. Then, the index values of the above power flow evaluation system and the comprehensive evaluation results of entropy-weight TOPSIS are respectively used as the input and output data of the rapid evaluation model of power flow based on DBN. DBN algorithm based on RBM is used to extract deep features to complete unsupervised learning process, and then the supervised BP neural network is used as the conventional fitting layer to obtain the evaluation results. The flexibility and practicability of comprehensive assessment is effectively improved. In this paper, an example of IEEE39 nodes system is used to verify the effectiveness of the proposed model and algorithm.

Keywords: operation mode, assessment Index, comprehensive evaluation of power flow, deep belief network, rapid evaluation

NONMENCLATURE

Abbreviations	
DBN	Deep Belief Network
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
RBM	Restricted Boltzmann Machine
MVR	Multivariate regression
DNN	Deep Neural Networks
MLP	Multilayer perceptron
DT	Decision Tree
RF	Random forests
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
BP	Back propagation

1. INTRODUCTION

The establishment of power system operation mode plays an important role in the safety, stability, economy and high quality operation of power grid[1]. The compilation process of operation mode is the process of repeated adjustment and simulation calculation of equipment maintenance plan and work plan under the condition of predicted load distribution. In the traditional operation mode compilation, the operation mode calculation personnel usually make the first draft of the power grid operation mode with their experience and knowledge. Then the feasibility of the typical operation mode is determined through a lot of calculation and analysis[2-3]. The traditional arrangement and adjustment methods rely heavily on manual experience, which has a large workload of manual checking, repeated adjustment and high repeatability of calculation. It is difficult to meet the future power network analysis needs of changeable operation mode and complex stability characteristics. In addition, the automatic analysis ability of existing simulation software is weak, and the adjustment process of power grid operation mode lacks comprehensive quantitative evaluation methods for power flow state and power flow operation point. Operation mode computing personnel need to manually process and analyze a large number of output charts and data for each step of adjustment, and then guide the flow adjustment of the next steps according to the feedback of the analysis results. It greatly increases the workload of calculation personnel and seriously affects the efficiency of power grid operation mode adjustment and analysis. If there are many adjustment schemes, operation mode computing staff is also faced with the choice of a variety of schemes. Therefore, how to use advanced technology and methods to establish a set of scientific operation mode power flow state rapid evaluation method is an important problem to be solved at present.

The establishment of power system operation mode plays an important role in the safety, stability, economy and high quality operation of power grid. In order to enable the mode compiler to judge the advantages and disadvantages of the mode flow more quickly according to the mode change and improve the flexibility and efficiency of the mode compilation, a fast evaluation method of the power flow based on the deep belief network is proposed. Firstly ,considering the safety and stability guidelines of power system, the method establishes the evaluation index system of power flow state from three aspects of safety, stability and economy of power flow state of operation mode. Then the comprehensive evaluation method based on entropy-TOPSIS is adopted to comprehensively evaluate the evaluation indexes of multiple operation modes. Then, the index values of the above power flow evaluation system and the comprehensive evaluation results of entropy-weight TOPSIS are respectively used as the input and output data of the rapid evaluation model of power flow based on DBN. DBN algorithm based on RBM is used to extract deep features to complete unsupervised learning process, and then the supervised BP neural network is used as the conventional fitting layer to obtain the evaluation results. The flexibility and practicability of comprehensive assessment is effectively improved. This method can be combined with the intelligent adjustment algorithm of power grid operation mode to evaluate the rationality of power flow adjustment results of power grid operation mode, and give the direct numerical relationship between operation points and comprehensive indicators, so as to quickly correct the direction of power flow adjustment and improve the efficiency of power grid operation mode adjustment and analysis . In this paper, the IEEE39 node system is used to verify the effectiveness of the proposed model and algorithm.

2. POWER FLOW STATE EVALUATION INDEX SYSTEM

Considering the safety and stability guidelines and requirements of power system, this paper establishes the evaluation index system of power flow state from three aspects of safety, stability and economy, so as to carry out scientific and comprehensive analysis and evaluation of power flow operation points.

2.1 The safety indexes

Line load rate, bus short-circuit current and bus voltage all affect the safe and stable operation of power system. Therefore, N-1 pass rate, static safety level, line load rate, short-circuit current index, the voltage qualified rate and bus voltage overlimit index are used as safety indexes in this paper.

2.1.1 N-1 pass rate

N-1 pass rate refers to the ratio of the number of times when no overload occurs in any component in the system and the frequency and voltage are not over the limit to the total number of n-1 check in the power grid[4]. The expression is as follows:

$$I_{(N-1)pass} = \left(\frac{C_{(N-1)pass}}{C_{(N-1)}} \right) \times 100\% \tag{1}$$

Where, $I_{(N-1)pass}$ is the N-1 parity pass rate, $C_{(N-1)}$ is the total number of N-1 checks, $C_{(N-1)pass}$ is the number of N-1 check passes.

2.1.2 The static safety level

The static safety level index is mainly used to verify the overload level of the line and the main transformer in the power grid. It quantifies the deviation level of the distance from rated power of the line and the main transformer. The expression is as follows:

$$I_{SS} = \max\left(1 - \frac{S_i}{\overline{S}_i}\right) \times 100\% \tag{2}$$

Where, S_i is the actual operating power of the line or main transformer i , $\overline{S}_i$ is the rated operating power of the line or main transformer i .

2.1.3 The line load rate

Transmission line load rate is an important index to measure the safety of power grid operation. Therefore, the index should take into account the average load rate, heavy load and even overload of transmission lines[5]. The expression is as follows:

$$k_L = \frac{1}{m_1} \sum_{i=1}^{m_1} \frac{i_{Li}}{i_{Li,N}} + \sum_{j=1}^{m_2} \lambda_j \frac{i_{Lj}}{i_{Lj,N}} \tag{3}$$

Where, k_L is the load rate of the line, m_1 is the number of lines whose load rate does not exceed the limit, m_2 is the number of lines whose load rate exceeds the limit, In this paper, heavy load is defined when the load ratio is between 0.8-1, and overload is defined when the load ratio exceeds 1. i_{Li} is the actual current on line i , i_{Lj} is the actual current on line j . λ_j is the correction factor. When the line is heavy load, λ_j is 1.2, and when the line is overloaded, λ_j is 1.5.

2.1.4 The short-circuit current index

When the power grid short-circuit fault occurs, the power grid short-circuit current is the basis of ensuring the safe operation of the power grid within the range of the breaking capacity of the breaker [5]. The expression of the short-circuit current index is as follows:

$$k_{sc}=\frac{1}{n_1}\sum_{i=1}^{n_1}\frac{i_{sci}}{i_{i,br}}+\sum_{j=1}^{n_2}\mu_j\frac{i_{scj}}{i_{j,br}} \tag{4}$$

Where, k_{sc} is the indicator of bus short-circuit current, n_1 is the number of busbars whose short-circuit current does not exceed the limit, n_2 is the number of busbars whose short-circuit current exceeds the limit, i_{sci} is the actual short-circuit current of bus i, $i_{i,br}$ is the blocking current of the circuit breaker at bus i, μ_j is the penalty factor, and the value is 1.2 .

2.1.5 The voltage qualified rate

The voltage qualified rate index mainly inspects the voltage qualified level of the operating point and reflects the voltage operating quality of the node globally. The expression is as follows:

$$N_q=\begin{cases}1, & \text{if } U_q\in\left[\underline{U}_q,\overline{U}_q\right], q\in\Omega_B\\ 0, & \text{else}\end{cases} \tag{5}$$

$$I_{VQ}=\frac{\sum_{q\in\Omega_B}N_q}{N} \tag{6}$$

Where, I_{VQ} is the voltage qualified rate, N_q is the number of nodes with qualified voltage, N is the total number of power grid nodes. $\overline{U}_q$ and $\underline{U}_q$ indicate the upper and lower limits of node voltage respectively.

2.1.6 The bus voltage overlimit index

During the adjustment of the operation mode, the voltage of each bus may exceed the allowable limit. Therefore, it is necessary to evaluate the over-limit of bus voltage. The expression of the bus voltage overlimit index is as follows:

$$k_U=\frac{1}{N_{q1}}\sum_{i=1}^{N_{q1}}\frac{\left|U_i-U_{iN}\right|}{U_{iN}}+\sum_{j=1}^{N_{q2}}\gamma_j\frac{\Delta U_j}{U_{jN}} \tag{7}$$

$$\Delta U_j=\begin{cases}0 & 0.95U_{jN}\le U_j\le 1.05U_{jN}\\ U_j-1.05U_{jN} & U_j>1.05U_{jN}\\ 0.95U_{jN}-U_j & U_j<0.95U_{jN}\end{cases} \tag{8}$$

Where, k_U is the bus voltage overlimit index, N_{q1} is the number of buses whose voltage does not exceed the threshold, N_{q2} is the number of buses whose voltage exceeds the threshold, U_i is the actual operating voltage of bus i, U_{iN} is the rated voltage of bus i. γ_j is the penalty factor, and the value is 1.2 .

2.2 The stability index

The load variation, line outage and power flow distribution all affect the transient stability of the power system. In this paper, transient power angle stability is selected as the stability index and a practical engineering power angle stability index is established:

$$TSI=\frac{\Delta\delta^{\text{Threshold}}-\max\left|\Delta\delta_{ij}\right|}{\Delta\delta^{\text{Threshold}}+\max\left|\Delta\delta_{ij}\right|},\forall i,j\in\Omega_G \tag{9}$$

Where, TSI is the transient stability index, $\Delta\delta^{\text{Threshold}}$ is the preset threshold of power Angle difference, and the value is 360°. $\left|\Delta\delta_{ij}\right|$ represents the absolute value of the Angle difference between generator i and generator j.

2.3 The economic index

The economic level of power grid operation is usually measured by network loss rate and energy efficiency level. Therefore, this paper adopts network loss rate as economic index.The expression is as follows:

$$I_{loss}=\frac{\sum P_{Gen}-\sum P_{Load}}{\sum P_{Gen}} \tag{10}$$

Where, I_{loss} is the network loss rate index, $\sum P_{Gen}$ is the total active power generated, $\sum P_{Load}$ is the total load active power.

3. THE MODEL OF FAST EVALUATION METHOD BASED ON DBN

3.1 The comprehensive evaluation method of power flow state based on entropy-weight TOPSIS

In this section, the entropy-weight TOPSIS method is selected to comprehensively evaluate the power flow state of power grid operation mode. Firstly, the entropy weight method is used to determine the index weight, and then the determined weight is assigned to the normalized matrix in TOPSIS to obtain the weighted matrix, so as to establish the comprehensive evaluation method based on entropy weight and TOPSIS. The specific implementation steps of entropy-weight TOPSIS method are as follows:

(1) Calculate the value of each index in the evaluation index system of power flow state

(2) Build the initialization decision matrix and standardize the processing

There are n plan to be evaluated and m evaluation indicators, and a_{ij} is the value of the j evaluation indicator of the plan i to be evaluated. A judgment matrix composed of n plan to be evaluated and m evaluation indicators is constructed and standardized as follows:

$$\boldsymbol{P}=(p_{ij})=\begin{bmatrix} p_{11} & \cdots & p_{1m} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nm} \end{bmatrix} \tag{11}$$

$$p_{ij}=\frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \tag{12}$$

(3) The entropy weight method is used to calculate the index weight

Calculate the weight w_j of index j:

$$w_j=\frac{d_j}{\sum_{i=1}^{m} d_j} \tag{13}$$

Where, d_j is the difference coefficient of index j:

$$d_j=1-e_j \tag{14}$$

Where, e_j is the entropy value of index j:

$$e_j=-\frac{1}{\ln(n)}\sum_{i=1}^{m} P_{ij}\ln P_{ij} \tag{15}$$

(4) Construct the weighted normalization matrix $\mathbf{Z}$

$$\mathbf{Z}=(Z_{ij})_{m\times n}=r_{ij}w_j \tag{16}$$

$$r_{ij}=\frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{17}$$

(5) Calculate the distance of positive ideal point and negative ideal point of each evaluation scheme

$$\begin{aligned} S_i^+ &= \sqrt{\sum_{j=1}^{n}(Z_{ij}-Z_j^+)}, i=1,2,\cdots m \\ S_i^- &= \sqrt{\sum_{j=1}^{n}(Z_{ij}-Z_j^-)}, i=1,2,\cdots m \end{aligned} \tag{18}$$

$$Z_j^+=\begin{matrix} \max\limits_i(Z_{ij}), j\in J^* \\ \min\limits_i(Z_{ij}), j\in J^{'} \end{matrix}, Z_j^-=\begin{matrix} \min\limits_i(Z_{ij}), j\in J^* \\ \max\limits_i(Z_{ij}), j\in J^{'} \end{matrix} \tag{19}$$

Where, Z_j^+ is the optimal value of the index, Z_j^- is the worst value of the index, J^* is the benefit indicator set, $J^{'}$ is the cost indicator set .

(6) Calculate the relative closeness to the ideal solution

$$C_i=\frac{S_i^-}{S_i^+ + S_i^-} \tag{20}$$

Based on the above steps, the schemes are sorted according to the calculated relative closeness degree. The larger the value is, the better to find the optimal evaluation scheme.

3.2 Fast evaluation model of power flow state based on deep belief network

In this section, DBN model based on RBM is constructed to rapidly evaluate the power flow state. Then, the index values of the above power flow evaluation system and the comprehensive evaluation results of entropy weight-TOPSIS are respectively used as the input and output data of the rapid evaluation model. This method directly mines the historical data pattern, gives the direct numerical relationship between the operation point and the comprehensive index, and then can assist the dispatching department to quickly evaluate the rationality of the operation mode power flow. The deep belief network regression evaluation model is shown in Fig.1 . The model consists of multiple RBM and a BP neural network. DBN based on RBM is used to extract deep features to complete the unsupervised learning process. Then an RBM layer is used for output and the output results are input into BP neural network. The supervised BP neural network is used as the conventional fitting layer to obtain the evaluation results.

DBN is a deep expression learning model which is superimposed by several layer RBM, with the output of each layer as the input of the next layer. RBM contains visible layer v and hidden layer h . There is no connection between the neurons of visible layer v and hidden layer h, while each neuron of hidden layer h is connected to each neuron of visible layer v . RBM is an energy based model. The joint configuration energy function of the input layer and the hidden layer is as follows:

$$\begin{aligned} E(\mathrm{x},\mathrm{h}\,|\,\theta) &= -\sum_{i=1}^{n} a_i x_i - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} h_j W_{ij} x_i \\ &= -\mathrm{a}^T\mathrm{x} - \mathrm{b}^T\mathrm{h} - \mathrm{h}^T W\mathrm{x} \end{aligned} \tag{21}$$

Where , $\theta=\{a_i,b_j,W_{ij}\}$ is the parameter of RBM. a_i and b_j represent bias of neurons in the input layer and the hidden layer respectively. v_i and h_j represent the states of the input layer neurons and the hidden layer neurons respectively. W_{ij} is the connection weight between input layer neuron i and hidden layer neuron j.

Due to the special structure of RBM, it can be seen that when the states of visible units are given, the activation states of each hidden unit are conditionally independent. In an RBM, When the activation state is represented by logistics function, it is known that the activation probability of each node in the input layer and the hidden layer are shown as follows:

$$P(h_j=1\,|\,v,\theta)=\mathrm{logistic}(\textstyle\sum_i W_{ij}v_i+b_j) \tag{22}$$

$$P(v_i=1\,|\,\mathrm{h},\theta)=\mathrm{logistic}(\textstyle\sum_j W_{ij}h_j+a_i) \tag{23}$$

The deep structure of the DBN is not easy to train. The DBN training adopts the two-stage method of RBM unsupervised pre-training and reverse supervised parameter fine adjustment from bottom to top. The training process is shown in the Fig.1 below.

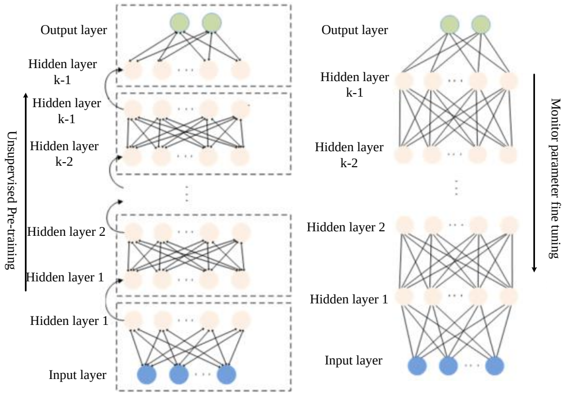

Fig. 1 Deep belief network training method

4. RESULTS

4.1 Basic data and parameters

In this section, the IEEE39 nodes system is used to verify the above proposed rapid evaluation method of power flow rationality of power system operation mode based on DBN. The system has a total of 10 generators, 34 lines and 19 loads. Python is used to call PSASP to randomly obtain 1000 operation mode, and the steady-state simulation and transient simulation are carried out respectively, so as to obtain the evaluation index value of each mode. The status of power flow of operation mode is evaluated and ranked respectively, and the value of ranking is used as the data label of supervised training. 700 groups of samples are selected from 1000 groups of data for training and 300 groups for testing.

4.2 Evaluate model parameter Settings

In the process of DBN model training, model parameters need to be tuned through several experiments. In order to optimize the model of deep structure and minimize the error of evaluation results, the selection of related parameters such as the number of layers, nodes and training algebra is crucial. If the number of hidden layers and nodes is small and the network depth is insufficient, the data analysis ability and deep feature extraction ability of the network will be affected. If there are too many hidden layers and nodes, the over-fitting phenomenon will occur in the training process, which will affect the generalization performance of the network on the test set. Therefore, this section considers the influence of the number of layers and the number of nodes on the evaluation results respectively, the optimization experiment of hidden layer number and node number is carried out by using the ten-fold cross verification method and adopts the longitudinal comparison scheme to optimize the parameters. The influence of the number of hidden layers and nodes on model performance are shown in Tab.1 and Tab.2.

Tab. 1 The influence of hidden layers on model performance index

layers	MAPE	R^2 Score	Time/s
1	2.2383	0.9928	24.5
2	1.5866	0.9966	61.2
3	1.2169	0.9973	97.3
4	0.6163	0.9992	146.5
5	0.7923	0.9987	191.2
6	0.8495	0.9985	248.3

As can be seen from the results in Table 1, when the hidden layer number of the model is 4, the R^2 Score value of the model reaches the maximum and the MAPE value is the minimum, and the performance of the model is optimal. When the number of layers increases from 1-4, the MAPE value of test samples decreases gradually, R^2 Score value increases gradually, and the performance of the model improves gradually. When the number of layers is larger than 4, the spatial and temporal complexity of the model increases, resulting in the over-fitting effect. Therefore, taking the performance and training time of the model into consideration, the hidden layers of the model are selected as 4 layers in this paper.

The selection range of the hidden layer nodes number of hidden layers is $\{32, 64, 128, 256, 512\}$. The DBN models with different structures are obtained by the experiment procedure of searching node number layer by layer. The performance index values under different model structures is shown in Tab.2. As can be seen from the results, MAPE index value of the model decreases and R^2 Score value index value increases with the increase of the number of nodes in each layer. When the number of nodes in each layer of the hidden layer is 512, the model performance is optimal, but the training time cost of the model is large at this time. In order to give consideration to the rapidity and accuracy of the model, we designed an experimental scheme in which the number of nodes in the first hidden layer is 256 and the number of nodes decreases with the increase of the number of layers. As can be seen from the results in the Tab.2, when the model structure is 256-128-64-32, the MAPE index value of the model is 0.6917, and the R2 Score index value is 0.9992. The performance is slightly lower than that of the model structure with 256 nodes per layer, but the training time of the model is improved by nearly 35 seconds. The optimal structure of DBN model is not unique. Therefore, this paper chooses the model structure with four hidden layers and 256-128-64-32 nodes in each layer. The evaluation error curve of the test set is shown in Fig 2.

Tab. 2 The results of model performance indexes with different network structures

nodes	MAPE	R^2 Score	Time/s
32-32-32-32	1.2701	0.9974	85.7
64-64-64-64	0.9183	0.9985	95.2
128-128-128-128	0.8256	0.9988	110.2
256-256-256-256	0.6163	0.9992	146.5
512-512-512-512	0.5765	0.9994	294.2
256-128-64-32	0.6917	0.9992	111.8

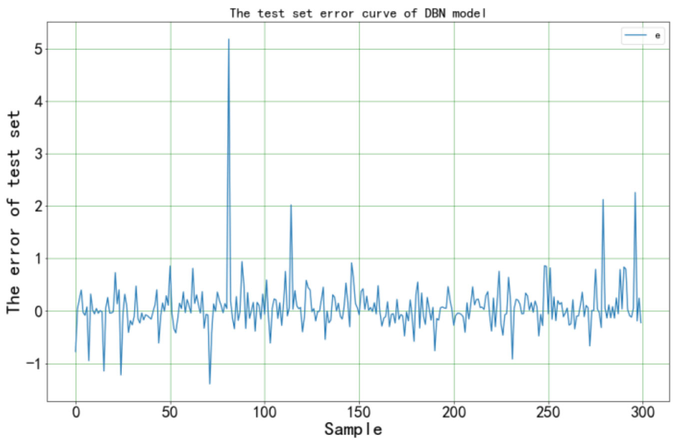

Fig. 2 The evaluation error curve of the test set

4.3 Model performance analysis

In order to further verify the learning and generalization ability of DBN model in power system power flow state rationality assessment, the performance of DBN algorithm is compared and verified. DBN model, MVR model, DNN model MLP model DT model and RF model were used to train and predict the operation mode power flow evaluation index data, and the effect of evaluation models was compared. The performance results of each evaluation model is shown in Tab.3

Tab.3 The performance results of each evaluation model

	R^2 Score	MAE	MSE	MAPE
MVR	0.9822	1.078	2.008	2.493
DNN	0.97	2.097	6.825	4.778
MLP	0.9923	1.041	1.76	2.52
DT	0.93	3.18	16.133	7.627
RF	0.972	1.966	6.277	4.789
DBN-BP	0.9992	0.2625	0.183	0.6163

As can be seen from the results in the Tab 3, for the same samples, the DBN model presented in this paper has optimal values under the indexes of R^2 Score, MAE, MSE and MAPE. As an important evaluation index of regression model, R^2 Score value corresponding to the best model is usually close to 1, and the smaller the value is, the worse the evaluation effect of the model is. The R^2 Score value of the DT model is the smallest, and the R^2 Score value of the DBN model is the largest .The evaluation error of DBN model is relatively small, in a relatively ideal range, and the comprehensive evaluation effect is the best. Comprehensively, the model proposed in this paper can better evaluate the rationality of power system operation mode power flow.

5. CONCLUSIONS

The establishment of power system operation mode plays an important role in the safety, stability, economy and high quality operation of power grid. In order to enable the mode compiler to judge the advantages and disadvantages of the mode flow more quickly according to the mode change and improve the flexibility and efficiency of the mode compilation, a fast evaluation method of the mode flow based on deep belief network is proposed. The main conclusions are as follows:

(1) DBN algorithm based on RBM is used to extract deep features to complete unsupervised learning process, and then the supervised BP neural network is used as the conventional fitting layer to obtain the evaluation results. The proposed method can make use of the self-learning advantages of DBN algorithm and BP neural network algorithm to directly mine historical data patterns, and give the direct numerical relationship between running points and comprehensive evaluation indexes, which improves the flexibility and practicability of comprehensive evaluation. This method can assist dispatching department to quickly evaluate the rationality of power flow of operation mode, so as to quickly correct the direction of power flow adjustment, improve the efficiency of power network operation mode adjustment and analysis, and better meet the needs of operation mode compilation.

(2) Compared with the manual evaluation method, the flexibility and practicability of the fast evaluation method of power flow rationality based on the deep belief network algorithm are improved obviously. In the future, with the development of deep learning and artificial intelligence technology, it is the further research direction of this paper to select more scientific and reasonable evaluation indicators, use artificial intelligence method to calculate and analyze the evaluation indicators, and improve the theory and method of power flow intelligent evaluation of power system operation mode.

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