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Construction and reduction methods of Grid Security Situation Assessment index system for intelligent scheduling

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Abstract: The development of smart grid construction in our country has put forward much higher requirements on power grid dispatching operation, which needs to develop the corresponding supporting system of the intelligent scheduling. It is aimed to accurately control the development trend and process of power grid operation by building automatic intelligent scheduling system architecture based on the situational awareness. In order to assess the security situation of the smart grid, this paper firstly uses the Delphi method and analytic hierarchy process (AHP) and constructs the situation assessment index system. Secondly, in allusion to several characteristics of situation assessment index of power grid, such as strong affinity and high dimension, Autoencoder method was adopted to decrease the dimension of index data, thus high-dimensional data being shown in a low dimensional space. Autoencoder method got the optimal initial weights in the training process, which was used in fine-tuning process to adjust weight by reversely propagating error and to get the optimal results by minimizing reconstruction error function. Under the MATLAB experiment platform, there had a simulation experiment for reconstruction error in the training and fine-tuning process. The experimental result is that the coding after dimensionality reduction can completely show high-dimensional data information and use lower dimensional code as input can significantly reduce the complexity of the grid situation assessment model in later period.

Keywords: Power grid security; Intelligent scheduling, Situation assessment, Index system, Autoencoder, Indicators reduction.

I. INTRODUCTION

With the expansion and complication of the scale of power grid, technical support system is required to become more intelligent, and its operation personnel also need a quick and comprehensive grasp for the situation of grid's safety risk in practiced and predicted tense, understand the situation of grid security under the influence of various risk factors, and then make corresponding decision timely. The existing electric power dispatching system is based on experience and analysis, and its automation and intelligence have not reached a high level, which is because the lack of accurate control for development and changes in the grid operation state. At the same time, the analysis results provided by various kinds of application software are only focused on a particular aspect of grid operation, which lacks the abilities to make comprehensive analysis and decision-making from the entire network operation situation, so operation personnel need to act control by manually reading all kinds of analysis results based on the artificial experience and off-line strategies [1]. As the power grid's scale expands rapidly and the complexity of operation improves, operation personnel's working pressure is increasing and the difficulty to ensure the safety and economic operation of power grid is growingtoo. Therefore, there has a special significance for grid to study a risk index system, which is suitable for all kinds of application scenarios and respectively indicates situation of grid's operational risks in time and space dimension and accurately assess its security situation. Through collecting and understanding all sorts of factors connected with the changes of grid in the wide area, it is aimed to accurately grasp the safety situation of grid and become its safety management from passive to active [2-4]. Dispatchers can judge the trend of power grid system's security and adopt defensive measures and safe strategies before disturbance and malfunction.

To conduct a comprehensive assessment of power grid situation, it firstly needs to build the perfect index system for situation assessment. Index as a grid security risk indicator should be able to fully indicate the risk status of power grid in different sides and help dispatcher make corresponding decisions. There have some related researches for risk index system at home and abroad. Literature[5] uses Delphi method and AHP (Analytic Hierarchy Process) to build an index system of vulnerability risk assessment, and Autoencoder is proposed toreducedimensionality of indexdata by representing high-dimensional data in a low dimensional space. Literature [6] presents a risk assessment method for evaluating the cyber security of power systems considering the role of protection systems and use the expected load curtailment index to quantify potential system losses due to cyberattacks. Literature [7] presents a new risk assessment method that is applicable to extreme cases in power systems and analyzes the interactions among protection system components and the power grid in extreme events pertaining to simultaneous faults and cascading failures. Literature [8] proposes a security-oriented stochastic risk management technique that calculates cyber-physical security indices to measure the security level of the underlying cyber-physical setting. Literature [9] proposes a cross-entropy (CE) based simulation method to evaluate two indices of loss of load probability and expected demand not supplied, as well as the empirical distribution of demand not supplied. A novel approach to estimate the impact of transient instability is presented in [10], by modeling several important protection systems in the transient stability analysis.

For methods of reducing dimensionality of high-dimensional data, a lot of researches have existed both at home and abroad. The method of rough set is proposed to solve the problem of attribute reduction in classification aspects and reviews about hybrid methods, rough set combined with the fuzzy sets and neural networks [11].A cascaded co-evolutionary model for Attribute reduction and classification based on coordinating architecture with bidirectional elitist optimization (ARC-CABEO) is proposed in [12]. A new feature evaluation criterion based on community modularity in complex network is proposed to select the most informative features in [13]. In [14], the rough set theory is applied to the interlaced system to reduce the database and remove unnecessary information, and improves the accuracy of the operation. Extended rough set methods of attribute reduction based on approximation set model of rough set are discussed in algebraic view and information view [15], and it proposes a distribution reduction method on the basic of discernibility matrix. Literature [16] performs attribute reduction for decision systems with symbolic and real-valued condition attributes by composing classical rough set and fuzzy rough set models. Literature [17] proposes a novel scheme for simplifying a surfel set with the resultant surfels computed and distributed to preserve prominent geometric and textural features.

The remainder of the paper is organized as follows: section2 analyzes and builds index system of power grid security situation assessment; section3 introduces Autoencoder method and describes the process of reducing the index of the grid; section4 gives the experimental results and detailed analysis of the reconstruction errors in the pre-training process and the fine -tuning process; section5 contains a conclusion of the paper and future work.

II. ESTABLISHMENT OF INDEX SYSTEM OF POWER GRID SECURITY SITUATION ASSESSMENT

A. The determination of index of situation assessment

Power system's security and stability requires power grid operation state can keep controlled under normal conditions, which be able to run under the expected accidents, and have certain resistance within the acceptable range under the various disturbance events influenced by system and external environment.

Reasonable security situation assessment index system should be able to measure its degree to satisfy the above requirements. On the one hand, the index system should reflect the situation of current power grid's running state; on the other hand, it should reflect the anti-jamming performance of power grid. Power grid security situation assessment aims to anticipate risk factors of power grid security and present risk's occurrence probability and consequence, then give the corresponding risk value, and make corresponding precautions and measures to ensure safe and reliable operation of power grid. In view of this, it is very important to construct a relatively complete situation assessment index system. This paper, on the basis of considering the requirements for grid's security and stability, combines with the Delphi method to determine the grid security situation assessment index system, which is divided into six categories. Grid risk factors can be divided into equipment risk, structural risk, operation risk, external risk, men-made security and economic risk. The general procedures of situation assessment index system are illustrated as Fig. 1.

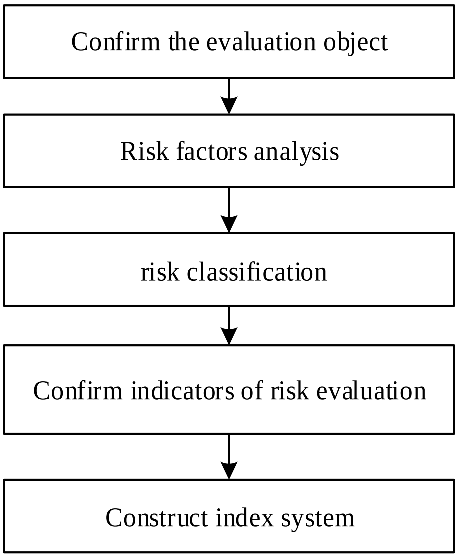

Fig. 1. The flow chart of constructing the index set

B. Hierarchical structure of index system

The paper built index set of power grid security situation assessment with Delphi [18], and used Analytic Hierarchy Process (AHP) to construct hierarchical index system [19]. The top level is also known as grid security. The index system includes two categories: technical factors producing power grid risk includes device risk (DR), structure risk (SR), operational risk (OR); managerial factors includes external risk (ER), Human hazard Risk (HHR) and financial risk (FR). The paper has a total of 52 indexes. The hierarchical structures of power grid security situation are shown in Fig. 2 and Fig. 3 respectively.

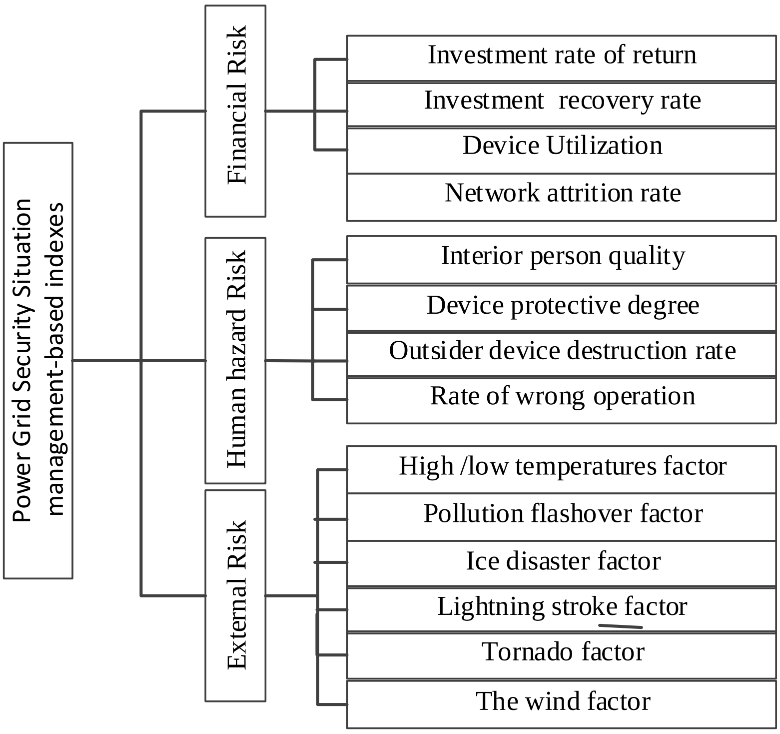

Fig. 2. Hierarchical structure of managerial indexes

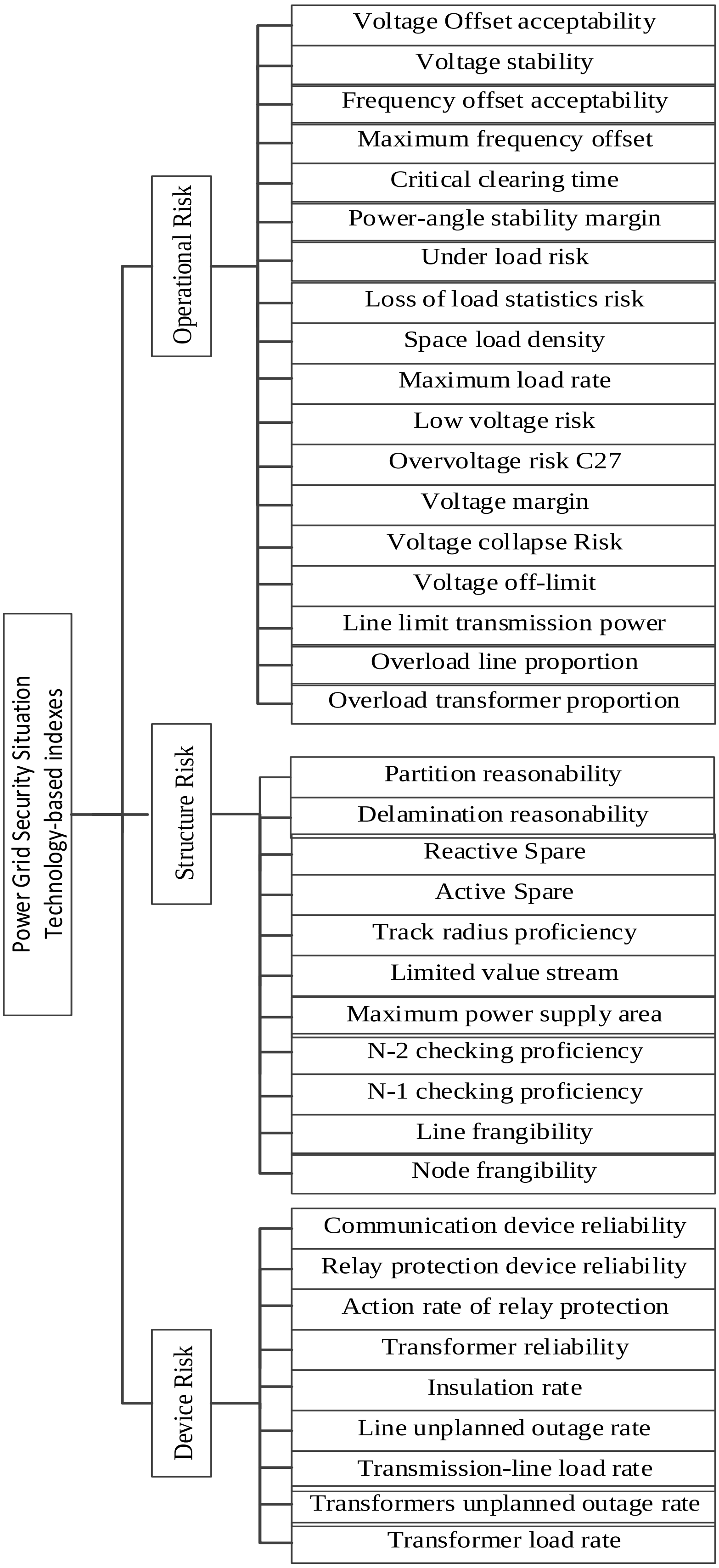

Fig. 3. Hierarchical structure of technical indexes

In Fig. 2 and Fig. 3, it shows that technological type includes 38 indexes and the management type includes 14 indexes. On the whole, power grid security situation assessment indexes system in this paper has 52 indexes in total, which can comprehensively describethe safe level of power grid.

C. situation assessment index data and its processing

Index system is shown in TABLE.1. Indicators divided into qualitative indexes and quantitative indexes: quantitative indexes data can be obtained by the historical data and it is available through system status or the routine's metrication, which can be used as data of training set. On the basis of classifying data sample, quantitative indicators' dimension is different and the descriptive ways of qualitative indicators are inconsistent. Without unified evaluation index data format, it can't support machine to calculate, so it's necessary to quantify, standardize and normalize the index data. Then use the data as the input of the system. After preprocessing for the index data, the method of scale conversion is adopted to normalize sample data.

TABLE 1. Index system of power grid security situation assessment

Secondary indices	Tertiaryindices	Secondary indices	Tertiaryindices
DR B1	Transformer load rate C1		Overvoltage risk C27
	Transformers unplanned outage rate C2		Low voltage risk C28
	Transmission-line load rate C3		Maximumload rate C29
	Line unplanned outage rate C4		Space load density C30
	Insulation rate C5		Loss of load statistics risk C31
	Transformer reliability C6		Under load risk C32
	Action rate of relay protection C7		Power-angle stability margin C33
	Relay protection device reliability C8		Critical clearing time C34
	Communication device reliability C9		Maximum frequency offset C35
	Node frangibility C10		Frequency offset acceptability C36
	Line frangibility C11		Voltage stability C37
SR B2	N-1 checking proficiency C12		Voltage Offset acceptability C38
	N-2 checking proficiency C13	ER B4	The wind factor C39
	Maximum power supply area C14		Tornado factor C40
	Limited value stream C15		Lightning stroke factor C41
	Track radius proficiency C16		Ice disaster factor C42
	Active Spare C17		Pollution flashover factor C43
	Reactive Spare C18		High /low temperatures factor C44
	Delamination reasonability C19	HHR B5	Rate of wrong operation C45
	Partition reasonability C20		Outsider device destruction rate C46
OR B2	Overload transformer proportion C21		Device protective degree C47
	Overload line proportion C22		Interior person quality C48
	Line limit transmission power C23	FR B6	Network attrition rate C49
	Voltage off-limit C24		Device Utilization C50

Voltage collapse Risk C25	Investment recovery rate C51
Voltage margin C26	Investment rate of return C52

For quantitative index x, the normalized process's formula is shown as follows.

$$y = \frac{x - \min x}{\max x - x} \tag{1}$$

For qualitative indicators x, the formula is shown as follows.

$$y = \frac{\max x - x}{\max x - \min x} \tag{2}$$

Among them: min(x) and max(x) are minimum and maximum values of the same data, X for the raw data, y for the data after normalized processing.

In process of power grid security situation assessment, the key step is to select the reasonable and scientific evaluation index system among many index summary, because minor or unimportant indicators will affect the scientific rationality and uncertainty of situation assessment. In this paper, we adopt Autoencoder method to attribute reduction, removed the smaller influence on situation evaluation index, reduced the complexity of time and spaced and improve the efficiency of evaluation.

III. ATTRIBUTE REDUCTION BASED ON THE NETWORK STRUCTURE OF AUTOENCODER

A. Network Structure Design based on Autoencoder

Autoencoder was introduced by G. E. Hinton in 2006 [20], which was a kind of nonlinear reduction method developing on the basis of neural network in multi-layer depth.

The dimensions of the security situation index system for power grid sample: 52, this experiment select Autoencoder network structure with three hidden layers. Autoencoder determines the complexity of the nonlinear structure by hiding the number of layers. In general, the hidden layer is selected to be 3-5 layers. The number of hidden units is gradually decreasing and finally getting the reduced size required, which can be done by experience. In our article, the network structure of Autoencoder is 52-200-100-50-5. The Autoencoder is a nonlinear simplified method whose initial weight is obtained by minimizing the difference between the pre-training main code and the reconstructed code. We can obtain the desired gradient information through the coding network. The decoding network propagate the reconstruction error through the encoder network, thereby achieving the optimal reconstruction result during the fine tuning. The pre-training network structure consists of four RBMs (restricted Boltzmann machines) with a structure of 52-200, 200-100, 100-50, 50-5. The output of each hidden layer of RBM is the input of the visible layer of the next RBM, respectively. The network structure of the autoencoder is encoder network 52-200-100-50-5, and the decoder network in the fine tuning process is 5-50-100-200-52. The upper neurons can capture the high correlation of the underlying neurons and use the non-linear relationship between the learning layer and the layer as the output. By adjusting the weight, important features can be acquired through smaller weights and redundancy. The high-dimensional data is set to low-dimensional linear space, so all high-dimensional data can be fully contained in the final output information. In our design of the network structure of the autoencoder, we mapthe 52-dimensional data to the 5 dimensional nonlinear space through the network structure, which can greatly reduce the modeling complexity of the risk assessment in the following work.

B. Reduction Process of Autoencoder

Generally speaking, the implementation of autoencoder consists of two main processes, namely pre-training process and fine-tuning process. Between pre-training and fine-tuning, the transition is unrolling process. During fine tuning, it is difficult to find a local minimum if the initial weight is too large. The gradient of the front layer is too small to train an automatic encoder network with multiple hidden layers at too much weight. Autoencoder compiles and expands by using the appropriate initial weights, which generate the encoder network and the decoder network.

1) Pre-training process and the unrolling process

Pre-training has learned to limit the Boltzmann machine (RBM) to multiple layers to adjust the network weight for each layer. RBM consists of two layers of network, which is composed of visible layer and hidden layer, and hidden layer is composed of multiple neurons. The RBM structure is shown in figure 4.

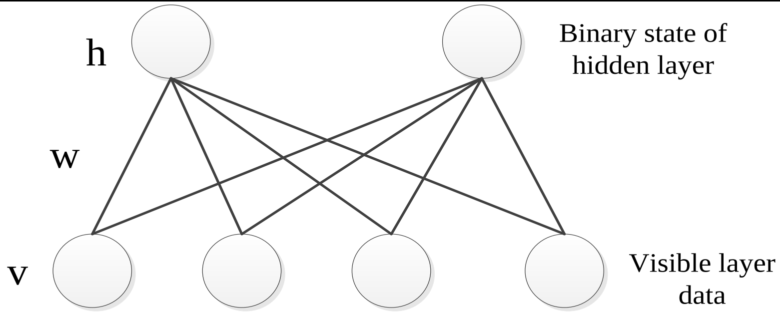

Fig. 4. The structure of RBM

Visible layer and hidden layer weight updated formula is as follows:

$$\Delta w_{ij} = \varepsilon\left(\left\langle v_i h_j \right\rangle_{data} - \left\langle v_i h_j \right\rangle_{recon}\right) \qquad (3)$$

where ε is a learning rate, $\left\langle v_i h_j \right\rangle_{data}$ is the product of the visible unit and the hidden unit j, as a binary state whose value is generated by the input data, and $\left\langle v_i h_j \right\rangle_{recon}$ is generated by the reconstructed data. By learning and adjusting the weight, we can obtain the output of an RBM, which is treated as the input of the next RBM of the learning weight. While the hidden unit of RBM is also the visible unit of the next RBM learning weight. Finally, the initial weight of the optimization is obtained through the learning layer, until the number of pre-training is returned in advance. The learning process of RBM is shown in Fig. 5.

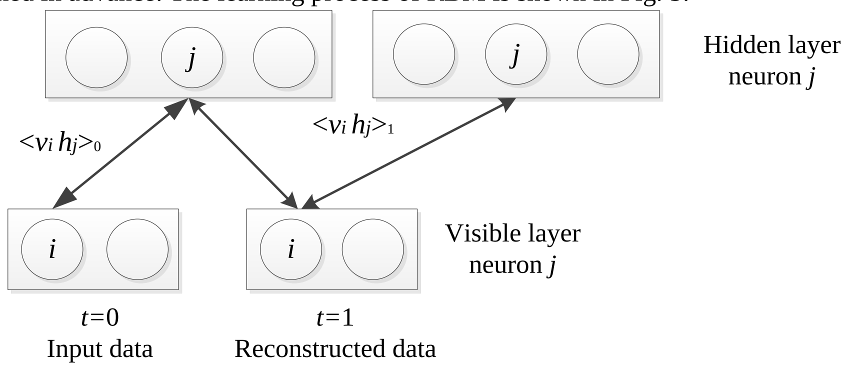

Fig. 5. The learning process of RBM

Fig. 5 shows the learning process of RBM, First, input data from the visible layer, and update the state of the hidden unit j according to the visible unit j, and then construct the state of the visible unit j using the hidden unit i. And then, the visible unit i is used to construct the hidden unit j status. The above process is the complete process of RBM training and learning, this process can adjust the weight. After learning multiple iterations, the last result will be entered as the next RBM, and then the learning process will be repeated several times in the next RBM.

The hidden layer of each layer RBM and the next layer of RBM visible layer merged into a layer, so that the merger of the self-encoding network, which encodes the network and the decoding network symmetry. The pre-training and unrolling processes of Autoencoder are shown as Fig. 6.

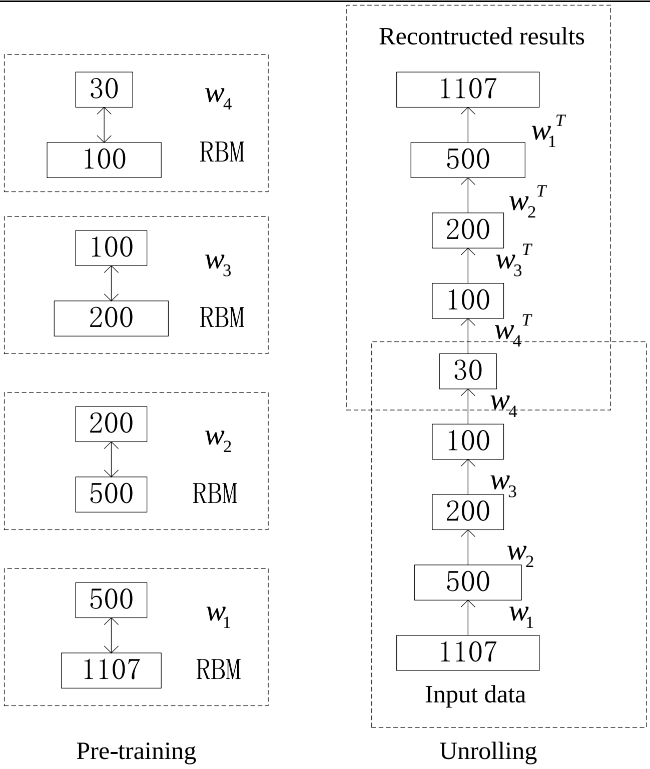

Fig. 6. The pre-training and unrolling processes of Autoencoder

2) Fine-tuning process

The fine-tuning process takes the initial weight obtained by the pre-training process and adjusts the weight based on the principle of minimization of the reconstruction error to achieve a better reconstruction effect [20]. The input data is encoded by the encoding network first, and the reconstructed data is obtained through the decoding network.Set the input sample set to $D=\{x_1,...,x_n\}$ encoder function (encoder) as f_θ, decoder function(decoder) as g_θ. The set of parameters is $\theta=\{W,b,W',d\}$, whereb、d are bias vectors of encoder and decoder, and W 、 W' are weight matrices of encoder and decoder.

The input of high-dimensional data through the encoder to obtain the low-dimensional encoding is as follows:

$$h_n = f_\theta(x_n) \tag{4}$$

$$r = g_\theta(h) \tag{5}$$

Under normal circumstances, the fine-tuning process through the decoding network and then through the encoding network to reverse the reconstruction of the error compensation mediation weight. The effect of the fine-tuning process parameters on the reconstruction results is very small. The initial weights obtained by the pre-training process are almost accurate and have little effect on the fine-tuning process. The main factors affecting the fine-tuning process are the range of weight. The reconstruction error function is usually selected according to the range and characteristics of the input sample. If the input data bits are continuous real numbers, the reconstruction error function is given by the formula (6). If the input data is a binary number, the reconstruction error function is The cross entropy loss function is given by equation (7).

$$L(x,r)=\|x-r\|^2 \tag{6}$$

$$L(x,r)=-\sum_{i=1}^{d_x} x_i \log(r_i)+(1-r_i)\log(1-r_i) \tag{7}$$

The fine-tuning process adjusts the weight by the conjugate gradient method to minimize the reconstruction error, and can pre-set the number of fine-tuning process, the adjustment has reached the best reconstruction effect. The structure used in the fine-tuning process is shown as Fig. 7.

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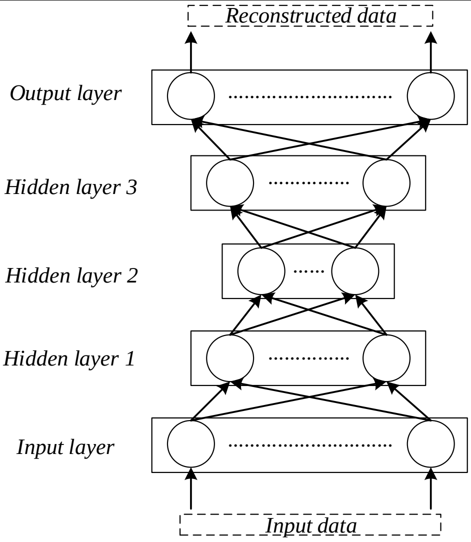

Fig. 7. The fine-tuning process of Autoencoder.

IV. THE EXPERIMENT AND ANALYSIS

Power grid security situation assessment index system use the Autoencoder reduction algorithm, the main flow chart of the algorithm are as follows.

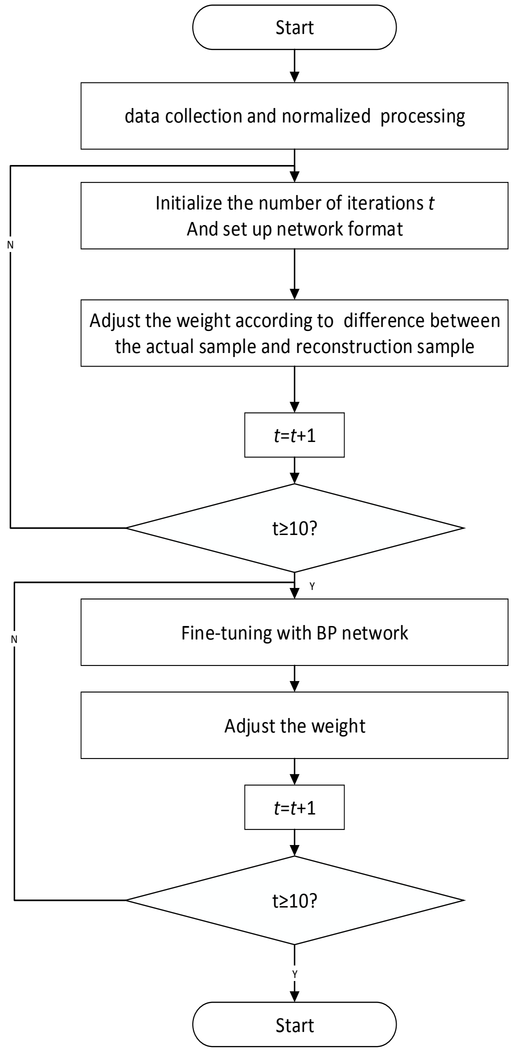

Fig.8. Flowchart of Autoencoder

Step 1: Data acquisition and process. Dehpi method and AHP method is used to get the index system, for all the sample data of every sample data $\{x_1,\ldots,x_n, n=1,\ldots,52\}$, preprocess the acquisition data as input data to Autoencoder network structure.

Step 2: Initialize parameters. Set the number of iterations initial value $t=0$, the maximum number of iterations of pre-training and fine-tuning is 10. Autoencoder network structure layer is 5.

Step 3: Pre-training process. After the input processing index data, adjust the weight according to the difference between actual sample data and reconstruct data until to maximum number of iterations. The attributes reduction of dimensions for the value of the five characteristics used to reflect 52 indicators.

Step 4: Fine-tuning process. Adjust the cross entropy function by using BP neural network, and then adjust the weights, and decreases the reconstruction error until maximum iterative coefficient, get the required results.

A. Evaluation criterion

In order to validate the training effectiveness of the pre-training process on the initial weight and the results of the trimming process, the Mean Squared Error (MSE) is chosen as the evaluation criterion pre-training and fine-tuning process. Where MSE is defined as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_{data} - y_{recon}\right)^2 \quad (8)$$

where N is the size of training sample or test samples, y_{data} is the training sample data or the test sample data, and y_{recon} refers to the fine-tuning process Autoencoder reconstructed data, or the data of the different RBM reconstructed during the pre-training process. However, since the variables involved in the experiment are almost always expressed in the form of a matrix, y_{data} and y_{recon} requires more complex calculation of conversion, so that the code implementation process in the experimental program for calculating the reconstruction error is very complicated and can be learned in the experiment of Hinton's paper [21], and they are transformed into the form applicable to formula (6).

B. Experiment Design

In this experiment, the total sample size was 220, among which 150 samples were randomly selected as training samples, and the remaining 70 samples were used as test samples. The pre-training process has four layers of RBM. The number of neurons in the visible layer of the first layer of RBM is the number of input samples, that is, 52. The number of neurons in the hidden layer is usually determined according to the reduced dimensions and the dimension of the number of neurons. Therefore, the number of neurons in the first RBM visible layer and hidden layer was recorded as RBM 52-200. In order to obtain the automatic encoder network structure required by this experiment, the RBM structure of the second, third and fourth layers is RBM 200-100, RBM 100-50 and RBM 50-5, respectively. In the experiment, the learning rate was set to 0.1 and the number of pre-training was set to 10, that is, the number of pre-training was set to 10 for each RBM, and the number of iterations in the fine-tuning process was set to 10. The range of simulated data is [0,1]. In order to verify the effectiveness of the automatic encoder method in reducing the grid security status dimension, the experiment is verified from the Angle of the pre-training process of the automatic encoder and the reconstruction error of the fine tuning process.

We select one of the training samples and test samples, after pre-training and fine-tuning process, the data obtained after the dimension reduction as shown in TABLE.2.

TABLE.2. Autoencoder reduction sample attribute value

Sample	attribute1	attribute 2	attribute 3	attribute 4	attribute 5
Training Sample	5.3000e-01	-3.2301e-02	-5.2764e-02	-9.6521e-03	1.1009e-01
Testing Sample	5.5370e-01	-3.2057e-02	-5.2332e-02	-9.9335e-03	1.0983e-01

According to Autoencoder output layer design, we can see five characteristics after reduction. These 5 characteristics are nonlinear mapping data of the original grid security situation assessment index system of 52 index, on behalf of the original sample data information. The experiment sets 10 epochs for pre-training to get the reconstruction error of different RBM. We use MSE to show the difference. The result is shown in Fig. 9.

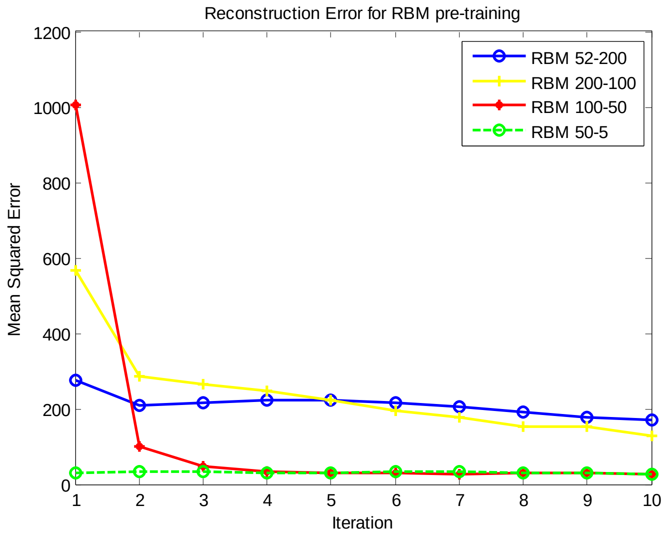

Fig. 9. The reconstruction error of RBM for pre-training

Figure 9 shows the variation of reconstruction errors during 10 pre-training sessions of RBM in different layers. Since the initial weight is randomly selected, the pre-training process mainly adjusts the initial weight so as to obtain a more appropriate initial weight for the fine-tuning process. It can be seen from the figure that the reconstruction error is large when the number of iterations is 0, and the reconstruction error reaches the equilibrium state when the number of iterations is 2. When the number of pre-training iterations is set to be greater than or equal to 2, the initial weight of the trim can be obtained. According to the above experiment results, the number of iterations was set as 10. During the fine tuning process, Autoencoder used the feedback network to adjust the weight of the network to make the dimensional data more accurate than the original sample information. In the experiment, the method proposed in this paper is applied to reduce the evaluation index of grid security condition, and the reconstruction errors of the input training sample and the test sample are compared. For 10 fine-tuning iterations, the reconstruction errors of training data and test data are shown in Fig. 10.

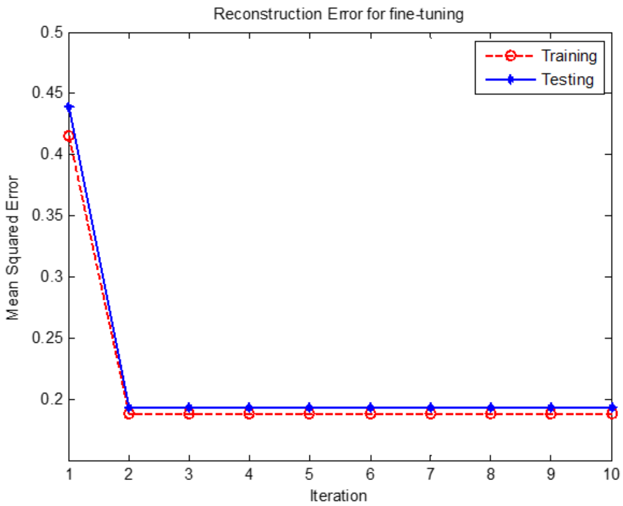

Fig.10 The reconstruction error in the process of fine-tuning

Fig. 10 is to fine tune the 10 training process and the test process of the reconstruction error. The initial weight of the fine-tuning process is the final weight obtained by the pre-training process and the final reconstructed data is obtained after 10 trimming. It can be seen from the figure that when the fine-tuning process iterates twice, the reconstruction error reaches the constant, and the reconstructed data obtained at this time has reached the optimal level. According to the results of Matlab experiments, we can see that the minimum reconstruction error of the training data is 0.188, the minimum reconstruction error of the test data is 0.193, the difference between the training and the test is small, and the information contained in the reduced data can basically represent the original data. The number of iterations of the fine-tuning process can be optimized by selecting 2 or more values. In our experiment, in order to illustrate the proposed method applicable to the power grid security situation assessment index reduction better than the traditional PCA(Principal Component Analysis),LDA(Linear Discriminant Analysis) dimension reduction algorithm, we compare the reconstruction error between input training samples and test samples of the different algorithms. The result is shown as Fig. 11.

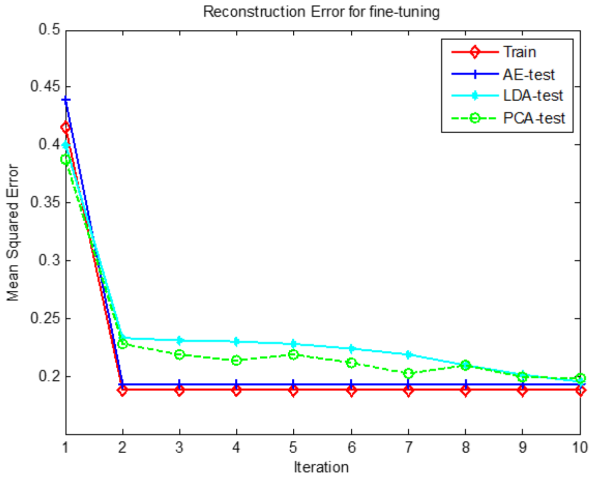

Fig.11 Mean Square error against size of reduced dimension

Fig. 11 shows the difference between reconstruction data and the original index data of different dimension reduction algorithm. Autoencoder is obviously better than the algorithm of PCA (Principal Component Analysis), the LDA (Linear Discriminant Analysis) dimension reduction algorithm. Through different dimension reduction algorithm, we can see the dimension data can reconstruct the original data in the lower dimensions and present the original information. We can greatly reduce the dimensions of indicators used for subsequent work and achieve the goal of the indicators reduction.

V. CONCLUSION

The paper has briefly analyzed and discussed the pros and cons of rough set, fuzzy rough set, PCA (Principal component analysis) and LDA linear dimension reduction algorithm and has proposed Autoencoder method for high-dimensional information of power grid safety situation assessment system. Autoencoder can automatically adjust the weight, the important indicators given to the larger weight, redundant indicators to give a smaller weight, reducing the objectivity of the human weight. The high-dimensional data can be mapped into lower dimensional space by Autoencoder and lower dimensional code can fully represent the information.

As data of assessment of power grid security situation belongs to confidential information and is difficult to obtain. The paper generates simulated data based on power grid security situation assessment. Though the index system is built incompletely and does not fully represent the risk of power grid, it does not have great impact on verifying effectiveness of Autoencoder to reduce the dimensionality of indexes of power grid security situation. Future work includes two aspects. On the one hand, we will perfect the index system of power grid security situation assessment to fully represent vulnerability in power grid system. On the other hand, we will build the model to assess the risk of power grid using the reduced data to reduce the complexity of modeling.

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