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Research on deep learning-based fault diagnosis of power metering system

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ABSTRACT

Power metering system is directly related to the production and operation level and benefit of power supply enterprises, and even has a close relationship with the national economic development and people's life. Numerous scholars have applied deep learning to the field of fault diagnosis. Accordingly, this paper proposes a fault diagnosis method for power metering system based on stacked autoencoder (SAE) algorithm. The deep learning data samples are formed by comprehensively collecting the historical operation data of the system and the feature data provided by the third-party manufacturers. And the fault diagnosis model is designed with the SAE algorithm, and the training and optimization fine-tuning of the algorithm model is realized by BP neural network. Finally, the model is trained using explicit test data samples, and the BP neural network can reach the set accuracy after 3804 training sessions with the output error. Compared to Elman neural network iterations are less and converge faster. Using the trained fault detection model of power metering system for fault diagnosis, the model can successfully classify the faults and achieve the expected diagnostic effect.

Keywords: SAE algorithm; BP neural network; power metering system; deep learning; fault diagnosis

1. Introduction

With the continuous development of social economy, its demand for energy is also growing, and electricity as an important energy source, has played a huge role in promoting its development. Power metering system is to measure, record and monitor the power usage, accurately measure the power consumption of users, and provide assistance for the normal operation of the power system, especially for the system with high voltage and capacity requirements [1-3]. Power metering is not only related to the interests of power providers and power users, it is also closely linked with the national economy, the establishment of accurate and reliable metering system is necessary and vital.

The causes of metering system failure are many, both natural and man-made. Power measurement system failure according to different classification standards, you can get different types of failure, but

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all can cause power measurement system measurement inaccuracy, are called measurement system failure. Power measurement system failure is mainly concentrated in the composition of the power measurement system components, according to these components can be categorized as faults, voltage transformer failure, current transformer failure and energy meter failure [4-6]. The classification of energy meter faults also exists in a variety of classifications. From the hardware side, mainly including laser head failure, display failure, communication interface failure, etc.; from the software side, mainly including data abnormalities, program crash, etc. [7-8]. Power measurement system failure also includes line failure, communication failure, measurement error of three cases [9]. Whichever is a measurement system failure, the measurement system failure, measurement system fault diagnosis technology should come into being.

With the continuous expansion of the power system, the relevant energy meter data is more and more, the energy meter error diagnosis carried out manually can not meet the current needs, the introduction of artificial intelligence technology improves the efficiency and accuracy of the energy meter error diagnosis [10]. And literature [11] designed a data-driven fault diagnosis method based on energy meter data. Similarly, literature [12] utilizes deep belief networks to enhance the feature extraction capability of energy meter data from power grids and inputs these features into a multilayer perceptual neural network for data processing and analysis in order to improve the accuracy of energy meter fault diagnosis. However, there already exists an energy meter with fault diagnosis function and theft detection function at the same time [13].

In addition, it was mentioned that current and voltage transformer faults are the most common equipment faults in power metering systems. In this regard, literature [14] constructed a fault diagnosis model based on radial basis function neural network for current transformer faults, and optimized this model using a hybrid multi-strategy whale optimization algorithm, and the diagnostic results showed that the accuracy rate was as high as 97%. Whereas, literature [15] provides a method for online diagnosis of conventional voltage transformer faults. Literature [16], on the other hand, designed a data-driven self-diagnostic method for capacitive voltage transformer metering error faults, and the results showed that the error identification of this method is at 0.02%, which can accurately locate the fault orientation and error expansion. In addition, literature [17] utilizes the field topology for fault reasoning, designs a fault diagnosis knowledge base based on metering and collected device data, and obtains intelligent fault diagnosis results in the field under an expert system.

The research introduces deep learning technology into the fault diagnosis of power metering system, and applies the method of stacked encoder to construct a fault detection model of power metering system. The model realizes feature extraction and fault classification of raw data through classification recognition technology. And after the BP neural network training of fault samples, the collected detection signals are input into the trained fault detection model of power metering system, so as to improve the accuracy of model determination. The model is tested by collecting power metering data from the power grid base in province H. The classification of faults by the model and the error value are used to judge the application effect of the model in this paper.

2. Method

2.1. Description of power metering system fault detection and judgment

Causes of common power metering system failure mainly include the following aspects:

First of all, the natural causes of failure, natural causes include natural factors mainly include power measurement devices and measuring instruments themselves, power measurement work is the use of power equipment by the user of electricity for scientific statistics and recording work, so the core measuring instrument for power measurement work is the power billing meter, on the one hand, due to the billing meter itself is not up to standard, or in the long-term use of the environment gradually weakened, the precision of its measurement greatly reduced, or even scrapped measuring instruments, resulting in the occurrence of common failures of the power measurement system. On the one hand, due to the substandard quality of the billing meter itself, or in the long-term use of the environment gradually weakened, the precision of its measurement is greatly reduced, and even scrapped measuring instruments, resulting in the occurrence of common failures of the power metering system, leading to the cessation of the power metering work, on the other hand, due to the power metering power meter asset card data, information information is incomplete, and inaccurate information on the asset card ledger, for example, in actual daily life, the power metering work is required to complete the users of the power equipment, meter reading, recording of electricity consumption. For example, in the actual daily life of power measurement work is required to complete the user's power consumption meter reading, billing, charging and other work processes, but in fact, most of the three-phase, four-element type of power metering power meter is not labeled kW-h × 10 data, resulting in the current transformer, voltage transformer malfunctioning, poor contact phenomenon, which seriously affects the accuracy of power measurement.

Secondly, the human causes of failure, its specific embodiment: three-phase power meter wiring errors caused by the power meter current, voltage failure. Current transformer primary and secondary circuit line connection isolation switch settings as well as CT primary and secondary circuits in the increase in the number of terminals, resulting in terminals are prone to loosening or corrosion phenomenon, which leads to CT primary and secondary circuits short-circuit faults or current transformer short-circuits between the two phases, so that the current can not flow into the power measurement of power meter, which seriously affects the accuracy of the measurement of power. Due to the power metering system or device design is not scientific, not optimized, the current transformer, voltage transformer secondary circuit wiring area of the design of the smaller, and in the secondary circuit does not take a different color or number for effective differentiation, which is likely to result in the CT primary and secondary circuit wiring errors or not in place, resulting in the current transformer, the voltage transformer secondary circuit connecting line of the disconnections or short-circuit faults, so that the power Measurement system is dysfunctional, which seriously affects the accuracy of the power measurement data, but also can not correct the data errors in power measurement in a timely manner.

2.1.1. Power metering system fault detection. The power metering system fault detection principle is shown in Figure 1. 1, 2 for the meter metering unit. CT_1, CT_2 for the current transformer. PT_1, PT_2 for the voltage transformer. I_C, I_A for the A-phase and C-phase current. I_c, I_a, U_c, U_a for the metering unit current and voltage. u_a, u_c for the current transformer detection signal.

Power metering system faults are categorized into hidden faults and explicit faults. Among them, the explicit fault can be determined by the detection instrument to determine whether there is a fault. Hidden faults are mainly determined by observing the power metering system network impedance changes to determine whether there is a fault [18].

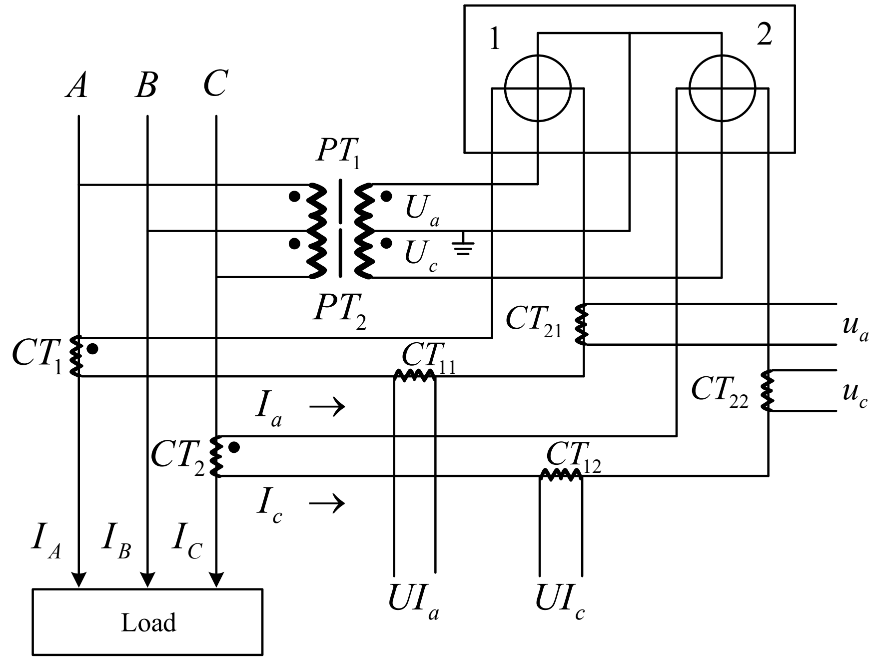

Fig. 1. Principle of failure detection of electric metering system

2.1.2. Judgment setting. According to the power metering system fault detection schematic diagram, this paper classifies its fault types into the following, specific power metering system fault types and judgment basis as shown in Table 1. A total of nine main faults are summarized in the sample characteristic mode.

Table 1. The type and judgment of the power metering system

Fault type	Judgment	Corresponding description
CT1 side short circuit	The change in ua is greater than 10%	0010
CT2 side short circuit	The change in ub is greater than 10%	0011
CT1 second side short circuit (back)	The change in Ia is greater than 10%	0100
CT2 second side short circuit (back)	The change in Ib is greater than 10%	0101
CT1 second side short circuit (front)	The change in Ia and ua is greater than 10%	0110
CT2 second side short circuit (front)	The change in Ib and ub is greater than 10%	0111
CT two-phase short circuit	The changes in the Ia, ua, Ib and ub were greater than 10%	1000
PT1 Open circuit	Ua is zero	1001
PT2 Open circuit	Ub is zero	1010

2.2. Deep Learning Based Fault Diagnosis of Power Metering System

2.2.1. Deep Learning. Deep learning is an important part of the machine learning module in the context of artificial intelligence, which focuses on building deep neural network models by mimicking the human mindset to learn the features of data automatically or abstractly. The deep learning model is connected in a way similar to the neuron connection of the human brain, and data processing is carried out in a neural network with multiple layers of classification, as a way to ensure that the learning model can automatically and efficiently deal with multiple types of complex data in accordance with the learned problem processing mode. In practice, deep learning has several application advantages. First, automatic extraction of relevant features. The traditional machine learning approach requires manual establishment of manual feature extraction, which requires higher expertise and experience of technicians and is more subjective. Deep learning, on the other hand, can actively propose relevant feature knowledge from data, simplifying the feature extraction process and making the extraction process and extraction results more objective. Second, deep learning has a stronger characterization ability, which can express the data in an abstract way using linear transformation, mapping, etc., bringing a stronger data representation ability to the whole model, further enhancing the accuracy of deep learning in complex task processing. Third, deep learning is end-to-end learning, which can directly map the original data to the target object, avoiding the complex processing and extraction process, reflecting the strong generalization ability in deep learning. Fourth, deep learning also has a more powerful batch data processing ability, can carry out calculations quickly and efficiently with the help of computer hardware, and has a good ability to expand [19]. In different fields, the application of deep learning is also different, and the characteristics and application advantages are also different. For the power metering system data characteristics, this paper identifies the deep learning method as stacked autoencoder (SAE).

2.2.2. Stacking autoencoders. Stacked autoencoder (SAE) is composed of the basic unit AE, in which the input and output layers have the same data size capacity, and the data encoding and decoding process is shown in Fig. 2. The data is transmitted from the input layer to the implicit layer, during which the data is encoded and the process is accomplished through the function F. The data is encoded by the function F. The data is then transmitted from the input layer to the implicit layer. Then transmitted from the implicit layer to the output layer, the process is decoding, which is done by function G. Finally the output data Y. The stacked autoencoder can extract the intrinsic features of the original data [20].

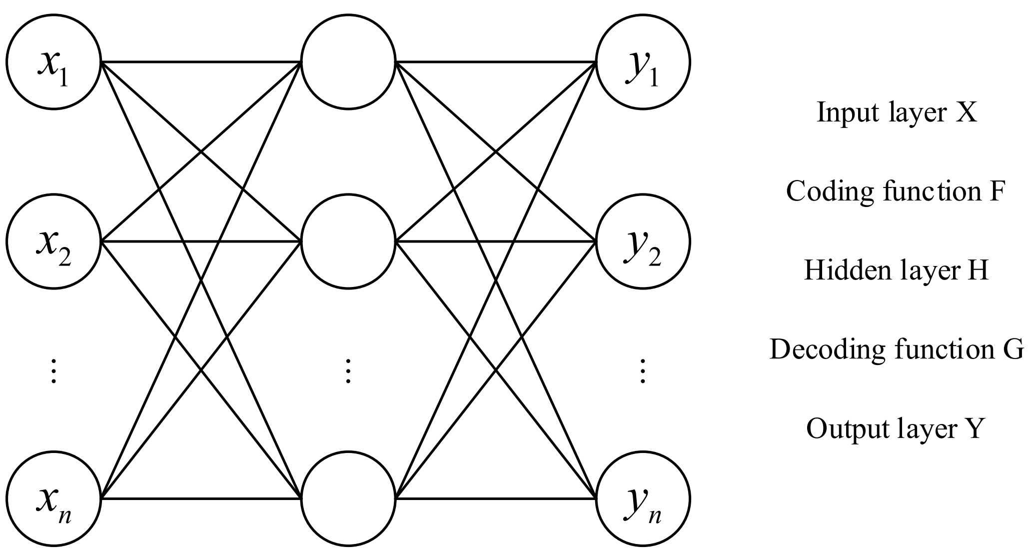

Fig. 2. Data encoding and decoding process

The autocoder coding and decoding operation process can be expressed as follows:

$$H = F(X) = S(WX + P) \tag{1}$$

$$Y = G(H) = S^{-1}(W^T X + Q) \tag{2}$$

where $S(x)$ is the sigmoid function:

$$S^{-1}(x) = e^{-x} / (1+e^{x})^2 = S(x)(1-S(x)) \tag{3}$$

Where W is the encoding weight when the data is transmitted to the implicit layer through the input layer, W^T is the decoding weight of the data from the implicit layer to the output layer, P is the bias vector of the implicit layer, and 0 is the bias vector of the output layer.

The corresponding model can be obtained by applying the method of stacked encoder, and the application of classification and recognition technology to realize the feature extraction and fault classification of the original data is more suitable for the case of the small amount of data in the metrology automatic calibration pipeline. Therefore, this paper introduces the SAE algorithm technique to realize the fault detection model of the power metering system, showing its excellent feature extraction ability and the robustness of the method.

2.2.3. Electric power metering system fault detection model construction. In this paper, a fault detection model for power metering system based on deep learning algorithm is investigated, which is based on existing system operation data set for machine learning through data preprocessing and multi-layer autoencoder AE stacking, thus obtaining a fault detection model for power metering system.

When applied to the power metering system, the data training of the model is divided into two steps: pre-training and fine-tuning. Pre-training selects sample data to the input layer, which is unlabeled, and is initialized by the BP algorithm for data encoding and decoding training. Fine-tuning, on the other hand, is a correction of the initialization, which optimally adjusts the data inside the model. Through the data fine-tuning operation, the model data can be made more accurate and the network determination accuracy can be improved.

The power metering system detection model contains a nonlinear function, and the nonlinear function has the following equation holds:

$$f(y) = \begin{cases} 1, y > 1; \\ (x+1)y - xy^3, -1 \le y \le 1 \\ -1, y \le -1. \end{cases} \tag{4}$$

where x represents the input parameters of the model, usually x taking the value 0.5.

To this model, the FRDS transfer function is added and the two functions are superimposed to obtain the output Y value function:

$$Y_{t+1} \mid= Y_t + \alpha[m[0], m[0]^T] : m[p] = f(ym[p-1]) \tag{5}$$

where m represents the labeling of the neuron, which is saved by memorizing the pattern, p is the value of the Y-value function acting p iteratively after back-passing, and a is the iteration coefficient. In general, a is taken as 0.4.

The Y value function generates the pseudo-inverse method weight function after passing through the neuron, and the weight function is determined by the following equation:

$$W = \sum\sum I \tag{6}$$

The Σ expression in Eq. sums the data of the memory schema A to form an initial matrix, and ΣI is a matrix of weights functions, which is mapped to a linear space by the method of projection. A pseudo-inverse matrix, which is known in the literature as the projection method, is projected to other linear subspaces by the generation of weights.

Through the above Y-value function and the variation of the weight function, the basic kernel of deep learning is formed, while the BP neural network is applied, which together form the basis of the hybrid neural network, consisting of input, hidden and output layers, and the data is transformed and transmitted within the neural network to the power metering system fault detection model. The model is a multi-layer feed-forward neural network, and its basic architecture and data transmission process rely on BP neural network, and has a good learning ability.

2.3. Model training process

2.3.1. Sample data set selection. In order to improve the accuracy of the model in recognizing faults, this paper collects the power metering data collected from the grid base in Province H. The model is tested and model training and validation work is carried out. In order to ensure the comprehensiveness of the sample dataset and at the same time to ensure a sufficient number of samples, a specific number of samples are randomly selected as unlabeled pre-training samples. When the data provided is the same, the labeled sample data prevails and fine tuning of the data is carried out.

2.3.2. Data pre-processing. In order to reduce inter-area variability among the data and to reduce computational errors, data preprocessing of the collected dataset was carried out using standardized formulas:

$$x_{new} = \frac{x - x_{mean}}{x_{std}} \tag{7}$$

Where x is the original value of the data in the training set, x_{mean} is the mean value of the data in the training set and x_{std} is the standard deviation value of the data in the training set.

2.3.3. Model training. The input of the model is the standardized power metering system operation parameter data, and the output of the model is the operation status of the power metering system and the probability of nine types of faults.

Test sample data with clear fault types are selected to test the trained model, and the algorithm model is considered real and usable when the fault detection accuracy reaches more than 90%. The fault detection model is encoded in binary and converted to decimal during transmission. The use of binary has a range of advantages that maintain the authenticity of the original data and reduce the distortion of the data during transmission. The input data is grouped to form a search space. Assuming that the data is divided into N groups, the system calculates the number of collisions required and queries the search algorithm, the number of queries is calculated as follows:

$$T = T_{2-array} + T_{4-array} \tag{8}$$

Dynamic search algorithm, and the search time can be calculated by the following equation:

$$T = \sum_{i=0}^{\log_4 \frac{N_i}{3}} 4i \tag{9}$$

The above equation is calculated as the total search time and the individual search time is:

$$T = \frac{5N_i}{3} + \sum_{i=0}^{\log_4 \frac{N_i}{3}} 4i \tag{10}$$

Assuming that the data is divided into M groups and each group obeys a probability distribution, the total number of total queries throughout the neural network and the detection model is:

$$Q(N) = \sum_{i=0}^{M} \frac{5N_i}{3} + \sum_{i=0}^{\log_4 \frac{N_i}{3}} 4i \tag{11}$$

Similarly, Individual $S(i)$ communicates with the network in the system as:

$$D(i)=\sum_{i=0}^{m} S(i) \tag{12}$$

3. Results and discussion

3.1. System Failure Characterization

According to the characteristics of the faults contained in the power metering system, we can categorize them into direct diagnostic faults and indirect diagnostic faults. The former refers to the fault diagnosis process through the measurement results of the instrument, you can directly get whether the fault occurs. Such as TV open-circuit fault occurs, only need to detect the secondary side voltage value can accurately determine the fault is relatively simple. CT short-circuit occurs is an indirect diagnostic fault, according to the results of the system modeling and analysis, resulting in CT short-circuit fault example analysis of the data shown in Table 2. According to Table 2 it can be seen that the network impedance changes greatly when a fault occurs, when the load changes almost unchanged, can be used as a basis for judgment, but it is not convenient to measure the fault modeling analysis was applied to the 1KHz excitation signal for detection. The detection signal obtained by sampling is the superposition of multiple signals, and the information of the required band is obtained through spectral analysis for judgment. When a short circuit occurs between the phases of the CT secondary, the network impedance will change with the change of the load, and multiple detection information is also needed to judge the fault. The analysis found that there are many types of faults in the power metering system, and some faults can not be identified by a single signal, so we can train the fault samples through the BP neural network, and input the collected detection signals into the trained fault detection model of the power metering system for fault diagnosis.

Table 2. Analysis of CT short circuit failure

Experimental variable name	Experimental variable
Grid voltage valid value	10KV
Grid rated load	50KVA
Full load power factor	0.9
Current current coil impedance ZB	0.05Ω
Short circuit copper conductor impedance RD	1.0×10-3Ω
Rated load equivalent impedance ZL	200Ω
Current transformer winding ratio n	10
Full load network equivalent impedance Zi	1×105Ω
CT primary circuit equivalent impedance Z'i	0.1775Ω
CT secondary circuit equivalent impedance Z"i	0.05Ω

3.2. Sample data processing

According to the operation experiments and field conditions of the metering system, some faults are modeled and simulated, and the fault characteristics are extracted using eight operation parameters, and the sample characteristic patterns of nine main faults are summarized. A large number of input samples are needed in the training process, and a set of data is listed here as shown in Table 3, UAB indicates the line voltage between phase A and phase B, 0001 indicates the normal condition, and the corresponding descriptions of the other fault phenomena refer to Table 1.

Table 3. A set of input sample Numbers

N	U_{AB}/kV	I_A/A	I_a/mA	I_c/mA	U_a/V	U_c/V	u_c/V	u_c/V	Corresponding description
1	17.42	1.021	100.03	100.1	173.1	173.4	1.415	1.408	0001
2	17.37	1.022	128.42	100.1	173.2	173.2	0.149	1.411	0010
3	17.28	1.021	100.02	128.6	173.2	173.3	1.414	0.127	0011
4	17.37	1.037	49.95	100	173.3	173	1.423	1.399	0100
5	17.36	1.021	99.84	51.11	173	173.2	1.404	1.414	0101
6	17.43	0.993	4.556	100	173.2	173.2	0.072	1.412	0110
7	17.11	1.02	99.96	4.557	173.1	173	1.4	0.072	0111
8	17.26	1.009	50.04	50.21	173	173.1	0.722	0.701	1000
9	17.33	1.018	99.96	100	0	173.1	1.409	1.41	1001
10	17.24	1.033	100	100	173.5	0	1.416	1.411	1010

The 8 types of detection signals are processed to get the information corresponding to the faults, which are then used as input values to the network. A 4-bit binary number is used to represent the fault type and normal condition as the output of the network. The input samples are normalized as shown in Table 4 and the training sample pair N is 10.

Table 4. Normalization of input samples

N	U_{AB}/kV	I_A/A	I_a/mA	I_c/mA	U_a/V	U_c/V	u_c/V	u_c/V	Corresponding description
1	0.68	0	0.778	0.776	1	1	1	1	0001
2	1	0.508	1	0.779	0.994	1	0.059	1	0010
3	0.668	0.005	0.759	1	1	1	0.999	0.073	0011
4	0.007	1	0.369	0.786	0.999	0.996	0.998	0.997	0100
5	0.675	0.008	0.772	0.383	1	1	0.997	0.992	0101
6	0.994	0.007	0	0.756	0.992	1	0	0.999	0110
7	0.323	0.511	0.777	0	1	0.998	1	0	0111
8	1	0.504	0.364	0.359	1	0.997	0.498	0.475	1000
9	0.999	0.014	0.781	0.775	0	1	0.999	0.982	1001
10	1	0.512	0.768	0.771	1	0.006	0.999	0.993	1010

3.3. Comparative analysis of training methods

Since eight operational parameters reflecting the working state of the metering system are selected in this paper, the BP neural network input is an 8-dimensional vector, and the output is a 4-dimensional vector, and a single hidden-layer neural network is used in this experiment, with the number of hidden layers set to 14, so the BP network structure used in this paper is 8-14-4. The number of training times is set to 10000, the error is 0.01, the learning rate is 0.1 and the momentum factor is 0.8.

The BP algorithm is trained for initialization of data encoding and decoding. The error curve of the BP network trained on the samples is shown in Fig. 3. The BP network is trained for 3804 times and the output error reaches the set accuracy.

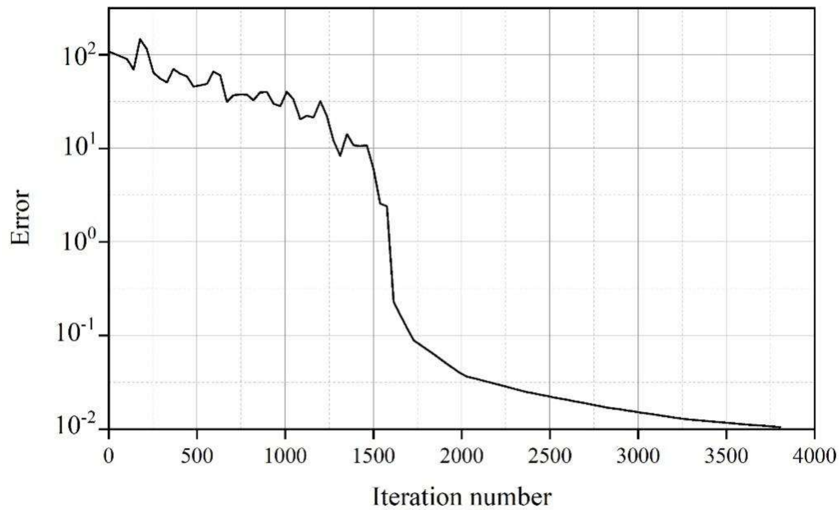

Fig. 3. Error curve of BP network on sample training

Elman network was chosen for the training error comparison experiment, and the error curve of Elman network on sample training is shown in Figure 4. It can be seen that the Elman network was trained for 8129 times before the output error reached the set accuracy. The comparison shows that the BP network has fewer iterations and converges faster.

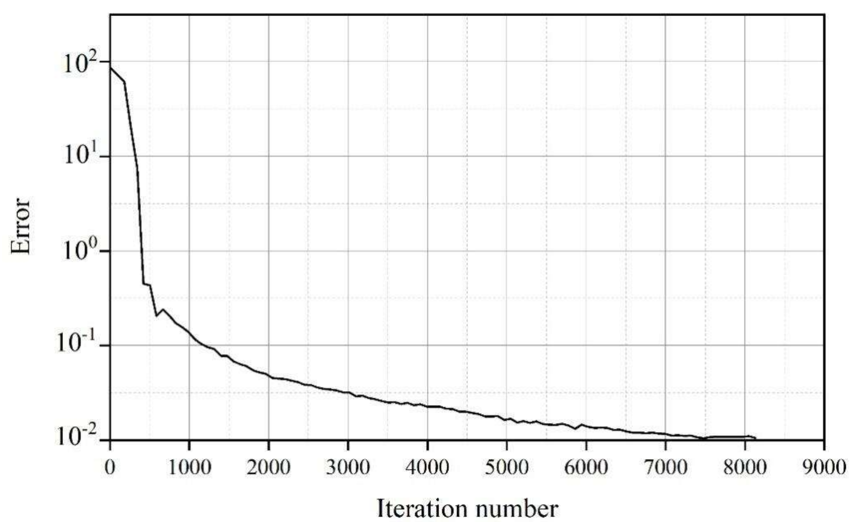

Fig. 4. The error curve of the sample training using the Elman network

The test results of all test samples and the comparison of fault diagnosis correctness between BP network and Elman network are shown in Table 5. It can be seen that the BP network accurately identifies the majority of faults in the power metering system, with an average identification accuracy of 98%, which is 6% higher than that of the Elman network. It shows that the use of BP algorithm for initial training of data encoding and decoding is practical and effective.

Table 5. Comparison of fault diagnosis accuracy

Corresponding description	Test sample total	Bp diagnosis			Elman diagnosis		
		Correctness	Misjudgment	Accuracy/%	Correctness	Misjudgment	Accuracy/%
0001	10	10	0	100	10	0	100
0010	10	10	0	100	10	0	100
0011	10	10	0	100	10	0	100
0100	10	10	0	100	10	0	100
0101	10	10	0	100	9	1	90
0110	10	8	2	80	7	3	70
0111	10	10	0	100	8	2	80
1000	10	10	0	100	8	2	80
1001	10	10	0	100	10	0	100
1010	10	10	0	100	10	0	100
Mean	-	-	-	98	-	-	92

3.4. Deep learning based fault diagnosis

After the initial training of data encoding and decoding using BP algorithm, the results of deep learning based fault diagnosis are shown in Table 6. By comparing the descriptions with the corresponding ones in Table 4, it is found that the method of this paper can successfully classify the fault samples. For example, the test results of sample 1 are 0.0434, 0.0194, 0.1096, 0.9658, and its corresponding 4-digit binary number description is 0001, which indicates the normal situation, and the classification of the remaining 9 samples are consistent with the above.

Table 6. Fault diagnosis based on deep learning

N	Experimental simulation results				Corresponding description
1	0.0434	0.0194	0.1096	0.9658	0001
2	0.0356	0.0136	0.9902	0.0921	0010
3	0.0228	0.0341	0.9552	0.9882	0011
4	0.1204	0.9489	0.0209	0.0461	0100
5	0.037	0.8211	0.0513	0.9715	0101
6	0.0848	0.8548	0.8803	0.0278	0110
7	0.0631	0.9427	0.8614	0.9949	0111
8	0.9004	0.1125	0.0789	0.064	1000
9	0.9172	0.0139	0.0083	0.9953	1001
10	0.9258	0.0011	0.9341	0.0551	1010

4. Conclusion

The study constructs a fault classification model for power metering system based on deep learning neural network, and tests and verifies the diagnostic effect of the model with actual system operation data. Comparing the training results of BP neural network and Elman neural network, the output error of BP neural network can reach the set accuracy after 3804 times of training, while Elman neural network needs to be trained for 8129 times. Fault diagnosis using the trained fault detection model of the power metering system results in a small diagnostic error value. Example validation shows that deep learning technology has a strong advantage in fault diagnosis and identification. Combined with other techniques, it can play a greater role in practical applications and can be used to check the daily fault diagnosis of power metering systems.

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