A method for improving the accuracy of wide-range current transformers based on deep belief networks

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ABSTRACT

With the proposal of the national dual carbon strategic goal, the permeability of new energy power generation in the power grid continues growing. The inherent intermittency and uncertainty lead to fluctuations in line power, which widens the working current range of the metering current transformer. Therefore, it is difficult for traditional methods to effectively meet the measurement error requirements. To this end, this paper proposes an adaptive error compensation method for wide-range current transformers based on deep belief networks. With its unique advantages in feature extraction and pattern recognition, deep belief network has become an effective method for transformer error feature extraction in the context of big data. In this method, the original data signal measured by the transformer is sent to the deep belief network algorithm for training, and the error feature is automatically extracted. An adaptive calibration system for wide-range current transformers is developed, and an error compensation experiment is carried out. The experimental results show that the method proposed in this paper can simply and efficiently identify the error characteristics of the wide-range current transformers and self-adaptively identify them, which improves the accuracy of the measurement results of the wide-range current transformers.

Keywords: Current transformer, transformer calibration, deep belief network, wide range

1. INTRODUCTION

A large number of power users have irregular electricity consumption such as seasonal electricity consumption, periodic electricity consumption, daily electricity consumption, intermittent electricity consumption and uncertain electricity consumption. As a result, the load fluctuates greatly, and the current of the current transformer has a wide range of magnitudes[1-3]. The rated primary current TA is stipulated in the "Technical Regulations for Design of Electric Energy Measurement and Electric Energy Metering Devices", and it should be ensured that the actual load current in normal operation reaches about 60% of the rated value, at least not less than 30%. At present, the selection of the current transformer transformation ratio in the distribution network is mainly based on the experience of residential electricity and industrial electricity. The selection of the current transformer transformation ratio is realized by considering the annual growth rate of residential electricity consumption and the maximum load current of industrial users[4-6]. Due to the lack of judgment on the growth of electricity consumption in the residential power distribution and transformation area during the selection and installation of current transformers in the early stage. The transformation ratio of the current transformer is not selected from the development point of view, resulting in a single transformation ratio. Therefore, after running, the transformation ratio cannot be switched adaptively according to the running situation[7-8]. When the load of the distribution network increases or decreases, the current transformer load current is too large or too small[9-10]. However, if the current transformer ratio is too large or too small, it will affect the accuracy of electric energy measurement and the vital economic interests of both power suppliers and consumers, and will affect the performance of the current transformer itself. In severe cases, the current transformer will fail, which will seriously threaten the reliability of the power supply of the distribution network. After testing, the load current of the traditional distribution network metering current transformer is within 120% of the rated current. The larger the load current, the smaller the TA error. When the load current is between 120% and 165% of the rated current, as the load current increases, the TA error increases, but it gradually tends to balance within the allowable range. This is because when designing the TA, the saturation multiple that determines the overload capacity of the TA is generally at least 2 to 3 times the rated current. As TA manufacturing technology becomes more and more mature and advanced, some TA can withstand dozens of times the rated current in a short time[11-13].

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The situation that the transformation ratio is too large often occurs in actual work[14]. When the current transformer is under light load, the actual load current will be lower than 30% of the primary rated current of the current transformer. In particular, when the load current is as low as 10% of the rated current value and below, the ratio difference increases and is a negative error. In addition, because the variable ratio is too large, the load current is not enough to reach the starting current of the meter, resulting in the leakage of electricity at this time. The electric energy meter should work within the range of 50% to 100% of the calibrated current to ensure the accuracy of the error. When it operates below 30% of the nominal current, the error may be out of alignment. Especially when working below 10% of the rated current, in order to the adjustment limitation of the compensation device of the meter, its accuracy cannot be guaranteed, and the error inaccuracy is more serious.

When the line current exceeds the normal working current range or the selection ratio of the current transformer is too small, the current transformer will have serious out-of-tolerance[15]. In overload operation, it will also lead to overheating of the iron core and secondary coil of the current transformer, aging of the insulation, and even equipment damage and line tripping. It seriously affects the normal operation of the measurement work, the on-site management, and the personal safety of the operators.

At present, in the design of current transformers, the transformation ratio is selected by changing the series-parallel connection mode of the primary winding, or using multiple sets of transformation ratios to select the secondary winding taps. By changing the series-parallel connection mode of the primary winding, the variation range of the transformation ratio is only 2 times, which does not meet the requirement of large variation in the peak-to-valley difference of the power load. In addition, a series of manual operations such as power outages and rewiring are required, and it is impossible to perform daily load changes[16-18]. There are some domestic and foreign researches on the use of multiple sets of variable ratio transformers, all of which use multiple windings, and use internal relays or power electronic devices to switch the number of turns of the secondary coil connected to the transformer to control the switching of the transformer ratio. However, because its transformation ratio changes by a maximum of 4 times, taking the 0.2-level current transformer for measurement as an example, it needs to meet the accuracy requirement of 0.2% within the range of 20% to 120% of the rated current. Calculated according to the adjustment range of 20% of the minimum ratio to 120% of the maximum transformation ratio, the adjustment range of its current is 24 times. Therefore, it is unable to fully meet the requirements of the large change in the peak valley difference of the existing electricity load, and it is also unable to adapt to the problem of the increasing load range of the distribution network[19-20].

The traceability of the value of the current transformer for traditional distribution network measurement adopts two regulations, “Power Transformer” and “Measuring Current Transformer”. The regulations stipulate that the primary current range for the current transformer to meet the error limit is: 1%In (Rated primary current)～120%In. It is no longer applicable to the traceability demand of the wide range current transformer studied in this article. There are no reports or literatures on the development of a wide range transformer calibration device at home and abroad.

2. THEORETICAL BASIS

Electromagnetic current transformers have a wide range of applications in distribution networks, and their working principle is similar to that of transformers. An instrument that transforms a high current on the primary side to a low current on the secondary side and performs measurement. A complete current transformer consists of two parts: winding and closed iron core.Because it has fewer turns on the primary side and more turns on the secondary side. The primary side is connected in series with the line of the current to be measured, and the secondary side is connected in series with the measuring instrument. The principle circuit is shown in Figure 1, and its characteristics are as follows: the primary winding is concatenated in series to the tested circuit, and the current flowing is the load current of the circuit under test, which has nothing to do with the secondary side current. The secondary winding is concatenated in series to the current coil of the protective device. Due to the small impedance of the current coils of the measuring instruments and protection devices, the current transformers are normally short-circuited.

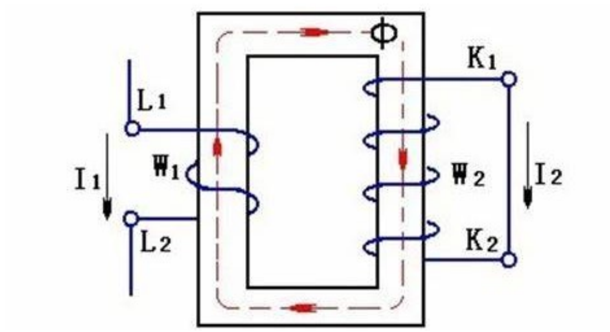


Figure 1. Current transformer principle wiring diagram.

The ratio of the rated primary current IN_1 to the secondary current IN_2 of the current transformer is called the rated mutual inductance ratio, expressed in K_i. Like the transformer, K_i is alternately proportional to the number of turns N_1 and N_2.

$$k_{\mathrm{i}} = \frac{I_{\mathrm{N1}}}{I_{\mathrm{N2}}} \approx \frac{N_2}{N_1} \tag{1}$$

IN_1 and IN_2 are standardized, K_i is also standardized. The excitation current and core loss lead to current transformer errors including ratio difference and phase error. Current error (ratio difference): After the secondary current is converted to one time according to the rated current ratio, it is not equal to the actual primary current, resulting in the ratio error of the current transformer. The percentage error of the ratio is expressed by Equation (2). Phase error is the difference in phase angle of the current phasors on both sides of the current transformer.

$$\varepsilon_i = \frac{K_n I_2 - I_1}{I_1} \times 100\% \tag{2}$$

where Kn is the rated current ratio; I_1 is the actual primary current; I_2 is the measured value of the secondary current.

3. DEEP BELIEF NETWORKS

3.1 Theory

A deep belief network[21-24] is a deep learning algorithm model. Compared with traditional machine learning, which requires manual feature extraction, expert prior knowledge and other defects, it can use big data to automatically extract features nonlinearly. It has good generalization ability and robustness. As shown in Figure 2 below. First, the RBM units inside the DBN network perform the process of unsupervised pre-training from top to bottom. Complete the initialization of the parameter θ. Second, the RBM units inside the DBN network perform a supervised fine-tuning process from bottom to top. The network parameters of the entire DBN are supervised and fine-tuned according to the difference between the actual value of the current and the predicted value of the model, so that it converges to the global optimum point.

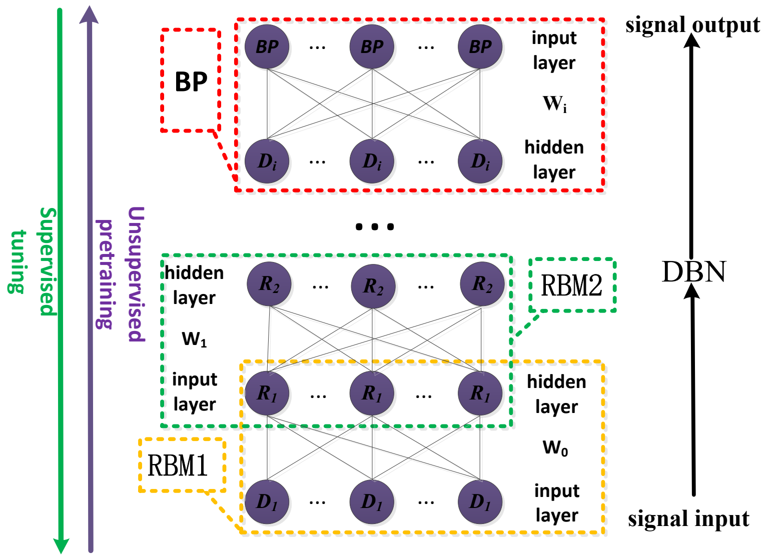


Figure 2. Deep belief network model.

RBM is the main module for feature self-extraction in DBN model[25-26]. Among them, D=[D_1, D_2, D_3, …, D_n], R=[R_1, R_2, …, R_m] represent the neurons in the visual layer and the conceal layer respectively, and *n* and *m* respectively the number of neurons. W_{nm} is the weight of the connection between the two layers. The energy function between the two layers is:

$$E(D,R\mid\phi)=-\sum_{i=1}^{n}\mathrm{x}_i\mathrm{d}_i-\sum_{j=1}^{m}\mathrm{t}_i\mathrm{r}_i-\sum_{i=1}^{n}\sum_{j=1}^{m}\mathrm{d}_i w_{ij}\mathrm{r}_i \tag{3}$$

In formula (3), φ=(W_{ij},x_i,t_j) represents the parameter value when training the RBM; W_{ij} is the weight of the connection between the two layers of neurons; x_i,t_j are the biases of the visual layer and the conceal layer, respectively.

Through the energy function, the joint probability distribution of (D, R) can be obtained as formula (4). Z(Φ) is the normalization factor.

$$p\left(D,R\mid\phi\right)=\frac{1}{e^{E(D,R|\phi)}z(\phi)} \tag{4}$$

$$z(\phi)=\sum_{D,R}\frac{1}{e^{E(D,R|\phi)}} \tag{5}$$

$$p\left(R_j=1\mid D\right)=\sigma\left(\mathrm{x}_i+\sum_{i=1}^{n}\mathrm{d}_i w_{ij}\right) \tag{6}$$

$$p\left(D_i=1\mid R\right)=\sigma\left(\mathrm{t}_i+\sum_{i=1}^{n}w_{ij}\mathrm{d}_i\right) \tag{7}$$

$$\sigma\left(\mathrm{x}\right)=\frac{1}{1+\mathrm{e}^{-\mathrm{x}}} \tag{8}$$

$$\Delta W_{ij}=\tau(\left\langle D_{\mathrm{i}}R_{\mathrm{i}}\right\rangle_{\mathrm{d}}-\left\langle D_{\mathrm{i}}R_{\mathrm{i}}\right\rangle_{\mathrm{m}}) \tag{9}$$

In equation (9), τ denotes the learning rate, and $\tau \in [0,1]$; $\langle \bullet \rangle_d$ denotes the mathematical expectation of the input training set; $\langle \bullet \rangle_m$ denotes the mathematical expectation defined by the model, which is difficult to solve directly due to the huge computational effort. This paper adopts the fast learning algorithm Contrastive Divergence (CD)[27-29].

3.2 Deep belief network flowchart

The flow chart for single battery inconsistency fault detection based on deep belief networks is shown in Figure 3 below, with detailed implementation steps as follows:

(1) Network input initial parameters. Generally, the initialization work is completed according to the following empirical formula.

$$\begin{aligned} &\mathrm{w}=0.1\times \mathrm{randa(n,m)} \\ &x=0.1\times \mathrm{randa(1,n)} \\ &t=0.1\times \mathrm{randa(1,m)} \end{aligned} \tag{10}$$

Among them, w represents the weight of the network connection, x represents the bias of the visual layer, t represents the bias of the conceal layer; n represents the number of neurons in the display layer, and m represents the number of neurons in the conceal layer.

(2) Preprocessing the input data. The data is first normalized, and then the preprocessed data is divided into training set, tuning set, and test set proportionally.

(3) Determining DBN network parameters. Including initialization, learning rate ε, number of network layers, number of conceal layer neurons, number of iterations, momentum parameters, number of network layers, etc.

(4) Unsupervising pre-training of the DBN network in the model. The parameters of each layer of neurons in the network are determined by training each layer of Restricted Boltzmann Machines from the bottom up until all RBMs are trained.

(5) Supervising tuning of the DBN network in the model. The network parameters in the DBN model are fine-tuned multiple times using the gradient descent algorithm. Until the set number of iterations is reached, the model performance is optimized.

(6) When the set training times are reached, the trained DBN-based wide-range current transformer adaptive compensation model is obtained by entering test data and outputting results.

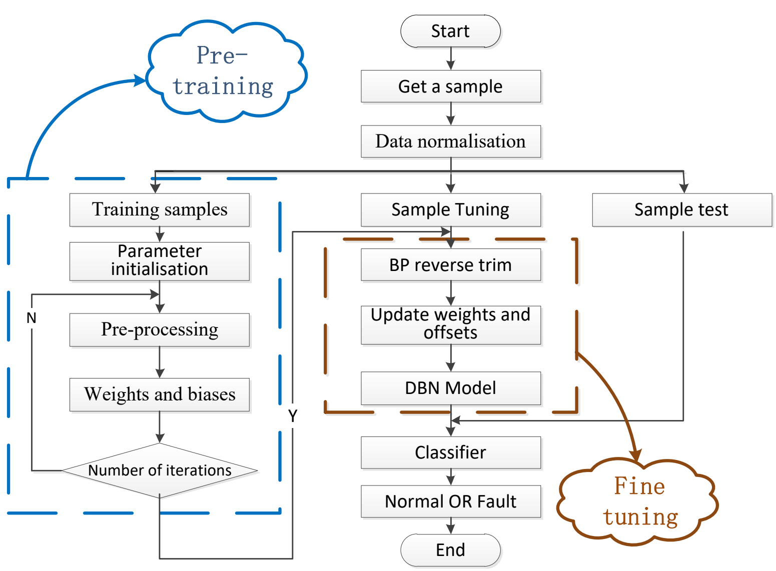


Figure 3. Flow chart of DBN.

3.2 DBN parameters

Table 1 shows various network parameters of DBN. Including the learning rate, the number of network layers k, the number of conceal layer neurons p, the number of iterations y, and the momentum parameter x.

Table 1. DBN network parameters.

Symbol	DBN parameters	Numerical value
τ	learning rate	0.1
k	number of network layers	3
y	number of iterations	900
x	Momentum parameter	0.8
p	conceal layer neurons	259

4. ANALYSIS OF ADAPTIVE ERROR COMPENSATION RESULTS

4.1 Test data source

According to the theoretical analysis of the current transformer adaptive error compensation method, this paper designs the hardware and software parts of the synchronous data acquisition circuit, builds the experimental system, and finally conducts the synchronous simulation experiment.

In this paper, a current transformer simulation operation system is built to measure the error of a current transformer with a ratio of 600A/5A under different loads. The system is built based on the principle of difference measurement stipulated in the regulations, including voltage regulating power supply, current boosting unit, standard current transformer, transformer calibrator, and current load box. T_0 is the standard current transformer; T_X is the tested current transformer. The schematic diagram of the system is shown in Figures 4 to check the function of the low-voltage current transformer for wide-range measurement.

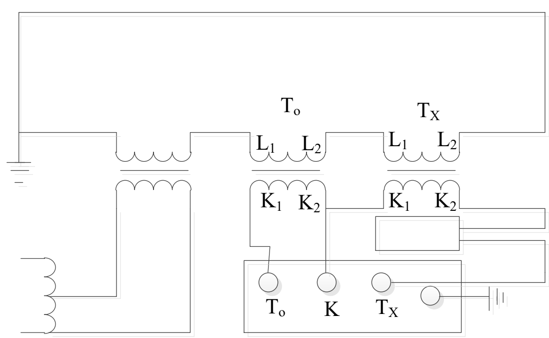
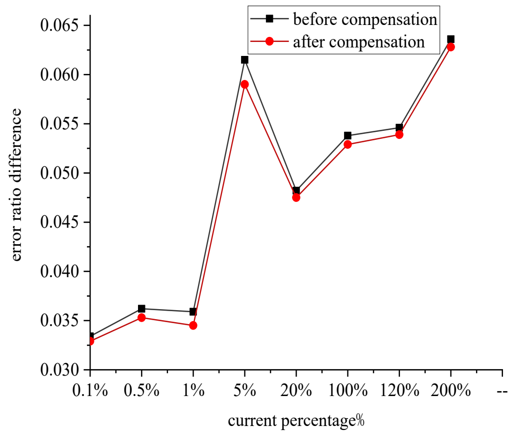


Figure 4. Schematic diagram of current transformer simulation operation system.

4.2 Analysis of running results

After inputting the real data of the original transformer current into the deep belief network algorithm, the current signals of the two channels are collected. After changing the junior input current of the current transformer, adjust it to 0.1%, 0.5%, 1%, 20%, 100%, 120% and 200% of the rated current to obtain the ratio difference of each measurement point. As shown in Figure 5 below, the deviation ratio difference after compensation by the deep belief network is significantly smaller than the error ratio difference before compensation. It can be seen that the DBN algorithm can realize the adaptive error compensation function of the wide-range current transformer. To reflect the deviation compensation characteristics of deep belief network, the paper conducts the same test 10 times for DBN, GA-BP and SVM. The red line is the national standard requirements, the three methods (Figure 6) are strictly lower than the national standard requirements, and the DBN-based wide-range current transformer error is the smallest. The above experiments effectively and fully demonstrate the superiority of using the deep belief network for adaptive compensation of wide-range current transformers.



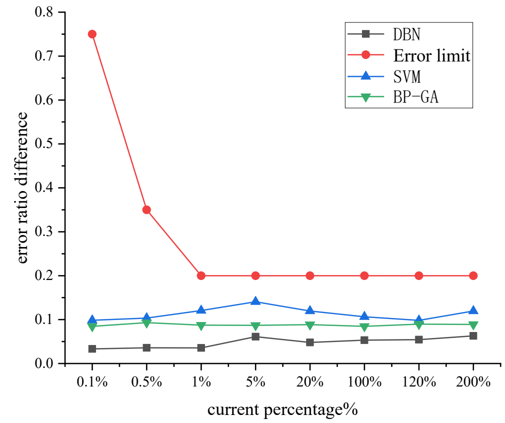


Figure 5. Error ratio diagram before and after compensation. Figure 6. Comparison diagram of error ratio difference of three methods.

5. CONCLUSION

In this article, an adaptive deviation compensation method for wide-range current transformers based on deep belief network is proposed. An adaptive calibration system for wide-range current transformers is developed, and a deviation compensation experiment is carried out. The method can simply and efficiently identify the error characteristics of the wide-range current transformer and carry out self-adaptive identification, which improves the accuracy of the measurement result of the wide range transformer. The main features of the proposed method are summarized as follows:

(1) Using self-extracted features, a deep belief network algorithm combining unsupervised learning and supervised learning. Good results are obtained in both accuracy and training efficiency.

(2) Developed a wide-range current transformer self-adaptive calibration equipment, and carried out error analysis. It can realize the function of error compensation and has good application value.

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