Research Article

Data Anomaly Diagnosis Method of Temperature Sensor Based on Deep Neural Network

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As one of the indicators of whether all kinds of machinery and electrical appliances work normally during use, temperature has an important basis for judging the normal work of related machinery. In order to reduce the probability of safety and quality problems caused by inaccurate temperature measurement in the use of these machines and electrical appliances, this paper uses RBF neural network and EEMD modal analysis two deep neural network models to build a deep neural network-based temperature sensor data anomaly diagnosis method. This method first excavates a large number of historical temperature data samples of temperature control sensors in machinery and electrical appliances and analyzes the change law of relevant sample data, so as to build a data anomaly diagnosis database, and then establish a temperature prediction model based on RBF to predict the temperature of electrical appliances and mechanical components; Second, real-time temperature monitoring and sampling are carried out for the normal temperature sensor. Based on the constructed sample database, automatic identification of various abnormal conditions is realized, and the real measured value of the sensor is reconstructed or estimated under abnormal conditions. EEMD feature extraction is carried out for the difference between the predicted temperature and the actual temperature; Finally, the RBF temperature anomaly diagnosis and classification model is constructed, and the feature vector sets are constructed by variance, variance percentage, energy and energy percentage methods, respectively, or jointly, and these vector sets are used as the input of the fault model for temperature anomaly diagnosis and monitoring. Through the diagnosis of the measured temperature sensor data, the established model has a good ability of fault diagnosis and classification.

1. Introduction

Sensor is an indispensable and important part of measurement and control system, and it is the main tool to collect signals. With the increase and complexity of industrial machinery and civil electrical appliances, the complexity of measurement and control system is gradually increasing, the number and types of sensors are greatly increased, and the working environment is getting worse and worse. In addition, the performance of the sensor is not only directly related to the running state of the equipment but also related to the vital security issues. In particular, the working condition of sensors that provide control signals directly affects the state of the system, so it is more important [1]. The sensors composed of precision components are often in a bad working environment, and failure is inevitable. At this time, the performance of the automation system will be degraded at least, and disastrous consequences will be caused at most. Accidents that cause equipment damage and huge economic losses due to sensor failure also occur from time to time. According to statistics, the sensor failures in general automation systems account for more than 45% of all failures [2, 3]. However, once the sensor fails, the performance of the control system will be degraded at first, and then catastrophic consequences will be caused. Therefore, the demand for on-site fault diagnosis of sensors is becoming increasingly strong, and it is very necessary to carry out fault diagnosis of sensors.

In the field of automatic control, the sensor converts the measured physical signal into electrical signal, which is very important for the operation of the monitoring system. When it fails, it will have a serious impact on the subsequent
monitoring, control, fault diagnosis, and other systems [4]. For example, in the locomotive transmission control system, temperature is an important indicator of the working environment and state of the equipment, such as the oil temperature of the traction transformer, the temperature sensor temperature of the water inlet and outlet of the traction converter water cooling system, the air temperature of the cabinet, and the temperature of the traction motor. If the temperature is too high, it is necessary to reduce the power of the locomotive, disconnect the main circuit breaker, and other protective actions to ensure the safe operation of the equipment. The operation environment of traction drive system device is complex, and corrosion, temperature, humidity, electric surge, static electricity, and other factors will affect its operation state [5, 6].

In foreign countries, the research on abnormal diagnosis of temperature sensor data has a long history. As early as the 1950s, scientists used grain monitoring system to ensure food security. Developed countries in Europe and the United States have an early scientific and technological revolution and have always been in the lead in technical research in related fields. They have an efficient temperature monitoring system and standards. On the basis of previous studies, Zhao et al. introduced the concept of dynamic radius support vector data description (DR SVDD) and the idea of kernel space angle to detect turboshaft engine faults based on Dr SVDD [7]. Msi et al. proposed a new fault detection system for large-scale grid connected photovoltaic power stations. The fault detection system makes a cascade comparison between the DC power supply of the actual photovoltaic power station and the simulated photovoltaic power station, distinguishes the fault situation, and identifies the nature of the fault [8]. Hid et al. proposed a fault detection method based on asymmetric pole inductance (APIL), which has certain accuracy in fault detection [9]. Li et al. systematically studied the application of ANN and hybrid ANN models in photovoltaic fault diagnosis. For each application, the target photovoltaic fault, detectable fault, data type and amount used, model configuration, and FDD performance were extracted and analyzed [10]. Duan et al. used the correlation between atmospheric data and granary historical data to propose SVR method to predict the average temperature of grain pile [11]. Kurpaks et al. established a dynamic model of water content and greenhouse heat flow, and expounded the movement of indoor heat and mass [12]. Chang et al. proposed the finite difference method to establish a model to predict the moisture content and distribution of grain [13]. Szke et al. used the temperature of the last two days in combination with the maximum and minimum temperature given by the weather forecast to predict the temperature in the next 24 hours [14]. Fan et al. described the actual greenhouse system based on the greenhouse temperature prediction model of SVR [15]. These scholars have done a lot of research on fault diagnosis, but the abnormal monitoring of temperature sensor data based on deep neural network is not comprehensive enough, and there is a lack of practical prediction system.

However, in China, the research of sensors is relatively lagging behind. The traditional way to improve the reliability of sensor output signal is to set up multiple redundant sensors. Take the average value or multiple values, of course, this will pay a high cost. With the development of sensor technology, some intelligent sensors have been developed, which makes self-detection and self-diagnosis possible. At present, most sensor neural network fault diagnosis methods use BP neural network [16–20]. Generally, offline training and online work processing mode are adopted in data processing. However, BP neural network has the problem of slow convergence and easy to fall into local minima. In addition, the offline processing method requires that when training the network, a large number of training samples containing all the characteristics of the sensor must be provided to the network. Otherwise, when the field data exceed the coverage of the neural network training samples, the network will often output error information due to the lifting capacity of the network.

In recent years, ANN has been widely used in sensor fault diagnosis, especially for BP neural network. At present, it covers most fields. The principle of BP artificial neural network is relatively simple. It was originally evolved from multilayer perceptron and used for network training with unique back propagation [20–23]. However, when adjusting the weight of BP neural network, it is different from other neural networks, which often adopts the negative gradient descent method. It is precisely for this reason that the network is prone to fall into local extremum and poor convergence speed for some complex training samples, which limits its scope of application. Therefore, people turn their attention to another radial basis function (RBF) neural network that can solve the above shortcomings. It is superior to BP neural network in approximation ability, classification ability, and so on [24, 25]. At the same time, Wang et al. [26] used the limit learning machine method to classify the faults of the fuel system. Guo et al. [27] combined the circular model with the limit learning machine (ELM) to form a fault diagnosis method for linear analog circuits. Xia et al. [28] reported an effective diagnosis method for early faults of water chillers by combining nuclear entropy component analysis (KECA) and voting based ELM (VELM). Li et al. [29] proposed a method based on extreme learning machine and ADABoost Samme’s nuclear power plant fault diagnosis framework. Liu et al. [30] proposed a new gear personalized fault monitoring model in combination with two different neural networks (finite element method and elm method) to solve the problem of gear fault when mechanical devices work. The above research combines various methods with limit learning machine for fault diagnosis and has achieved good results, but most of them have poor universality. Moreover, due to the randomness of the weights and thresholds of ELM, the results of each time are unstable, which is easy to affect the prediction results. Therefore, many scholars have studied a fault diagnosis classification model based on empirical mode decomposition (EEMD). After analysis, it is found that the model has strong signal analysis technology ability and is very suitable for dealing with this kind of problems.

In order to solve the above problems, this paper proposes an intelligent temperature data anomaly diagnosis method.
based on RBF neural network and empirical mode decomposition (EEMD), which is based on historical fault data samples and normal historical data of temperature sensors. The rule base of sensor fault diagnosis is established by analyzing the characteristics of fault samples, and the fault-tolerant estimation method of fault conditions is obtained. For the fault conditions that cannot be reconstructed from the fault samples, the normal historical data of the sensor are used to establish the grey prediction model of the measured value of the sensor, so as to realize the fault-tolerant estimation of the nonisolated fault samples, and carry out the research on the abnormal diagnosis method of temperature sensor data based on deep learning.

2. Fundamental Theory

2.1. Brief Introduction of Signal Sampling Circuit of Temperature Sensor. Thermal resistance (such as PT100) is a temperature sensor that converts temperature into resistance based on the principle that its resistance value changes with temperature. The temperature measurement circuit obtains the resistance value (voltage/current) by first applying a known excitation current to the thermal resistance and then measuring the voltage at both ends and converts the resistance value into the temperature value, so as to realize the temperature measurement [31].

There are three connection modes between thermal resistance and temperature measuring circuit: two-wire system, three wire system, and four wire system. Because the four wire measurement method is not affected by the resistance of connecting wires, it has been widely used in the field. This wiring method is also used in most locomotive transmission systems. Therefore, this paper takes the four wire temperature sensor as an example to study its signal sampling circuit principle, fault diagnosis, and fault-tolerant estimation methods.

The typical temperature signal sampling principle is shown in Figure 1.

In Figure 1, both ends of PT 100 are connected to 4 through A1 and A2 ends 9 mA constant current source, and then the temperature signal sampling circuit obtains its differential input voltage $U_{in}$ through B1 and B2. $U_{in}$ generates a single ended voltage signal $U'_{in}$ through the voltage follower and then enters the in-phase proportional operation amplification circuit to generate a voltage signal that meets the sampling requirements of the analog to digital converter (ADC) of the control unit.

If the amplification factor of the in-phase proportional operation amplification circuit is $k$, the relationship between the sampling temperature value $t$ of the temperature sensor (PT100) and the output voltage value $u$ of the temperature signal sampling circuit is shown in formula (1).

$$U = (0.385T + 100) \times 0.0049K.$$  

2.2. Basic Principle of RBF Neural Network. MP model describes neurons from the perspective of logic functional devices, which is a mathematical simplification of biological neuron information processing mode and establishes the theoretical research foundation of neural networks.

In 1988, broomhead and low e introduced radial basis function into neural network to form RBF neural network [32]. RBF neural network is a three-layer feedforward network. Its basic idea is to use RBF as the “base” of hidden units to form the hidden layer space and transform the low-dimensional input vector into the high-dimensional space through projection. So that the original linear inseparable problem becomes linear separable. Figure 2 shows the basic structure of RBF neural network.

For the structure of RBF network, its principle is relatively special. The hidden layer space formed by it can directly map the input vector to the hidden layer through neurons, so as to reduce the weight association of the middle layer. Therefore, the association weight from the input layer to the hidden layer of this neural network is also relatively
special, which is 1. The hidden layer is only responsible for the nonlinear projection of the input vector of the input layer, and the output layer is only responsible for the weighted sum of the values mapped by the hidden layer. The parameters to be learned and optimized in RBF neural network include the center and variance of radial basis function and the connection weight from hidden layer to output layer. The output layer is responsible for optimizing the weights through linear optimization strategy, and the learning speed is usually fast. The hidden layer needs to use nonlinear optimization method to adjust the parameters of the activation function, so its learning speed is relatively slow. In the learning process of RBF neural network model, the learning method of its parameters is not unique, but the selection of radial basis function center is mostly used, mainly including orthogonal least square method and supervised center method, as well as random center method and self-organizing selection method. In addition, the learning process of RBF neural network includes two stages: the first stage is to solve the center and variance of the hidden layer basis function, which is also called unsupervised learning process; the second stage is the supervised learning process, which determines the connection weight between the hidden layer and the output layer. RBF neural network belongs to local approximation network, which omits the learning behavior of hidden layer weights and avoids the time-consuming layer by layer transmission process of errors in the network. Therefore, the learning convergence speed of the network is very fast. Compared with other neural networks, RBF neural network can approach any nonlinear function with any accuracy and has the best approximation performance, classification ability, and global optimization characteristics. Moreover, it has simple topology, small amount of calculation, good applicability of the network, the basic parameters such as the structure of the network, the number of hidden layer units, and constants can also be dynamically adjusted and determined, with fast convergence speed.

Radial basis function is a real valued function whose value only depends on the distance from the fixed point, and any function satisfying the \( \phi(x, c) = \phi(||x - c||) \) characteristic \( \phi \). Both are radial basis functions, which can also be the distance to the origin in a simplified case, that is, \( \phi(x) = \phi(||x||) \). Using Gaussian kernel function as the basis function of radial basis function neural network, the output of hidden unit of radial basis function neural network is

\[
\phi_i(x, c_i) = G(||x - c_i||) = \exp \left( -\frac{1}{2\sigma^2} ||x_p - c_i||^2 \right), \tag{2}
\]

where \( \phi \) is the radial basis function, \( x \) is the sample, \( c_i \) is the \( i \)th center point of the kernel function, and \( \sigma \) is the width of the \( i \)th center point of the function. The selection of the central point of kernel function is very critical. The improper central position cannot make the network correctly reflect the actual distribution of the input sample space, and the input space cannot be well fitted. The width of the central point of the kernel function controls the radial range of the function, which is an important factor affecting the performance of RBF neural network. When the width is too small, the dividing line between classes will become blurred, which will reduce the classification accuracy. When the width is too large, the coverage area of the basis function will become relatively small, thus reducing the generalization ability of the network.

Then the output of RBF neural network is

\[
y_j = \sum_{i=1}^{h} w_{ij} \exp \left( -\frac{1}{2\sigma^2} ||x_p - c_i||^2 \right), \quad j = 1, 2, \ldots, n, \tag{3}
\]

where \( y_j \) represents the output of the RBF neural network, \( x_p \) represents the \( p \)th input sample, \( c_i \) represents the \( i \)th center point of the function, \( w_{ij} \) represents the connection weight coefficient between the hidden layer neuron \( i \) and the output layer neuron \( j \), \( h \) represents the number of nodes in the hidden layer, and \( n \) is the number of output samples or classifications.

Based on the above theory, it can be found that the performance index is less than the given error by increasing the number of hidden layer elements, so as to continuously improve the fitting accuracy. However, in practical applications, if the number of hidden layer elements is too large, it may cause the redundancy of the model and numerical ill conditioned. Therefore, effective methods must be adopted to select the network center and determine the network weight.

1. Cluster analysis method is used to select RBF Network Center. After selecting the center of RBF network, the determination of weight becomes a problem about parameter linearization. The least square method can be used to determine the network weight. The advantage of this method is that the center is easy to determine, the calculation time is short, and it is not easy to appear numerical ill conditioned. The disadvantage is that the selection of RBF center is separated from the determination of weight, and the center obtained cannot be guaranteed to be the best.

2. The least square problem is orthogonalized by orthogonalization algorithm. When all centers of RBF network are determined, the center of the next layer is determined according to the method of the previous layer, and the least square method is used to determine the weight of the layer. After all the centers are selected, the least square method can be used to determine the weight of the next layer.
neural network are selected, the weights are also determined. The advantage of orthogonalization method is that it can ensure to select the best sample point as the center. Its disadvantage is that when the number of sample points is large, the workload of orthogonalization is large, the calculation time is long, and numerical ill condition often occurs.

(3) The ideal method is to combine the clustering method with the orthogonalization method, that is, the clustering method is used for primary selection, and then the orthogonalization method is used for selection, and the weight of the network is determined at the same time.

2.3. Set Empirical Mode Decomposition (EEMD). Empirical mode decomposition (EMD) is a decomposition method that can reflect the instantaneous frequency of data [33], but because the added noise is random, it is easy to cause modal aliasing, endpoint effect, screening iteration stop standard, and other problems. To solve the above problems, Hafida et al. [34, 35] proposed integrated empirical mode decomposition (EEMD). This method solves the phenomenon of modal aliasing by adding white noise to fill the discontinuous signal segment. In the process of noise signal decomposition, the filtering characteristics of white noise signal are used to solve the average value of intrinsic mode component (IMF) for many times to eliminate the interference of white noise on the original signal at discontinuous points [36].

EEMD is an improved method of empirical mode decomposition EMD [35]. The method of decomposing the original signal into several intrinsic mode functions (IMF), each IMF must meet two conditions:

(1) In all decomposed data sets, the number of extreme points and zero crossings is equal or at most 1 difference;

(2) The average value of the upper and lower envelope determined by the local maximum point and the local minimum point is 0. After EMD decomposition, the original signal \( x(t) \) can be expressed as

\[
x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t).
\]

(3) If \( j < M \), repeat steps 1 and 2, adding different random white noise, \( j = 1, 2, 3 \cdots M \), and \( M \) is the number of tests.

where: \( x_j(t) \) is the signal after adding random white noise, \( j = 1, 2, 3 \cdots M \), and \( M \) is the number of tests.

(2) \( x(t) \) is decomposed into a series of IMFs \( (c_{i,j}) \), using EMD:

\[
x_j(t) = \sum_{i=1}^{n} c_{i,j}(t) + r_{n_j}(t),
\]

where \( c_{i,j} \) is the \( i \)th IMF of the \( j \)th test; \( r_{n_j} \) is the residual of the \( j \)th test, and \( n_j \) is the number of IMFs of the \( j \)th test.

(3) If \( j < M \), repeat steps 1 and 2, adding different random white noise signals each time.

(4) Obtain \( I = \min \{N_1, N_2, \ldots, N_M \} \) and calculate the overall average of the corresponding components as the final result:

\[
c_i = \frac{\sum_{j=1}^{M} c_{i,j}}{M}.
\]

3. Design of Temperature Sensor Data Anomaly Diagnosis Model Based on RBF Neural Network and EEMD Modal Analysis

3.1. Data Acquisition and Pretreatment

3.1.1. Data Acquisition. To fully reflect the authenticity of the experiment. The author selected five normal sensors with good performance to collect the experimental data. When the system was put into operation, the sensors were also in normal operation and no fault occurred. At this time, the sampling data sequence within 1 hour of the sensor obtained through time-sharing data acquisition is shown in Table 1.

3.1.2. Data Preprocessing. At present, the longest method in data standardization processing is Z-score standardization, which is also one of the default methods of SPASS. This method is to standardize the data through the mean value (i.e. mean value) and standard deviation (i.e. standard deviation) of the original data set and preprocess the measured data according to the characteristics of the signal transmitted and output by the temperature sensor. The preprocessing
code is shown in formula (9), and the data processed by this method are shown in Figures 3 and 4. From the law of the data in Figures 3 and 4, it can be seen that the data preprocessed by Z-score standardization only change in the direction of the value of the data, but does not change the size relationship of the data itself, and the data processed by this method can eliminate the influence of the value of the data itself on network training and feature selection, so as to speed up network learning and accurately assign training weights.

\[ x_{\text{normalization}} = \frac{x - \mu}{\delta}, \quad (8) \]

3.2. EEMD Abnormal Data Feature Extraction. Taking a sensor with a lot of abnormal data as an example, the residual signal between the predicted temperature and the measured temperature is converted into a continuous time series, as shown in Figure 5. The abnormal data occur in each sequence of sampling points and has the property of random distribution.

The EEMD method is used to decompose the abnormal data features of the results in Figure 5 layer by layer, and the results are shown in Figure 6. Imf1 refers to the high-frequency random noise of the sensor, which fluctuates violently, and has obvious random variability, strong nonlinearity, and insignificant periodicity; Imf2 is the high-frequency periodic component of the output signal of the sensor under external influence; Imf3 refers to the sharp fluctuation of the output signal caused by the abnormal data fluctuation of the sensor; and Imf4 represents the low-frequency periodic component of the sensor output signal caused by the long-term influence of influencing factors.

Follow the same steps to extract the features of the abnormal data of the four temperature sensors used in this paper.

3.3. Model Design. The fault diagnosis modeling of temperature sensor drift fault, accuracy decline fault, impact
fault, and fixed deviation fault is mainly composed of three parts: temperature prediction model is based on RBF neural network; EEMD method is used to extract fault features of temperature difference between prediction and measurement; and the anomaly diagnosis scheme based on RBF neural network is shown in Figure 7.

The residual signal between the predicted temperature and the measured temperature still has large fluctuations. When the fault signal is not obvious, it is easy to be hidden by high-frequency fluctuations. The simple threshold discrimination method cannot identify the fault and judge the specific fault type. At the same time, when the temperature prediction accuracy is low, the converted continuous time series fluctuates greatly, which is easy to cause misjudgment. Therefore, the temperature residual signal is decomposed by EEMD, the fault features are extracted from each component, and the fault signal is highlighted to improve the recognition rate.

4. Analysis of Experimental Results

In the test experiment, the normal sensor and the faulty sensor are sampled once every 1 min, respectively, and 240 samples are collected by four temperature sensors within 60 min. Figure 8 reflects the fault transmission signal of an abnormal temperature sensor within 60 min of sampling, and Figure 9 shows the normal output signal of the normal sensor within 60 min of sampling. From the two temperature data transmission signal curves, it can be seen that the failure of the temperature sensor generally occurs 20 minutes after
the sensor works normally, that is, the sensor temperature rises to a certain temperature, which leads to large fluctuations in the signal value.

At the same time, 240 sets of sample data measured by the above four sensors are used to evaluate the classification effect of combined eigenvectors and RBF neural network. First, input the collected acceleration data and filter, then read the model training parameters, and then quickly classify the data through correlation operation to identify and judge whether the sensor temperature is in an abnormal state. Finally, output the alarm signal according to the actual situation of temperature detection. The process of temperature anomaly detection algorithm is shown in Figure 10.

The standard system used to evaluate the effectiveness of temperature sensor anomaly diagnosis algorithm in this paper mainly includes three indicators: accuracy, sensitivity, and specificity. Accuracy refers to the proportion of accurately detecting all abnormal data and nonabnormal data.
The higher the accuracy is, the better the effect of this method is; sensitivity refers to the proportion that all abnormal data are accurately detected. The higher the sensitivity, the lower the misjudgment rate; specificity refers to the proportion that all nonabnormal data are correctly detected. The higher the specificity, the lower the misjudgment rate.

\[
\text{accuracy} = \frac{TP + TN}{TP + FN + FP + FN},
\]

\[
\text{sensitivity} = \frac{TP}{TP + FN},
\]

\[
\text{specificity} = \frac{TN}{TN + FP}.
\]

Among them, TP (real case) is the number of abnormal temperature data events and falls detected, which belongs to correct judgment; FN (false counterexample) refers to the number of abnormal temperature data events but not detected, which belongs to missed judgment; FP (false positive example) is the number of times that no abnormal temperature data event occurs but abnormal temperature data are detected, which is a misjudgment; TN (true counterexample) is the number of times when no abnormal temperature data event occurs and no abnormal temperature data are detected, which belongs to correct judgment. The number of hidden layer nodes of neural network affects the generalization ability and complexity of neural network. If the number of hidden layer nodes is too small, the network will get less useful information, the model description ability is insufficient, and the fault tolerance is poor; too many hidden layer nodes will increase the training time, and the network may store irregular information in the samples, which may lead to the “over fitting” problem and the decline of generalization ability. At present, there is no perfect theory for the selection of the number of hidden layer nodes of artificial neural network, which is mainly verified by numerical value based on previous experience. The input layer of the RBF neural network constructed in this paper contains 4 neurons, the output layer contains 2 neurons, and the number of neurons in the hidden layer is 200 according to the initial value, 20 steps, and 20 iterations. The number of numerical experiments is finally determined to be 280. The abnormal temperature data diagnosis model formed by this is shown in Figure 11. The test results are shown in Table 2.

As can be seen from Table 2, a total of 240 samples were tested. According to the defined formula, the accuracy, sensitivity, and specificity of the algorithm are 97.5%, 96.8%, and 97.9%, respectively. The test results confirm the effectiveness, accuracy, and feasibility of the algorithm.

5. Conclusion

With the promotion of household appliances and industrial machinery, temperature, as one of the indicators of normal operation of various machinery and electrical appliances in the process of use, also occurs from time to time due to equipment damage and huge economic losses caused by sensor failure. This paper analyzes the above problems and draws the following conclusions:

(1) Based on RBF neural network and empirical mode decomposition (EEMD) deep neural network and based on the historical fault data samples and normal historical data of temperature sensors, an intelligent temperature data anomaly diagnosis method is proposed to solve the temperature anomaly problem that is easy to occur in temperature sensors at present.

(2) The sensor in actual work is taken as the object, and the measured data are used as the input of the fault model to diagnose and monitor the temperature abnormality. Through the diagnosis and verification of the measured temperature sensor data, the established model has a good fault diagnosis and classification ability, with an accuracy rate of 97.5%, a sensitivity of 96.8%, and a specificity of 97.9%. It shows that the method constructed in this paper can effectively provide data abnormal diagnosis services for the temperature sensor.

Data Availability

The data used to support the findings of this study can be obtained from the author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

References


