

Research on temperature compensation method for photoelectric sensors

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Abstract: In order to make the temperature error of fiber-optic current sensor (FGB) based on polarization modulation principle meet the requirements of engineering applications, the temperature error characteristics of FGB are analyzed theoretically, and the optimized BP neural network is used for the temperature compensation of FGB, which realizes the nonlinear temperature error correction of the sensor, and compares and analyzes the experimental results with those of other types of temperature compensation algorithms. The results show that the temperature compensation results based on the neural network algorithm are better than other compensation effects. Finally, the repeatability of the FGB was experimentally verified using its full temperature experiment, and the temperature errors of the FGB in the range of 20 °C ~ 100 °C were less than 0.5% after the correction of the neural network algorithm.

Keywords: polarization modulation; fiber optic current sensor; temperature compensation; neural.

1. Introduction

In recent years, the requirements of industrial production on the voltage level of the power grid continue to improve, the traditional current transformer has been difficult to meet the development needs of the smart grid. With the continuous breakthrough of fiber optic sensing technology, based on the selective reflection of grating on specific wavelengths of light to achieve the strain information encoded in the fiber optic current sensor (FGB, fiber optical current sensor) with its unique advantages has been in the power industry to emerge. Compared with the traditional current transformer, it is free from external electromagnetic interference, and at the same time, the advantages of large dynamic range, good insulation, small size, light weight and so on have been more and more widely concerned.

Although fiber optic current sensors have obvious application advantages, there are also technical difficulties that the accuracy is easily affected by temperature, and temperature error compensation is necessary to meet the needs of engineering applications. The residual stress introduced in the packaging of the sensing fiber makes the temperature characteristics of the FGB has deviated from the linear category. In addition, the temperature characteristics of the various optical devices that make up the FGB are also different, which increases the complexity of the FGB's temperature characteristics and makes it show nonlinear characteristics. In order to realize the nonlinear temperature error compensation of FGB, people have also proposed a variety of solutions, for example, the use of software methods for photoelectric sensor temperature compensation, compared with the hardware method, the method is flexible, high precision, and relatively low cost, so it has become the main compensation method at present. Software compensation method has linear method and non-linear method, linear method mainly has multiple linear regression, the method is very simple, the requirements of the conditions are not high, but the photoelectric sensor temperature change is regarded as a linear law of change, which is not very consistent with the actual, resulting in poor temperature compensation[1-2] . As well as the use of special photonic crystal fiber, so that the temperature of the fiber remains unchanged and through the wave plate and the sensing fiber contrary to the temperature characteristics of the sensing fiber, the sensing fiber temperature error offset compensation and other hardware improvements[3-4] . The above compensation schemes, however,

have limitations, and the temperature compensation effect still cannot meet the actual engineering requirements.

Artificial neural network (ANN, artificial natural network) has been widely used in the field of artificial intelligence and achieved good results, its superior nonlinear mapping characteristics provide a good method for nonlinear temperature compensation in FGBs, which can be compensated in software without increasing the cost of hardware development and production[5]. Based on these studies, the temperature characteristics of polarization-modulated FGBs are analyzed and the complexity of temperature compensation is pointed out. The results of BP neural network and classical regression algorithm and SVM compensation are compared, and it is proved that all of the above are not as effective as BP neural network compensation, and the practicality of neural network temperature compensation is verified by the experiment of fiber optic sensing ring.

2. Temperature Compensation Fundamentals

2.1. FBG Sensing Principle

Fiber grating refractive index along the core was a periodic change, when the incident light into the grating area, to meet the Bragg conditions of the incident light will be reflected back to the original region, forming the reflectance spectrum: does not meet the Bragg conditions of the incident light will be transmitted along the direction of incidence to continue to propagate, when the strain and the temperature and other external environmental factors change, it will make the reflectance spectra of the central wavelength of the wavelength of the drift, and therefore, based on the size of the central wavelength drift can be measured by strain and temperature. When the external environmental factors such as strain and temperature change, the center wavelength of the reflection spectrum will be drifted, so according to the size of the center wavelength drift can be measured strain and temperature The center wavelength of the FBG reflection spectrum λ_B meets the structural principle of the fiber grating as shown in the following equation.

$$\lambda_B = 2n_{\text{eff}} \Lambda$$

where n_{eff} is the effective refractive index of the fiber core and Λ is the grating period. Strain and temperature have a cross effect on the center wavelength of the FBG, the elastic-optical effect produced by strain and the thermo-optical effect produced by temperature make the effective refractive index of the core produce Δn_{eff} changes in the effective refractive index of the fiber core, the deformation caused by strain and the thermal expansion effect caused by temperature to produce a grating period of change $\Delta \Lambda$. The change amount of the center wavelength of the FBG is the final change amount of the FBG.

$$\Delta \lambda_B = 2(\Lambda \Delta n_{\text{eff}} + n_{\text{eff}} \Delta \Lambda)$$

Since temperature and strain cross-influence the wavelength at the center of the FBG, the effect of temperature on wavelength needs to be rejected and compensated for when the FBG is used to measure strain.

2.2. Current Sensing System Diagram

The entire FBG current sensing system consists of a light source, coupler, FBG sensing head, power supply system, spectrometer, and a computer (PC), as shown in Figure 1.

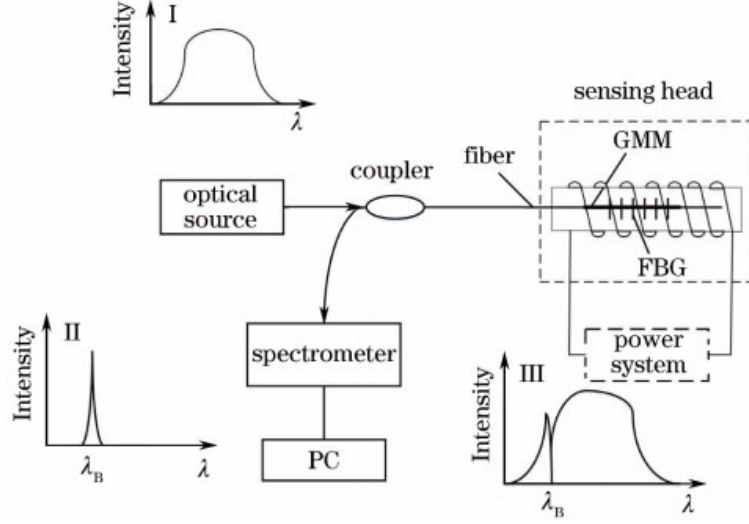


Fig. 1 Schematic structure of the FBG current sensing system (inset I shows the incident spectrum of the light source, inset II shows the FBG reflection spectrum, and inset III shows the FBG transmission spectrum)

When the center wavelength produces a shift. The reflected light enters the spectrometer through the coupler, the spectrometer demodulates the center wavelength and passes it into the PC and then inputs the demodulated center wavelength of the FBG and the ambient temperature measured by the thermometer into the trained neural network to perform the temperature compensation, and finally outputs the measured current value.

2.3. Backward propagation (BP) neural networks

A BP neural network is a learning network with forward input computation and backward propagation of error, consisting of an input layer, an implicit layer and an output layer. In general, a three-layer network can approximate any continuous function according to the accuracy requirements. A 3-layer BP neural network model is shown in Figure 2.

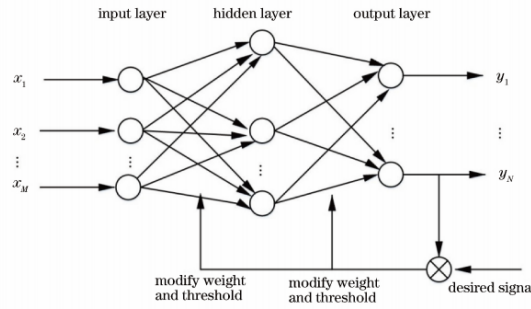


Fig. 2 3-layer BP neural network model

The input layer has M nodes; the hidden layer is a single layer with L nodes; and the output layer has N nodes. x_i ($i = 1, 2, \dots, M$) are the inputs of the neural network, s_j , a_j are the inputs and outputs of the j th node of the implicit layer, w_{ij} , b_j are the weights from the input layer to the implicit layer and the queues of the implicit layer, p_k , t_k are the inputs and outputs of the k th node of the output layer, w_{jk} , b_k are the weights from the implicit layer to the output layer and the queues of the output layer, and $f(x)$ is the excitation function. The inputs and outputs of the implied and output layers satisfy.

$$s_j = \sum_{i=1}^M w_{ij} x_i + b_j, a_j = f(s_j), p_k = \sum_{j=1}^L w_{jk} a_j + b_k, t_k = f(p_k)$$

Input signals from the input layer, according to the above equation for the input signal processing, the output signal from the output layer, this process is the forward input process; the output value of the output layer is compared with the desired output value, according to the size of the error reverse

correction of the weights and thresholds, this process is the process of error back-propagation. The relationship between the error function E_p and the desired output values y_k and t_k and the weights and threshold correction coefficients are.

$$E_p = \frac{1}{2} \sum_{k=1}^N (y_k - t_k)^2$$

$$\Delta w_{jk} = -\eta \frac{\partial E_p}{\partial w_{jk}}, \Delta w_{ij} = -\eta \frac{\partial E_p}{\partial w_{ij}}, \Delta b_k = -\eta \frac{\partial E_p}{\partial b_k}, \Delta b_j = -\eta \frac{\partial E_p}{\partial b_j},$$

where η is the learning rate coefficient, the Δw_{jk} , Δw_{ij} are the weight correction coefficients from the implicit layer to the output layer and from the input layer to the implicit layer, respectively. Δb_k , Δb_j are the threshold correction coefficients for the output layer and the hidden layer, respectively. This process of forward input computation and error back propagation is carried out iteratively until the required error accuracy is achieved. The neural network is used for temperature compensation, the wavelength and temperature are used as input data and the current is used as output data, the current value output from the BP neural network is constantly compared with the desired value, the training is terminated when the required error accuracy is reached, and the network is verified with test data.

2.4. Optimization study of FBG current sensing temperature compensation algorithm

Although BP neural networks have powerful nonlinear mapping ability, self-learning and self-adaptation ability, and outstanding generalization ability, they also have the defects and shortcomings such as long time to reach the objective function, easy to fall into the trap of local minima, and uncertainty of network learning and memory. At present, the optimization of the algorithm for the shortcomings of BP neural network mainly focuses on the optimization of network structure and weight threshold. If the learning of network structure and weights and thresholds are combined together to solve the problem, it requires a computer with strong processing power, so in this paper, genetic algorithm (GA) is integrated with BP neural network algorithm to optimize the weights and thresholds of the network.

Genetic algorithms first randomly generate candidate solutions that satisfy the constraints of the actual problem, and then repeatedly perform genetic operations of crossover and mutation on the candidate solutions to obtain the optimal solution or the most satisfactory solution, which is manifested as having the best fitness to the environment for organisms.

The process of its realization is as follows:

Step 1: Encoding of weights que values. The weights and values of the BP neural network are encoded, and the encoded weights and values are arranged and combined together to form the chromosome of the GA algorithm. In this paper, we use decimal coding, BP neural network has been determined network structure is: the number of nodes in the input layer is 2, the number of nodes in the hidden layer is 5, the number of nodes in the output layer is 1. So the number of weights and values is $2 \times 5 + 5 \times 1 = 15$, the number of smell values is $5 + 1 = 6$, and the length of the chromosome is $15 + 6 = 21$.

Step 2: Write the fitness function. The fitness function is actually to evaluate the degree of superiority of the chromosomes in the population. For the optimization of BP neural network, the optimal chromosome is the chromosome that has the optimal weight queue, that is, the weight queue that minimizes the prediction error of the BP neural network, so the inverse of the sum of the squares of the errors between the predicted output and the desired output of the BP neural network is used as the fitness function.

Step 3: Roulette selection of excellent chromosomes. Selection operation is the process of retaining the excellent chromosomes within the population and screening out the undesirable chromosomes.

Roulette method is used to retain chromosomes with excellent fitness values and eliminate those with low fitness values.

Step 4: Crossover operation. The crossover operation is mainly to randomly select two chromosomes at a time to crossover from the selected good chromosomes, and the crossover position is also randomly selected in the expectation of generating more excellent individuals.

Step 5: Mutation operation. The mutation operation is to randomly select one from the population according to a certain probability to artificially change the value of a certain part of the chromosome, so as to ensure the chromosome diversity within the population.

2.5. K fold cross validation

- (1) The original sample is randomly divided into $K = 10$ non-overlapping subsets.
- (2) One of the subsets is used as the validation set and the remaining $K-1$ subsets are used as the training set.
- (3) Build the model on the training set and calculate the prediction performance of the model on the validation set.
- (4) Repeat steps 1-3, but each time take out a different subset as the validation set and the rest as the training set.
- (5) After K repetitions, the prediction performance of K models is obtained and then averaged as the final prediction performance of the model.

3. Algorithm Flow

The integration of K -fold cross validation, GA and BP neural network algorithms can improve the reliability and accuracy of the whole network, and the specific implementation process of this optimized neural network algorithm is shown in Figure 3.

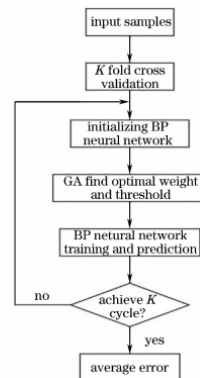


Fig. 3 Flowchart of optimization neural network algorithm

4. Experimentation and Analysis

4.1. Data Acquisition and Network Training

The light source used in the experiment is a tunable laser with a wavelength tuning range of 1490~1650 nm, and a platinum resistance thermometer is used to measure the external ambient temperature in real time. The center wavelengths of FBG reflected waves were measured under different current and temperature conditions.

Using the method of K -fold intersection and validation, the above data were randomly divided into 9 packets, 8 packets were used for training and 1 packet was used for validation, and 72 sets of sample

data were looped 9 times to form the input network. The data need to be normalized before training the sample input network.

The neural network adopts a 3-layer BP network model, taking the wavelength value and ambient temperature as inputs, and the current value as output, the network is first trained with training data, and then the prediction data are input into the already trained network and predicted, and the output current is the exact current value of compensation. According to the approximate relationship between the number of neurons in the input layer n_2 and the number of neurons in the hidden layer $n_2 = 2n_1 + 1$, the number of neurons in the hidden layer is set to be 5. The learning algorithm of the network is the Levenberg-Marquardt method, and the maximal number of generations is set to be 50, the learning rate to be 0.05, the training target to be 0.005, the number of generations of GA evolution to be 10, the size of the population to be 15, and the crossover and mutation probability both to be 0.005, the GA evolutionary generation to be 10, the crossover and mutation probability to be 15. variation probability are 0.1. The mean square error of some samples is calculated using the optimized BP neural network.

The prediction error of the optimized BP with 9 validations in the K-fold cross-validation is shown in Fig. 4. The single prediction error of the network in the cross-validation is not more than 7×10^{-3} , and the mean square error after the cross-validation is 0.0038, which achieves the desirable convergence effect. It is verified by many experiments, with the optimized BP neural network has high stability and reliability, and has high measurement accuracy.

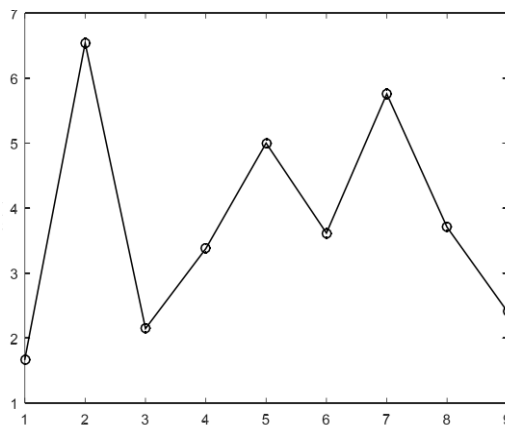


Fig. 4 Prediction error of optimized BP with 9 validations in K-fold cross-validation

4.2. Analysis of experimental results

The steady state accuracy of the composite temperature measurement system is checked as follows: from 20°C to 100°C at 10°C intervals, when the temperature is stabilized, the output temperature of the composite temperature measurement system is recorded. Figure 7 below shows the error curve of the composite temperature measurement system, the error value is obtained by subtracting the actual temperature value from the temperature measured by the composite temperature measurement system. As can be seen from the figure: the steady state accuracy of the composite temperature measurement system can reach ± 0.6 °C, and basically within ± 0.5 °C degrees Celsius.

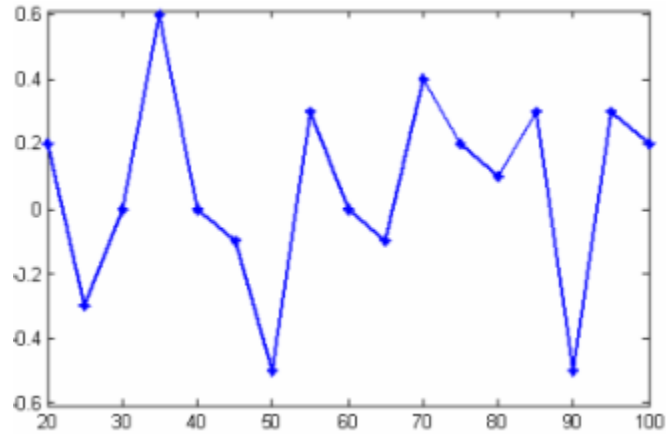


Fig. 5 Steady state error curve

The results of the dynamic characterization of the composite temperature system are shown in Fig. 6 below, Fig. 6(a)(b) shows the curve of temperature rising at different rates, and (c)(d) shows the curve of temperature falling at different rates. The dotted line in the figure is the actual temperature measured by the high-precision RTD RTD Pt100; the solid line is the temperature after compensation by the neural network compensator, i.e., the temperature measured by the composite temperature measurement system; the dotted line is the temperature measured without compensation by the neural network dynamic compensator. As seen in Figure 6, the uncompensated temperature has a certain hysteresis, while the temperature measured by the composite temperature measurement system can better follow the temperature changes, has good dynamic characteristics, can adapt to the real-time measurement of temperature requirements of the more demanding environment, such as may contain flammable and explosive gases inside the oil wells and mines, high-voltage and strong electromagnetic power system environment. That is, in the above environments, once the temperature change occurs, the temperature change can be detected quickly, so as to remind the staff to take appropriate measures to avoid serious consequences.

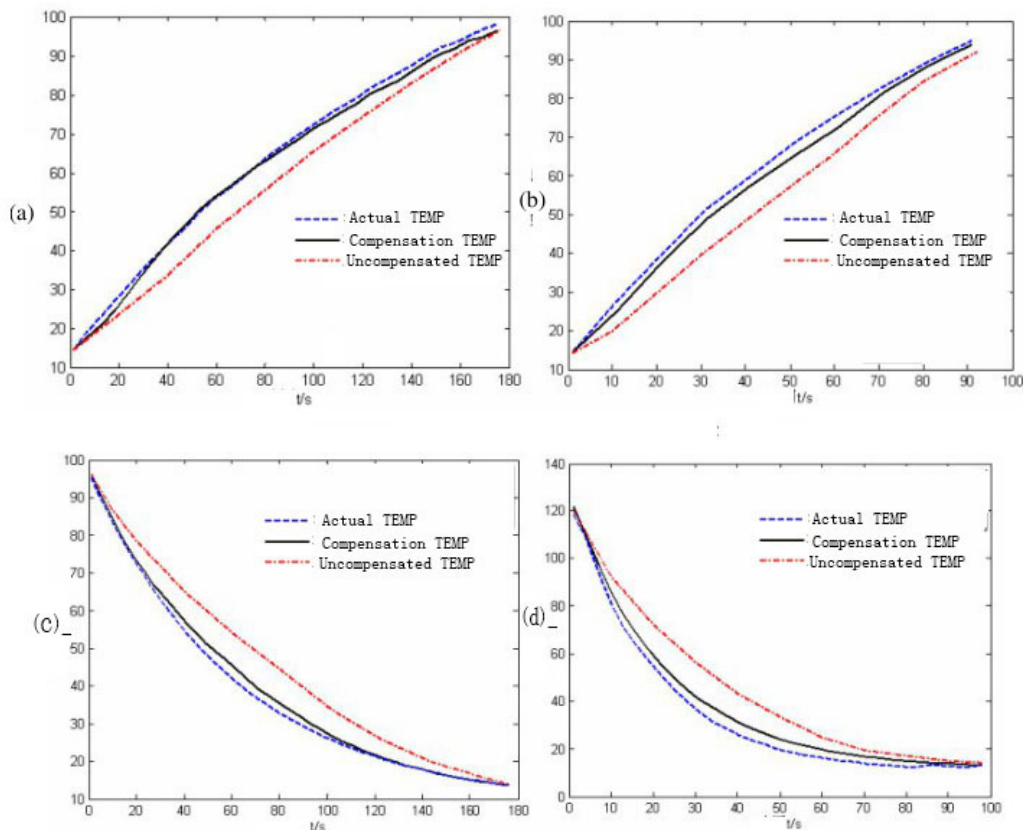


Fig. 6 Dynamic characterization of the composite temperature system examined

Finally, in order to test the response speed of the composite temperature measurement system, by applying a step signal to the fiber-optic temperature sensor, that is, the fiber-optic temperature sensor is first put into the water of 20 °C, and when it is stabilized, it is quickly put into the water of 100 °C, and when it is stabilized, it is put into the water of 20 °C again. After repeated experiments, the response speed of the fiber optic temperature sensor is about 15 s, and the response speed of the composite temperature system after compensation is about 4 s. It can be seen that the designed composite temperature measurement system greatly improves the response speed of the original sensor and has good dynamic characteristics.

4.3. Performance comparison with other methods

In order to test the superiority of the photoelectric sensor temperature nonlinear compensation algorithm in this paper, LSSVM algorithm, multiple linear regression algorithm, and support vector machine are selected for comparison test, and their time and accuracy for photoelectric sensor temperature nonlinear compensation are shown in Table 1. From Table 1, the following conclusions can be obtained.

- (1) The multivariate linear regression algorithm has the least execution time, but the photoelectric sensor temperature compensation accuracy is the lowest, and has almost no practical application value.
- (2) The photoelectric sensor temperature compensation accuracy of the LSSVM algorithm is higher than that of the multiple linear regression algorithm, but the execution time is more than that of the multiple linear regression algorithm, mainly due to the difficulty of determining the correlation structure in the LSSVM, as well as its slower convergence speed.
- (3) The temperature compensation performance of photoelectric sensor by support vector machine is better than BP neural network and multiple linear regression algorithm, but its execution time is the longest, which consumes longer time, and the real-time performance of temperature compensation is poor.
- (4) The temperature compensation performance of optimized BP nerve is better than other algorithms, and the execution time can fully meet the requirements of practical applications, which has obvious advantages.

Table 1 Performance comparison with other algorithms

arithmetic	Time/s	Accuracy/%
multiple linear regression algorithm	2.04	70.20
LSSVM	2.65	85.86
SVM	10.78	90.56
Optimizing BP Neural Networks	2.36	95.62

5. Concluding remarks

The measurement accuracy of photoelectric sensors is related to a variety of influencing factors, among which the error caused by temperature drift is the largest, for the change characteristics of photoelectric sensor temperature, the photoelectric sensor temperature nonlinear compensation model based on optimized BP neural network is proposed, and the measurement accuracy of photoelectric sensors is analyzed according to the results of temperature compensation. The results show that the optimized BP neural network can reflect the nonlinear characteristics of the photoelectric sensor temperature change, and can accurately compensate the photoelectric sensor temperature drift error, so that the photoelectric sensor measurement accuracy has been greatly improved, and has high practical application value.

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