Demodulating of the 3-D tip clearance of turbine blades using BP neural network optimized by genetic algorithm

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Abstract

The 3-D tip clearance refers to the three-dimensional space between the probe end face and turbine blade tip surface, which contains more abundant fault information than the traditional one-dimensional tip clearance. In this paper, an approach for demodulating of the three-dimensional (3-D) tip clearance of turbine blades is presented using BP neural network optimized by genetic algorithm (GA). Through the static calibration experiments, the ratios of outer circle voltage to inner circle voltage of three units from the optical fiber probe are used as the training and test data for demodulation. The maximum errors of the radial displacement z_0, the axial angle α and the circumferential angle β demodulated by the demodulation model based on BP neural network optimized by GA are 0.1321mm, 0.9875° and 0.6456°, respectively. The mean square errors of the radial displacement z_0 , the axial angle α and the circumferential angle β are 0.0006mm, 0.0528° and 0.0266°, respectively. The experiment results show that this demodulation method have an excellent precision, which can fulfil the requirements of the 3-D tip clearance detection and provide a basic guarantee for the fault diagnosis of turbine blades.

1 Introduction

As we all know, the health monitoring and fault diagnosis of the aero-engine have always been research hotspots and that of the aero-engine turbine blades are very important, which have been studied by many researchers. The monitoring of tip clearance of turbine blades is often used for both the active control and fault diagnosis, and it's an effective and significant monitoring method. Nevertheless, the traditional tip clearance of turbine blades refers to the radial displacement, which contains limited fault information of turbine blades. Xie et al. have presented the 3-D tip clearance of turbine blades which refers to the three-dimensional space between the probe end face and the surface of the turbine blade tip [1]. Teng et al. have utilized the 3-D tip clearance as the fault information carrier of turbine blades and have analysed the response characteristics of its characteristic parameters to a typical crack fault of the high pressure turbine blade by a finite element method [2]. Xiong et al. have researched on the response characteristics of the 3-D tip clearance of turbine blades to axial displacement of turbine rotor under the crack failure [3]. As a new fault feature carrier, the 3-D tip clearance contains more fault information than the traditional tip clearance and can reflect the health status of aero-engine turbine blades more comprehensively.

In order to monitor the 3-D tip clearance of aero-engine turbine blades, Xie et al. [4] have designed an optical fiber probe with three two–circle coaxial bundles based on intensity modulation and have researched its output characters. Based on this optical fiber probe, Zhang et al. [5] have built an optical fiber measurement system for the 3-D tip clearance of the aero-engine turbine blades and successfully demodulated the 3-D tip clearance from the output signals from the optical fiber probe using BP neural network. Xie et al. [6] have proposed a new demodulation technique for the 3-D tip clearance based on the ratio of the difference in the signal intensities between any two sensing units of the optical fiber probe. This demodulation method requires high consistency for the three sensing units of the optical fiber probe and an additional fast search algorithms must be needed.

The signals acquired from the optical fiber probe with three two-circle coaxial optical fiber bundles are modulated simultaneously by the distance and inclination angles between the optical fiber probe end face and the reflective surface. Therefore, it is difficult to demodulate the 3-D tip clearance from the optical fiber probe output signals. In this study, an approach for demodulating of the 3-D tip clearance of turbine blades is proposed based on BP neural network optimized by GA. This method combines the fitting ability of BP neural network and the global search ability of GA, and can improve the demodulation accuracy of the 3-D tip clearance, which provides a possibility for the subsequent fault diagnosis of turbine blades using the 3-D tip clearance.

2 Demodulation method

2.1 Demodulation method based on BP neural network

The back propagation (BP) neural network algorithm is a multi-layer feedforward network trained according to error back propagation algorithm and is one of the most widely applied neural network models [7]. In theory, any input and output function can be fitted when the appropriate structure and parameters of the neural network are chosen. Similarly, demodulation of the 3-D tip clearance is equivalent to fitting the input and output function of the optical fiber probe, which can be achieved through BP neural network. This study utilized an optical fiber probe with three two-circle coaxial bundles, of which the output signals are the ratios of the outer circle voltage to inner circle voltage corresponding to the three units respectively [8]. In order to demodulate the 3-D tip clearance from the output signals of the optical fiber probe, a three-layer BP neural network was used in this study. The input of the demodulation model based on BP neural network is the three ratios from the optical fiber probe and the output is the value of the 3-D tip clearance. The number of BP neural network input units is $n=3$ and the number of output units is $m=3$. The number of hidden units s_1 is estimated according to the formula [9]: $s_1=\sqrt{n+m}+a$, where a is an integer between 1 and 10. The value of s_1 is between 4 and 13, which is taken as 10 in this model according to the demodulation effect. The activation function between input layer and hidden layer is chosen as 'tansig' (Hyperbolic tangent sigmoid transfer function). The activation function between hidden layer and output layer is chosen as 'purelin' (Linear transfer function). Figure 1 shows the structure of the three-layer BP neural network used in this study. r_1, r_2, r_3 refer to the three ratios corresponding to the three units of the optical fiber probe, respectively. z_0, α, β refers to the radial displacement, the axial angle and the circumferential angle, respectively.

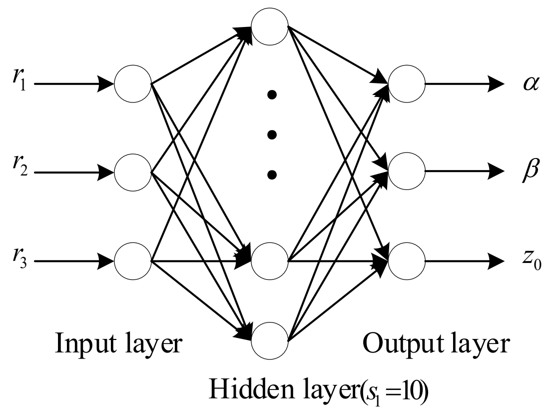

Figure 1: The BP neural network structure

The initial weights and thresholds are selected randomly in the traditional BP neural network, which seriously limits the precision and convergence speed of the network training and makes the network easily fall into local extremum. In order to improve the convergence speed of traditional BP neural network, GA was used to optimize the weights and thresholds of BP neural network in this study.

2.2 Genetic algorithm

Genetic algorithm is a computational model that simulates the natural evolution of Darwin's biological evolution theory and the biological evolution process of genetics. It is a method to search for optimal solutions by simulating natural evolutionary processes. The main steps of GA are as follows:

(1) Encode the parameters that need to be optimized to form a chromosome.

(2) Initialize population and related parameters such as crossover probability, mutation probability and population size.

(3) Calculate the fitness of each individual in the existing population.

(4) Select the candidate individuals based on the fitness using roulette wheel selection. As usual, the individual with high fitness is more likely to be selected than the individual with low fitness.

(5) Generate new individuals according to pre-set crossover probability.

(6) Generate new individuals according to pre-set mutation probability.

(7) Repeat generational process until a termination condition has been reached.

Because the search of GA only relays on the fitness not the gradient information of objective function, GA is fit for the problems that are complex and nonlinear. Therefore, GA is used to optimize the weights and thresholds of BP neural network in this study and it can improve the training accuracy and convergence speed of BP neural network.

2.3 Demodulation method based on BP neural network optimized by GA

There are some typical limitations of the BP neural network: The error is not sensitive to the change of the weights. The gradient descent algorithm is generally very slow. The number of iterations is large. The convergence speed is slow and the output of the neural network is easily trapped in the local minimum. As a global optimization algorithm, GA can compensate the deficiency of BP neural network to improve the accuracy of demodulation model. After determining the structure of BP neural network by the input and output, the initial weights and thresholds of BP neural network are encoded to generate the individuals and the length of individuals of the GA can be determined. Subsequently, by means of the selection, crossover and mutation, the best fitness value corresponding to the individual is obtained. Next, the BP neural network obtains the optimal initial weights and thresholds provided by the GA and predicts the demodulation output after the network has been trained [10-12].

As shown in Figure 2, the process of optimizing BP neural network by GA mainly includes [13]:

(1) Determine the structure and parameters of BP neural network.

(2) Optimize the initial weights and thresholds of BP neural network by GA.

(3) Continue the training of BP neural network after obtaining the optimal initial weights and thresholds.

(4) Predict the demodulation output using BP neural network.

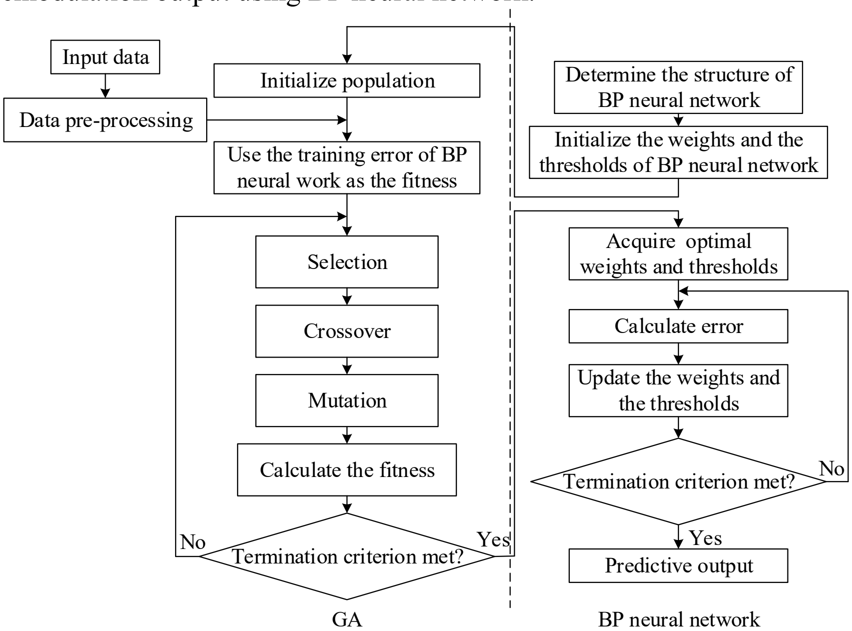

Figure 2 Flow chart of BP neural network optimized by GA

The data obtained through the calibration experiments, which contain the ratios from the output of the optical fiber probe and the 3-D tip clearance corresponding to the ratios, are used to build the demodulation model based on BP neural network optimized by GA. In other word, the three ratios (r_1, r_2, r_3) obtained by the optical fiber probe and the calibrated 3-D tip clearance (z_0, α, β) set by adjusting the calibration table are used as the input and output of the demodulation model. The BP neural network is composed of three input units, three output units and one hidden layer with 10 units. The population size, crossover probability and mutation probability of GA are 20, 0.8, and 0.1, respectively.

3 Experiments and analysis

3.1 Calibration experiments

As shown in Figure 3, the 3-D tip clearance consists of the radial displacement z_0, the axial angle α and the circumferential angle β, which are the vertical distance between illuminating fiber of Unit0 and the reflective surface, the intersection angle at x-axis direction between Unit0 and the reflective surface, and the intersection angle at the y-axis direction between Unit0 and the reflective surface [6]. The calibration table consists of a stage for adjusting radial displacement and two stages for adjusting angle. Different 3-D tip clearance between the probe end face and the reflective surface can be simulated through adjusting the radial displacement and two inclination angles of the calibration table. The range of the radial displacement of the calibration table is from 0mm to 10mm with the accuracy of 0.01mm. The range of the inclination angle of the calibration table in both direction is from -15° to +15° with the accuracy of 0.1°.

The steps of calibration experiments are as follows:

(1) Determining calibration points

According to the variation range of the 3-D tip clearance of the turbine blade under typical failure [14], the calibration range of the radial displacement is from 1.4mm to 2.5mm at interval of 0.02mm and the calibration range of the inclination angle in both direction is from -0.4° to 2.6° at interval of 0.02°. The total number of the calibration points are 14336.

(2) Calibrating the required points

According to the 3-D tip clearance need to be calibrated, the radial displacement stage and both the two inclination angle stages of the calibration table are adjusted manually. The output signals, three ratios of outer circle voltage to inner circle voltage with respect to the 3-D tip clearance is recorded.

(3) Pre-processing the calibration data

In order to prepare for training BP neural network and building the demodulation model of the 3-D tip clearance, the acquired calibration data are pre-processed based on the basic rules of the output from the optical fiber probe.

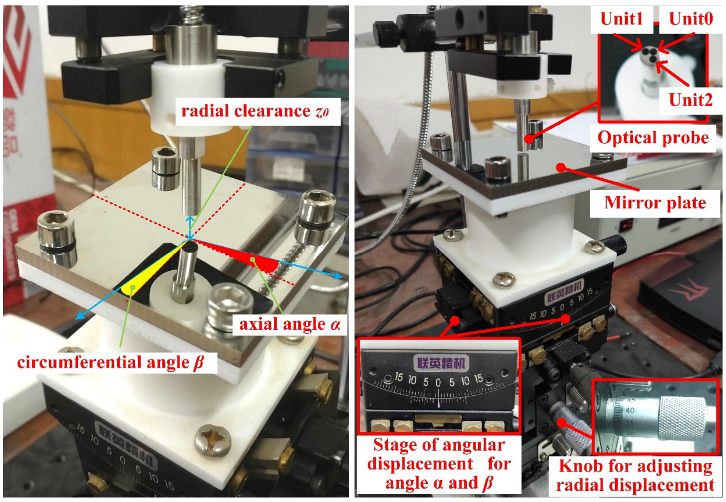

Figure 3 Calibration table for the 3-D tip clearance

3.2 Data pre-processing

The raw data of this study obtained according to the above calibration experiments have 14336 sets. Figure 4 (a), (b) and (c) show the raw data in the three-dimensional coordinate system of unit0, uint1 and unit2, respectively. The x-axis, y-axis and z-axis represent the axial angle, circumferential angle and the ratio of the outer circle voltage to inner circle voltage, respectively. In the picture, each layer represents the data measured at the same radial displacement and the radial displacement of the upper layer is larger than that of the lower layer. As indicated by the red circle marks, the calibration data are erroneously fluctuant due to the instability of the hardware circuitry of the detection system. These calibration data, which can't correctly reflect the input and output relationship of the optical fiber probe, will affect the demodulation accuracy of the neural network. Therefore, a simple processing method was utilized to deal with it. According to the experiment data, the ratios of the outer circle voltage to inner circle voltage of each unit increase with the increase of the radial displacement under the same axial angle and circumferential angle. Therefore, for each unit, the ratios of the outer circle voltage to the inner circle voltage and that of the adjacent radial displacement are compared in turn and the data that doesn't satisfy the aforementioned rules are eliminated. After the pre-process, 13157 sets of data are left, and 11000 sets of data are selected as the training data and the left are used as the test data.

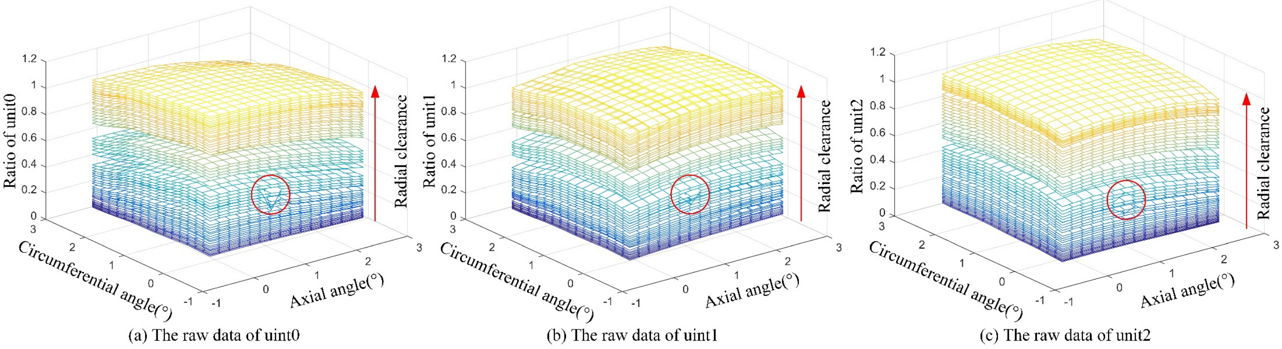

Figure 4 The raw data collected by the calibration experiments

3.3 Analysis of demodulation results

It can be seen from Figure 5 that when the neural network training target error is the same, the epochs of the traditional BP neural network are 90, and the epochs of the BP neural network optimized by GA are 20. Obviously, the epochs of BP neural network optimized by GA are significantly less than that of traditional BP neural network, and the convergence speed of BP neural network optimized by GA is fast.

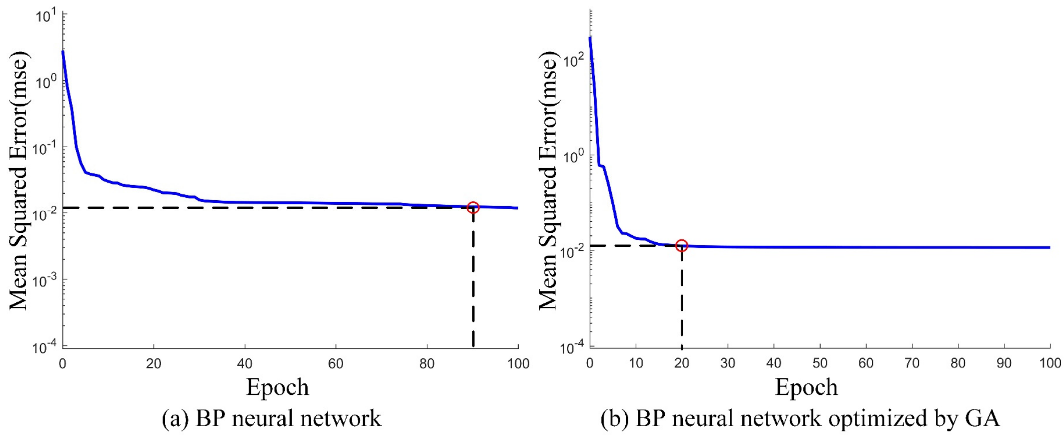

Figure 5 Neural network training error curve

Figure 6 shows a comparison between the predicted output of the 3-D tip clearance demodulated based on BP neural network optimized by GA and the expected output corresponding to that. According to the comparison results, it's obvious that the demodulation model based on BP neural network optimized by GA can demodulate the 3-D tip clearance from the output signals of the optical fiber probe and fulfil the requirements of the 3-D tip clearance detection system. The detailed analysis is presented as follows combined with the maximum error and the mean square error.

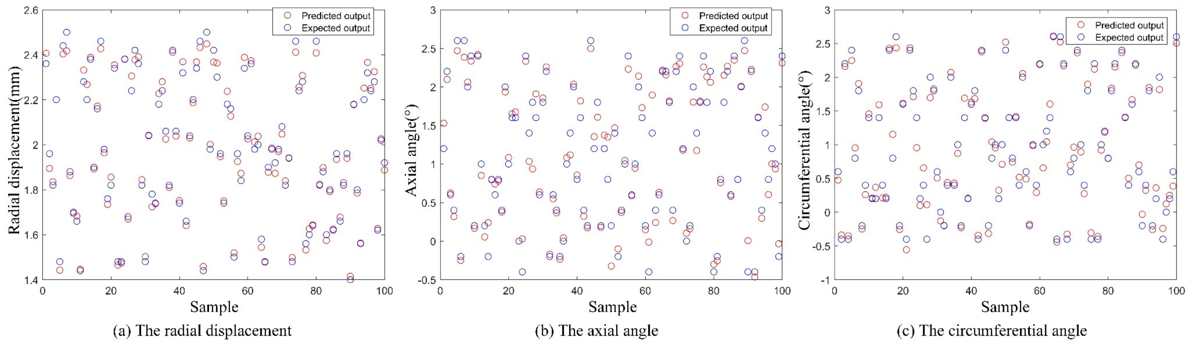

Figure 6 Comparison of the predicted output and the expected output of the 3-D tip clearance

Demodulated based on the traditional BP neural network, the maximum error of the radial displacement, axial angle and circumferential angle are 0.047mm, 0.49° and 2.32°, respectively. The mean square error of the radial displacement, the axial angle and circumferential angle are 0.010mm, 0.13° and 0.36°, respectively [5]. As shown in Figure 7, the maximum error of the radial displacement, axial angle and circumferential angle using the demodulation model based on BP neural network optimized by GA are 0.1321mm, 0.9875° and 0.6456°, respectively. The mean square error of the radial displacement, axial angle and circumferential angle are 0.0006mm, 0.0528° and 0.0266°, respectively. The comparison of the demodulation accuracy between BP neural network and BP neural network optimized by GA (GA-BP) is shown in Table 1.

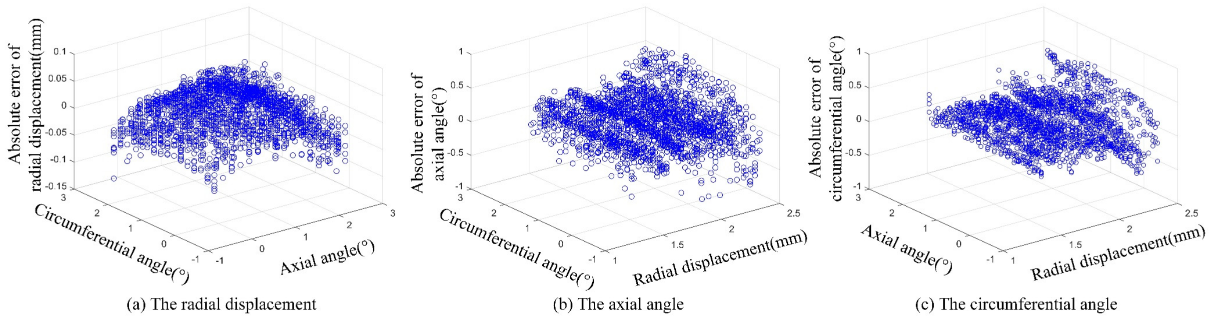

Figure 7 Demodulation error distribution of the 3-D tip clearance

Algorithm	The maximum error			The mean square error		
	z_0 (mm)	α (°)	β (°)	z_0 (mm)	α (°)	β (°)
BP	0.047	0.49	2.32	0.010	0.13	0.36
GA-BP	0.1321	0.9875	0.6456	0.0006	0.0528	0.0266

Table 1 The accuracy of BP and GA-BP

From the error analysis above, the demodulation model based on BP neural network optimized by GA has greatly improved the demodulation accuracy of circumferential angle and the maximum demodulation error is reduced from 2.32° to 0.6456°. In terms of the mean square error, the 3-D tip clearance demodulation accuracy based on BP neural network optimized by GA is an order of magnitude higher than the traditional BP neural network. The reasons why the maximum error of demodulating the 3-D tip clearance is relatively large contain the presence of dark current in the photoelectric conversion circuit, human error caused by the manual adjustment of the calibration table, and fluctuations of the light source caused by power fluctuations. In order to reduce the maximum demodulation error and make the training data of neural network more reliable, the static calibration system needs to be improved from the above aspects in the future.

In summary, the demodulation model based on BP neural network optimized by GA has a better performance and a higher accuracy than the demodulation model based on traditional BP neural network.

4 Conclusion

In this paper, an approach for demodulation of the 3-D tip clearance of turbine blades has been presented based on BP neural network optimized by GA. The large amount of data collected by the calibration experiments are used as the training data and test data of the neural network after data pre-processing. The mean square error of the 3-D tip clearance demodulated based on BP neural network optimized by GA are (0.0006mm, 0.0528°, 0.0266°), which is an order of magnitude lower than that based on traditional BP neural network. The demodulation results indicate that the demodulation method can fulfil the basic requirements of the optical fiber detection system and provide the basis for the subsequent real-time detection of the 3-D tip clearance on the rotor laboratory bench. The maximum error of the 3-D tip clearance demodulated based on BP neural network optimized by GA are (0.1321mm, 0.9875°, 0.6456°).The main reason of the relatively large errors is that the hardware circuit of the static calibration system is not stable enough. The subsequent improvement of that can greatly improve the stability and accuracy of the calibration data, which can further reduce the maximum error of the 3-D tip clearance demodulation.

Acknowledgments

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