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ORIGINAL ARTICLE

Spindle Thermal Error Optimization Modeling of a Five-axis Machine Tool

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Abstract Aiming at the problem of low machining accuracy and uncontrollable thermal errors of NC machine tools, spindle thermal error measurement, modeling and compensation of a two turntable five-axis machine tool are researched. Measurement experiment of heat sources and thermal errors are carried out, and GRA(grey relational analysis) method is introduced into the selection of temperature variables used for thermal error modeling. In order to analyze the influence of different heat sources on spindle thermal errors, an ANN (artificial neural network) model is presented, and ABC(artificial bee colony) algorithm is introduced to train the link weights of ANN, a new ABC-NN(Artificial bee colony-based neural network) modeling method is proposed and used in the prediction of spindle thermal errors. In order to test the prediction performance of ABC-NN model, an experiment system is developed, the prediction results of LSR (least squares regression), ANN and ABC-NN are compared with the measurement results of spindle thermal errors. Experiment results show that the prediction accuracy of ABC-NN model is higher than LSR and ANN, and the residual error is smaller than 3 μm, the new modeling method is feasible. The proposed research provides instruction to compensate thermal errors and improve machining accuracy of NC machine tools.

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Keywords Five-axis machine tool · Artificial bee colony · Thermal error modeling · Artificial neural network

1 Introduction

In recent years, influence of machine thermal errors on machining accuracy has become a research focus in precision machining field [1–3]. Studies show that thermal errors account for 40%–70% of workpiece errors during machining [4, 5]. These errors can be reduced mainly by optimization design of machine structure, heat sources control and thermal error compensation. In order to compensate thermal errors in real-time, more and more attention has been paid to thermal error modeling recently [6–8], which is the foundation of thermal error compensation technology, and the following research trends have appeared:

(1) Various regression modeling methods are widely used in thermal error modeling field, such as Lei used multivariate autoregressive model to model and forecast thermal error model for motorized spindle [9], and Lin applied least squares support vector machines method to predict thermal error of numerical machine tools [10], and Zhu applied optimal partition and stepwise regression method to model thermal error for machine tool [11], and Zhang used multisource information fusion to combine a dynamic thermal error model and a finite element model, and bulit a fusion model for lathe Z-direction thermal error [12], and Yao constructed error-sensitive degree matrix by grey correlation algorithm, and thermal error and geometric error was decoupled and modeled each other by multiple linear regression and GM(1,n) algorithm [13].

(2) Different artificial intelligent algorithms are used for thermal error modeling of five-axis machine tools [14–16], such as genetic algorithm(GA), ant colony algorithm (ACA), ANN, grey system theory(GST) and so on. However, different artificial intelligent algorithms have to deal with a series of issues, such as local minimum problem of ANN, precocity and stagnation problem of GA, et al. Consequently, prediction accuracy and computing efficiency of these methods still need further increase. Compared with traditional polynomial modeling method, ANN has advantages, such as learning and self-adaption ability, high speed of obtaining optimization solution [17, 18]. In addition, ANN can massively parallel process complex nonlinear models, which has been widely used in mechanical engineering field [19, 20], such as MA, et al used particle swarm optimization(PSO) and genetic algorithm (GA) to optimaze BP neural network, and established the enlongation and thermal tilt angle models based on GA-BP and PSO-BP neural network [21], and Abdulshahed designed the thermal error prediction model by employing an Adaptive Neuro-fuzzy Inference System with fuzzy c-means clustering(FCM-ANFIS), and introduced a new intelligent compensation system for reducing thermal errors of mahcine tools using data obtained from a thermal imaging camera [22], and XU, et al applied gray system theroy(GST) to obtain the 13 groups critical temperature measuring points, and established thermal error model of machine tool using GM(1, N) gray structure [23].

(3) The proposed models only can be used for specific machining conditions, robustness of thermal error model need to be improved, a new modeling method can be used for different cutting conditions is urgent to be proposed.

In this study, a new modeling method was proposed based on ABC-NN algorithm, which was used for thermal error prediction of a five-axis machine tool, and one thermal error model was presented finally, the prediction accuracy and computing efficiency of machine thermal error was increased. In section two, measurement experiments of different heat sources and thermal errors of the five-axis machine tool were fulfilled. In section three, temperature variables used for thermal error modeling were determined based on grey relational analysis(GRA) method, and a new modeling method based on ABC-NN algorithm was proposed, thermal error model of the five-axis machine tool was presented based on the proposed modeling method. In section four, an experiment system was developed and an experiment was carried out, which was used for performance test of presented model.

The main contribution of this study to the field was that a new ABC-NN model was proposed, which was used for thermal error prediction of a five-axis machine tool. And the main innovation point in this study was the combination of ANN and ABC. ABC algorithm is introduced to train the link weights of artificial neural networks (ANN), local minimum problem was solved, and prediction accuracy of ANN was improved.

2 Measurement Experiment of Heat Sources and Thermal Errors

In order to measure temperature variations of different heat sources and thermal errors of a five-axis machine tool, experiment was carried out in the study, Fig. 1 shows the five-axis machine tool used in experiment. According to long-time experience, the five-axis machine tool is mainly affected by 24 heat sources during cutting. In order to measure temperature variations of these heat sources, as shown in Figs. 2 and 3, 24 temperature sensors were installed on the five-axis machine tools, which were listed as follows:

(1) Sensors 1, 2, 13, 15 were used for measuring structure temperature of the machine tools;

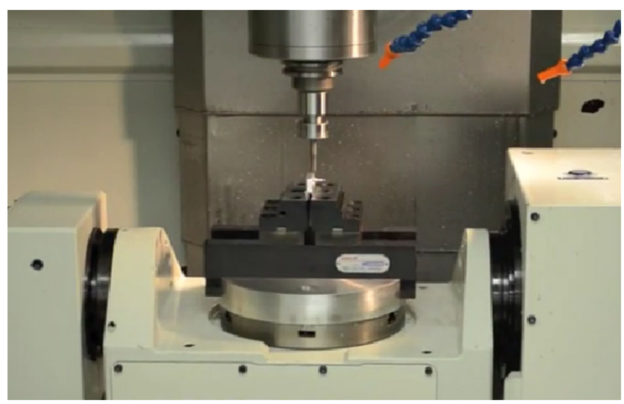

Fig. 1 Five-axis machine tool used in experiment

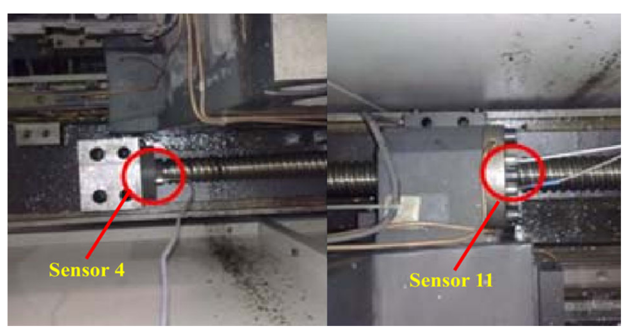

Fig. 2 Sensors 4 and 11 used for measuring screw nut temperature

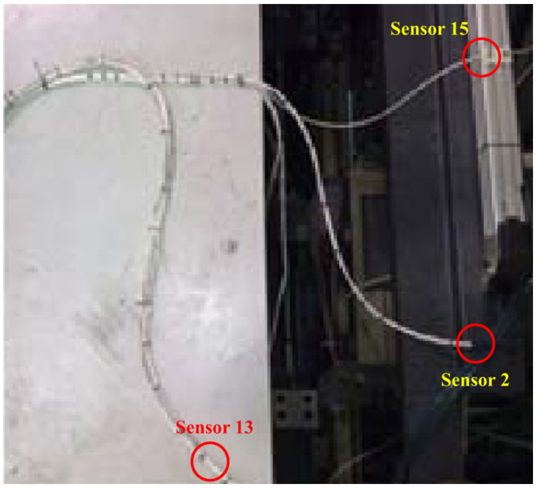

Fig. 3 Sensors 2, 13 and 15 used for measuring machine structure temperature

(2) Sensor 3 was used for measuring ambient temperature;
(3) Sensors 10, 17, 18, 19 were used for measuring spindle housing temperature;
(4) Sensors 22, 23, 24 were used for measuring motor temperature of *A, C* axis;
(5) Sensors 6, 7, 8, 9 were used for measuring column temperature;
(6) Sensors 4, 11, 14 were used for measuring screw nut temperature of *X, Y, Z* axis;
(7) Sensors 5, 12, 16, 20, 21 were used for measuring slide temperature of *X, Y, Z* axis.

In order to measure spindle thermal deformations of the five-axis machine tools, 5 capacitive sensors were installed on the worktable, as shown in Fig. 4. In this paper, just measurement results of thermal deformations in X-direction were presented, and other measurement results were not provided.

Measurement experiment was carried out to simulate cutting cycle of the five-axis machine tool. During measuring, the cutting parameters were shown in Table 1. The coolant kept running, and some surface parts were machined. First, the five-axis machine tool was warmed up gradually for 3 hours. Then, it was stopped for 1 hour. Next, the machine tool kept cutting for 3 hours, and stopped for another 1 hour. During the running cycle, temperature variations of the 24 heat sources were measured, and the measurement results were shown in Fig. 5. Thermal errors (Thermal deformations in *X*-direction) were shown in Fig. 6.

As shown in Fig. 5, different temperature curves coincided with the cutting cycle very well. For example, at the beginning of the cycle, screw nut temperature of *Z* axis (Temperature of sensor 14) gradually increased with the

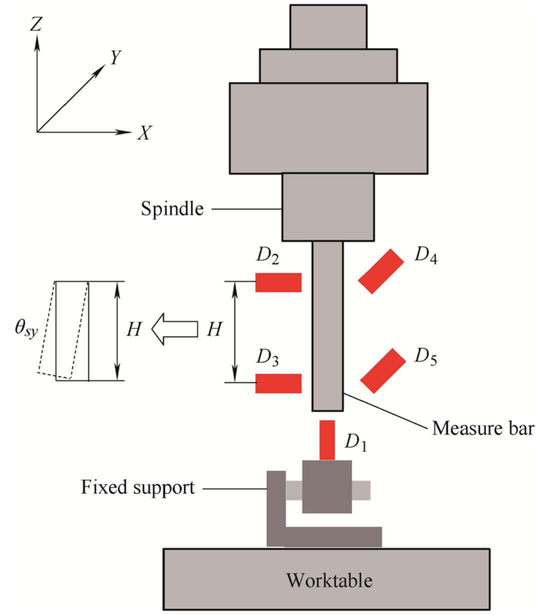

Fig. 4 Capacitive sensor installed on the worktable

Table 1 Cutting parameters during experiment

Parameter	Value
Speed of the spindle S_s / (r·min^{-1})	4000
Speed of A axis S_A / (r·min^{-1})	50
Speed of C axis S_C / (r·min^{-1})	50
Cutting depth in radial direction D_r / mm	0.4
Cutting depth in axial direction D_a / mm	0.3
Feed-rate F / (mm·min^{-1})	500
Feed per tooth F_t / mm	0.1

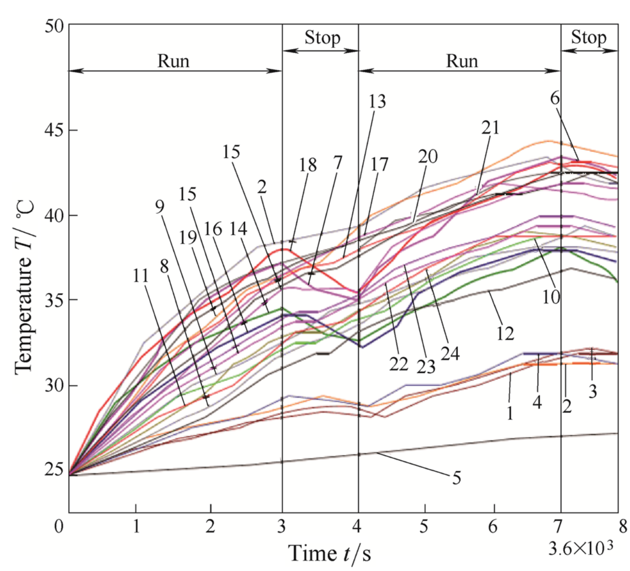

Fig. 5 Temperature variations of 24 heat sources

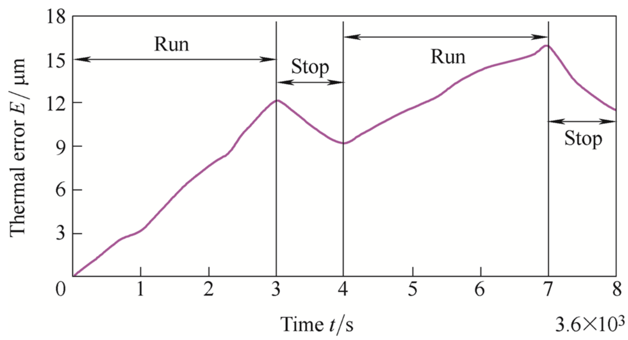

Fig. 6 Thermal error variations of the five-axis machine tool

warming of five-axis machine tool. When the machine tool was stopped, the screw nut temperature decreased too. Thermal error curve coincided with the cutting cycle too, as was shown in Fig. 6, at the first 3 hours, thermal errors of the five-axis machine tools gradually increased, because thermal deformations of the spindle increased. However, decreasing trend of the error curves appeared after 3 hours, because the machine tool was stopped.

3 Thermal Error Modeling

3.1 Selection of Temperature Variables

The main purpose of thermal error modeling is to establish relationship between thermal errors and different heat sources. Since there are too many heat sources on five-axis machine tools, thermal error model will be certainly very complex. In order to improve measurement efficiency of modeling variables and simplify thermal error model, optimization selection of temperature variables is the most common way. Many researchers have been working on this topic, and new research results are presented continuously in this field [24–26]. In this paper, GRAM was used for selecting temperature variables from 24 heat sources. Firstly, in order to select temperature variables, a GRA model was presented based on grey system theory, as follows:

$$\zeta_i(k) = \gamma(x_0(k), x_i(k)) = \frac{\min_{i\in m}\min_{k\in n}|x_0(k) - x_i(k)| + \xi \cdot \max_{i\in m}\max_{k\in n}|x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \xi \cdot \max_{i\in m}\max_{k\in n}|x_0(k) - x_i(k)|}. \tag{1}$$

where $\zeta_i(k)$ represents grey relational coefficient, $x_i(k)$ represents variable sequences, γ_i represents grey relational degree, which can be calculated as follows:

$$\gamma_i = \frac{1}{n} \cdot \sum_{k=1}^{n} \zeta_i(k). \tag{2}$$

During optimization selection of temperature variables, thermal errors of the five-axis machine tool served as mother sequence x_m, temperature of 24 heat sources served as son sequence x_i. According to Eqs. (1) and (2), grey relational degree between thermal errors and 24 heat sources were calculated.

In order to eliminate dimension influence, above calculation results were transformed using initial value transform, average value transform and polar difference transform in this study. Therefore, the calculation results listed in Table 2 were comparable data. Initial value transform means all data were divided by first data, average value transform means all data were divided by the average, polar difference transform means all data were divided by the largest data. According to above transform, comparable data of grey relational degree were obtained successfully, as was shown in Table 2.

According to grey relational degree shown in Table 1, sum of different transform were presented in last column of Table 1. Finally, data in the last column were sorted as inequality (3). According to grey system theory, a large sum implies more closely relationship between thermal errors and different heat sources. Therefore, sensor 2 has closest relationship with thermal error of the five-axis machine tool. However, sensor 1 is most irrelevant to thermal errors. In order to reduce sensor numbers, just temperature of the first 8 sensors(No. 2, 18, 7, 17, 13, 23, 6 and 19) were chosen as temperature variables for thermal error modeling in X direction. In the same way, temperature of sensors(No. 13, 18, 19, 8, 14, 21, 12 and 24) were chosen as temperature variables for thermal error modeling in Y direction. Although thermal error in Z direction were measured too, which was much smaller than the other two directions and almost has no influence on machining accuracy, so it was ignored. Because modeling variables were reduced from 24 to 8, measurement efficiency of the heat sources was greatly improved, and thermal error model of the five-axis machine tool would be simplified obviously.

$$\begin{aligned} &\gamma_{25,2} > \gamma_{25,18} > \gamma_{25,7} > \gamma_{25,17} > \gamma_{25,13} > \\ &\gamma_{25,23} > \gamma_{25,6} > \gamma_{25,19} > \gamma_{25,10} > \gamma_{25,15} > \\ &\gamma_{25,22} > \gamma_{25,16} > \gamma_{25,12} > \gamma_{25,8} > \gamma_{25,11} > \\ &\gamma_{25,21} > \gamma_{25,5} > \gamma_{25,20} > \gamma_{25,9} > \gamma_{25,24} > \\ &\gamma_{25,3} > \gamma_{25,4} > \gamma_{25,14} > \gamma_{25,1}. \end{aligned} \tag{3}$$

3.1.1 *New Thermal Error Model Based on ABC-NN Algorithm*

In this study, ABC algorithm was used for training the link weights of BPN, and a new ABC-NN algorithm was

Table 2 Grey relational degree between thermal errors and 24 heat sources

Grey relational degree	Initial transform	Average transform	Polar difference transform	Sum of different transform
$\gamma_{25,1}$	0.255	0.314	0.287	0.856
$\gamma_{25,2}$	0.813	0.725	0.711	2.249
$\gamma_{25,3}$	0.327	0.404	0.398	1.129
$\gamma_{25,4}$	0.521	0.302	0.278	1.101
$\gamma_{25,5}$	0.412	0.544	0.459	1.415
$\gamma_{25,6}$	0.654	0.791	0.549	1.994
$\gamma_{25,7}$	0.695	0.683	0.799	2.177
$\gamma_{25,8}$	0.390	0.627	0.515	1.532
$\gamma_{25,9}$	0.529	0.384	0.425	1.338
$\gamma_{25,10}$	0.587	0.644	0.637	1.868
$\gamma_{25,11}$	0.491	0.505	0.487	1.483
$\gamma_{25,12}$	0.526	0.488	0.571	1.585
$\gamma_{25,13}$	0.722	0.689	0.667	2.078
$\gamma_{25,14}$	0.333	0.471	0.286	1.090
$\gamma_{25,15}$	0.663	0.492	0.525	1.680
$\gamma_{25,16}$	0.621	0.511	0.529	1.661
$\gamma_{25,17}$	0.632	0.818	0.655	2.105
$\gamma_{25,18}$	0.756	0.803	0.664	2.223
$\gamma_{25,19}$	0.575	0.596	0.747	1.918
$\gamma_{25,20}$	0.515	0.357	0.476	1.348
$\gamma_{25,21}$	0.375	0.466	0.583	1.424
$\gamma_{25,22}$	0.568	0.485	0.609	1.662
$\gamma_{25,23}$	0.598	0.687	0.724	2.009
$\gamma_{25,24}$	0.429	0.394	0.443	1.266

proposed. Because ABC algorithm has a merit of global performance [27], the local minimum problem of BPN can be overcome, and the convergence rate will be improved. Based on the proposed algorithm, thermal error model of the five-axis machine tool was presented. The modeling process of thermal errors is as follows.

In order to approximate thermal errors of the five-axis machine tool, one BPN structure was established. 8 temperature variables (No. 2, 18, 7, 17, 13, 23, 6 and 19) were used as input layer, and thermal errors were used as output layer. During training, BPN parameters were listed in Table 3. Finally, 50 samples were obtained by temperature and capacitive sensors, ABC algorithm were used to train the link weights of BPN, the flowchart of ABC-NN algorithm was shown in Fig. 7.

As shown in Fig. 7, food sources denote optimized weights of BPN, quality of the food sources denote training performance of the weights. At beginning of the training process, all bees served as foragers, finding new food sources was the task of scouts, which generated randomly, and food source evaluation was finished based on back propagation method.

Table 3 BPN parameters

Parameter	Value
BPN structure	8-17-1
Original weights	Random of (0,1)
Learning rate	0.01
Momentum rate	0.3
Learning adjusting coefficients	0.5

Assume W denotes weights of different neurons, θ denotes bias of different neurons, and O denotes output of BPN, so output of the network can be calculated as follows:

$$O^{(k+1)}(m) = \sum_{n=1}^{3} (W^{(k+1)}(m,n)a_n + \theta^{(k+1)}). \tag{4}$$

where $k = \{1,2,3\}$ denotes the layers, a_n denotes the output of the n^{th} layer, which can be calculated as follows:

$$a_n(m) = F_n(O_n(m)) \tag{5}$$

where F_n denotes the transform function of the nth layer. During back propagation, total squared errors of every

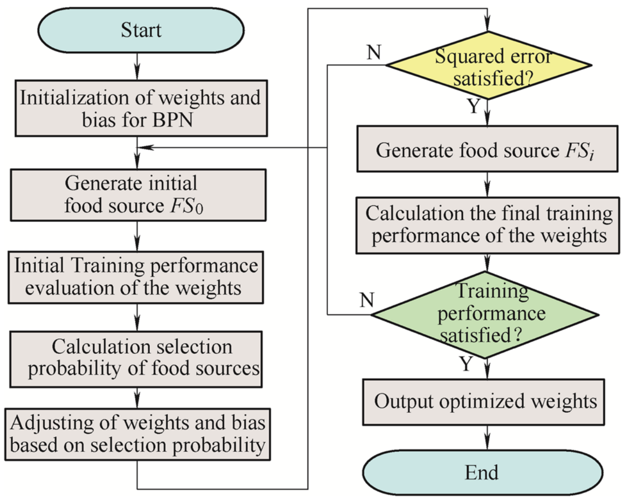

Fig. 7 Flowchart of ABC-NN algorithm

input data need to be calculated, which is used for evaluating training performance of the weights, and the training performance can be determined by the average of total squared errors:

$$P(x) = \frac{\sum_{j=1}^{N} P_F(x)}{N}. \tag{6}$$

where $P(x)$ is the final training performance of the weights, N denotes bee number of the bee colony, $p_F(x)$ denotes the performance index, which can be calculated as follows:

$$P_F(x) = \sum p_f(x)^T \cdot p_f(x). \tag{7}$$

where $p_f(x)$ denotes sum of the squared errors, which can be calculated as follows:

$$p_f(x) = \sum_{i=1}^{k} (t_i - p_i)^T \cdot (t_i - p_i). \tag{8}$$

where t_i denotes ith target, p_i denotes ith input. So, the first order derivative of $P_F(x)$ can be calculated as follows:

$$\nabla P_F(x) = \left[\frac{p_f(x_1)}{x_1}, \frac{p_f(x_2)}{x_2}, \ldots, \frac{p_f(x_N)}{x_N}\right]. \tag{9}$$

Assume the best food sources found by scouts can be represented as follows:

$$FS_i = \min\{P(x_1), P(x_2), \ldots, P(x_N)\}. \tag{10}$$

So, selection probability of a food source by the scouts can be represented as follows:

$$P_{fsi} = \frac{FS_i \cdot D_{ij}}{\left(\sum_{j=1}^{m} FS_i\right) \cdot D_{ij}}. \tag{11}$$

where m denotes the number of employed foragers, D_{ij} denotes the distance between food source FS_i and FS_j, which can be calculated as follows:

$$D_{ij} = \sqrt{(FS_i - FS_j)^2}. \tag{12}$$

Finally, the weights and the bias of back propagation can be adjusted as follows:

$$\begin{aligned} W_{(k,q)}^{(k+1)} &= W_{(k,q)}^{k} - L \cdot S^k (a^{(k-1)})^{\mathrm{T}}, \\ \theta_{(k,q)}^{(k+1)} &= \theta_{(k,q)}^{k} - L \cdot S^k. \end{aligned} \tag{13}$$

where L denotes learning rate, S^k denotes sensitivity of the kth layer, which can be calculated as follows:

$$S^k = F_k(O_k) \cdot (W^{(k+1)}) \cdot S^{(k+1)}. \tag{14}$$

And, sensitivity of last layer can be calculated as follows:

$$S^k = 2F_k(O_k) \cdot e_i, \tag{15}$$

where e_i denotes error between ith target and ith input, high error means low quality of the food source, which will be abandoned, and adjusting of W and θ will continue until the best food source was found and a group of optimized weights were obtained.

4 Performance Test of the Proposed Model

4.1 Design of the Experiment System

In order to test the prediction performance of the proposed model, an experiment system was developed based on DSP chip in this study. As shown in Fig. 8, during experiment, selected temperature variations was measured by temperature sensors, thermal errors of the five-axis machine tool were measured by capacitive sensor. Firstly, all these measurement signals were processed by DSP system, and then, the processed signals were sent to PC through serial port. Finally, according to measurement results of selected temperature variables, using software system of the PC, prediction results of thermal errors were obtained based on the proposed model, which were compared with measurement results of thermal errors collected from capacitive sensor.

4.1.1 Performance Test of ABC-NN Model

In order to verify predicting performance of ABC-NN model, experiment was carried out based on the developed experiment system, the experiment setup was the same as listed in Table 1, but temperature sensors were reduced from 24 to 8. The prediction results and measurement

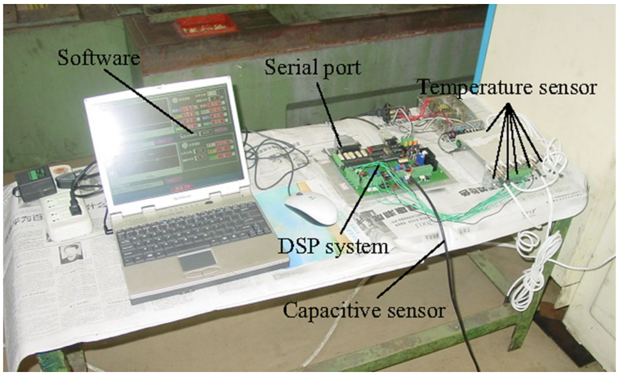

Fig. 8 Experiment system used for performance test

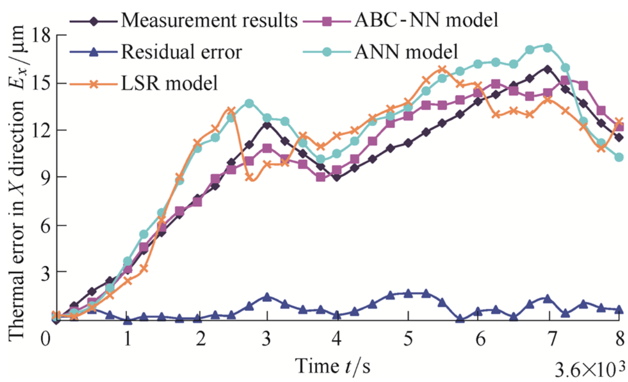

Fig. 9 Prediction results of thermal error in X direction

results of thermal errors were shown in Fig. 9. As was shown, prediction performance of ABC-NN model was very well, the residual errors of which were less than 3 μm. At the same time, prediction accuracy of the new model was higher than ANN model, the prediction performance was improved after weight training based on ABC algorithm. The prediction results and measurement results of thermal errors in *Y* direction were shown in Fig. 10, as was shown, the residual errors of ABC-NN model were less than 3 µm too.

In order to evaluate the convergence performance and generalization ability of ABC-NN model, train

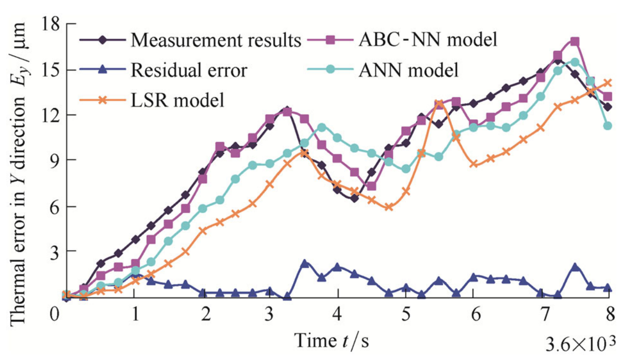

Fig. 10 Prediction results of thermal error in *Y* direction

Table 4 Performance comparison of different model

Different algorithm	Convergence time	Train times	Generalization error	Residual error
ABC-NN	2.541	371	0.066 7	2.3
ANN	4.683	787	0.146 1	4.2
Least squares regression	1.89	–	–	6.5

performance of different prediction models were compared, the results were listed in Table 4. As was shown, the convergence time of ABC-NN model is less than ANN model, and the residual error of ABC-NN model is the smallest. At the same time, the generalization error of ABC-NN model is smaller than ANN model, and it is the most important parameter, which proves a better solution of local minimum problem.

5 Conclusions

(1) According to GRAM method, selection of temperature variables is fulfilled, and the modeling variables are reduced from 24 to 8, the computational time of thermal error model decreased, and the measurement efficiency of the heat sources is greatly improved.

(2) Prediction performance of ABC-NN model is very well, the residual error of which is less than 3 µm. In addition, ABC algorithm is introduced to training the link weights of ANN, the local minimum problem of ANN is overcome.

(3) Thermal errors of the five-axis machine tool is time-dependent, which is a big challenge to thermal error compensation, and the robustness of the proposed model need to be verified with different machine tools, these are ongoing work of our team.

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