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A New Prediction Model for Thermally Induced Errors of a Turning Center

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Abstract. Thermally induced errors and geometric errors are two main sources that affect the machine tool accuracy when machining. In the last decade, real time compensation method had received wide attention for its ability to reduce the thermal error cost–effectively. Although real-time thermal error compensation techniques have been successfully demonstrated in laboratories, several difficulties hinder its widespread application. The selection of temperature variables and the setup of the error measurement system are the most critical ones among these difficulties. In this paper, a new on line measurement system and a new model that predicts the thermal error of a turning center are developed. The on-line measurement system using a Renishaw's LT02S probe system is capable of measuring thermal error of a CNC turning center in real cutting conditions. The neural network uses the cutting conditions as the mapping inputs to avoid problems occurred in the traditional temperature-error mapping model. Results show the proposed measurement system and prediction model can be used to accurately estimate the thermally induced error in real cutting conditions.

Introduction

The academic institutions and the manufacturing community have been working on improving the product quality for decades. The development of super precision machine tool has become an urgent challenge in response to the ever increasing demand for high accuracy machining. However, no matter how well the machine tools are designed and manufactured, the occurrence of machine tool errors is inevitable due to the physical limitations. The three major sources of machine tool error are geometric error, thermally induced error and cutting force induced error [1-7]. The thermally induced errors mainly come from the expansions and distortion of the machine elements caused by the heat produced by motors, friction between moving parts and various ambient heat sources, and is reported as the major sources that make up 40-70 % of the total positioning error of machine tools [8].

There are many approaches to eliminate or reduce the errors that affect the machine accuracy. These approaches can be divided into two categories 'error avoidance' and 'error compensation' [5-6]. The 'error avoidance' techniques are used in the design and manufacturing phase of machine tools such that the sources of error are eliminated or minimized. These techniques include the use of cooling systems, lowering the thermal sensitivity of structure, increasing machine elements' accuracy, etc. Unfortunately, the manufacturing costs usually rise exponentially with the level of accuracy required when the 'error avoidance' techniques are used. On the other hand, the 'error compensation' techniques are used after the machine tool being manufactured. Instead of attempting to reduce or eliminate the sources of error, these techniques measure the error, and compensate for it. The 'error avoidance' techniques are capable of improving the accuracy of machine tools without dramatically increasing the machine costs and are generally accepted as the primary methods for error reduction.

Various thermal error compensation technologies have been developed. These techniques can be classified into two categories: empirical and numerical modeling. The empirical approach is considered to be more effective and is widely used by researchers. The techniques based on the empirical modeling approach are different in the ways they measure the thermally induced error and how they model the compensation functions. Perhaps the most widely used empirical modeling techniques are multiple regression analyses (MRA) and multi-layered perceptron (MLP) neural networks by which the thermally induced error and temperature measurements of the machine are correlated. It has been shown that both MRA and MLP could successfully predict machine tool thermal errors[1,9]. However, these temperature-error mapping models have the following drawbacks:

1. The prediction accuracy is highly dependent on the number and locations of the sensors.
2. They are very sensitive to faulty or missing temperature readings. If one or more temperature readings are missing or faulty, the prediction function will not give good predictions.

In addition to the previously mentioned drawbacks, it's been reported that compensation models using air-cutting conditions can not fully address the thermally induced errors for real cutting conditions. Therefore, a measuring system that can be used for real cutting condition is desired. The setup of measurement system for real cutting conditions is difficult in some circumstances. It is even more difficult for a turning center than for a machining center due to the space limitations.

This study proposes a new approach of predicting real time thermal errors for a CNC turning center. A quick on line measurement system and a new model that predicts the thermally induced error are developed. The features of the proposed approach are summarized as follows:

1. The on-line measurement system uses a probing system (Renishaw LTO2S) that has been widely installed in turning center for part inspection. The cost for the error measurement is kept to a minimum.
2. Instead of using temperature readings, the new model uses the cutting conditions as the mapping inputs. As a result, the problems occurred in the traditional temperature-error mapping model can be avoided.
3. An artificial neural network is used to construct the approximate prediction model.

Measurement of thermally induced errors

Thermally induced errors of a turning center are generally contributed from every part of the machine; however, spindle thermal drifts are considered to be the dominate source[7] and are discussed in this study. In general, the spindle of a turning center is equipped with a radial bearing at each end of the spindle to resist the cutting force and a thrust bearing at the front end of the spindle to prevent the axial displacement. As the temperature distribution of the turning center changes, the position and orientation of the spindle change accordingly. The thermally induced errors due to the change of position and orientation of the spindle can be decomposed into three components namely radial, axial and tilt drifts and can be measured by a conventional measuring system as shown in Fig. 1. The radial drift can be estimated by the readings of probes A and B; the axial drift can be measured by probe C, while the tilt drift can be calculated by the difference in the readings of probes A and B divided by the distance between probes A and B.

It is pointed out by Chen[10] that the accuracy of precdiction model based on air-cutting conditions was questionable in real cutting. Unfortunately, the conventional measuring system as shown in Fig. 1, usually used for air-cutting conditions, is not suitable for measuring the thermally induced error in real cutting conditions; therefore, a new measurement setup is desirable for real cutting conditions. In this study, the Renishaw's LTO2S probe system, usually used for workpiece setup and inspection on medium and large CNC lathes, is used as the measurement device. The LTO2S probe system consists of a LP2 probe, an optical module probe (OMP), an optical module machine (OMM) and a machine interface unit (MIU). A signal is triggered when the LP2 probe touches an object, and the coordinate of the touch point is recorded.

As mentioned in the previous section, three components of the thermally induced drift need to be measured during the machining process.Since the workpiece can not be used as reference in real cutting, fixed points A, B and C on the spindle are choosen. The X coordinates of point A and B, Z coordinate of point C are measured before and after machining. The thermal drift of the spindle after amchining can be calculated by equations (1), (2) and (3):

$$\Delta X(t) = X_A(t) - X_A(0) \tag{1}$$

$$\Delta Z(t) = Z_C(t) - Z_C(0) \tag{2}$$

$$\theta(t) = [(X_A(t) - X_A(0)) - (X_B(t) - X_B(0))]/L_{AB} \tag{3}$$

where $\Delta X(t)$ is the radial drift, $\Delta Z(t)$ is the axial drift and $\theta(t)$ is the tilt drift.

In the repeatability test, the X coordinates of point A and B, the Z coordinate of point C were measured 30times before machining, and the average error was found to be ±0.001mm.

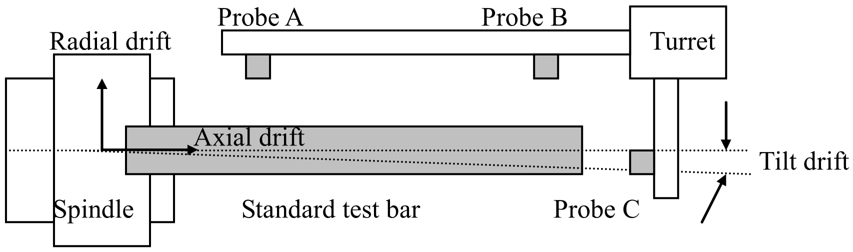

Fig. 1 Conventional measurement system and components of thermally induced errors

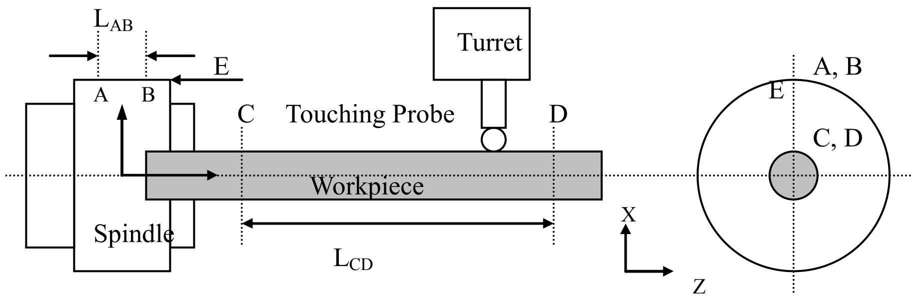

Fig. 2 Spindle thermal drift measurement using LTO2S

Modeling of thermally induced errors

A multilayer feedforward network (MLP) is used as a function approximator to predict the three components of the thermal drifts. A three-layer network with the tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer is used [11]. The architecture of the network is shown in Fig. 3. The neurons of the input layer are used to receive the mapping inputs, i.e. the cutting parameters such as feed rate, depth of cut, rpm of the spindle, etc.. The neuron of the output layer is used to send out the thermal drift components, i.e. axial drift, the radial drift and tilt drif. The input vector is normalized such that each input value is between [-1, 1]. A gradient-based training method, Levenberg-Marquardt algorithm (trainlm), is selected. This algorithm is designed to approach second-order training speed without having to compute the Hessian matrix. Training data are collected from the predetermined cutting experiments shown in Table 1 and 2 respectively. Experiments 1~6 in each table are those used for network training. Test1 and test 2 in each table are those used for network model verification. Each training pair is composed of several inputs, and one output,i.e. a thermal drift component.

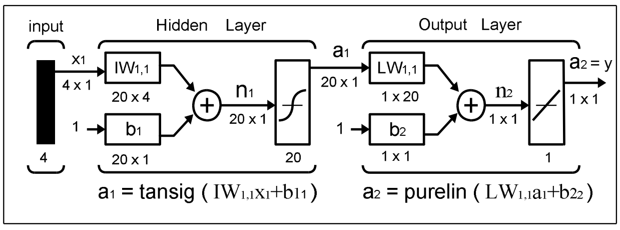

Fig. 3 Neural network architecture

The number of neurons in the hidden layer depends on how complicated the system is. By experiments, it is found that 4~8 neurons in the hidden layer provide reasonable accurate prediction models.

Table 1 Single cutting condition

Exp. No.	Spindle rpm	Feed rate (mm/min)	Depth of cut (mm)	Cutting time(min)
1	600	20	0.5	180
2	600	50	0.5	180
3	800	30	0.5	180
4	1000	40	0.5	180
5	1200	20	0.5	180
6	1200	50	0.5	180
test1	700	30	0.5	180
test2	1000	50	0.5	180

Table 2 Multiple cutting conditions

Exp. No.	1st condition				2nd condition			
	S (rpm)	*F* (mm/min)	*D* (mm)	*T* (min)	*S* (rpm)	*F* (mm/min)	*D* (mm)	*T* (min)
1	600	50	0.75	90	1200	20	0.25	90
2	600	30	0.50	90	1200	40	0.50	90
3	1200	50	0.75	90	600	20	0.25	90
4	1000	40	0.50	90	800	30	0.50	90
5	1000	40	0.75	90	800	30	0.25	90
6	600	20	0.75	90	800	50	0.25	90
test1	600	40	0.6	90	900	40	0.4	90
test2	700	30	0.5	90	1100	25	0.5	90

Experiments and Results

Carbon steel S45C with 100 mm in diameter, 300mm in length are used for each experiment. Experiments in table 1 and 2 are conducted and the thermal drift data are measured every ten minutes. It is found that the tilt drifts in all these experiments are not significant and therefore not discussed in this study.

The cutting conditions are used as the mapping input to the network, the generic form of the mapping function is given as

$$y_n = f(S, F, D, T_i, T_c, y_{n-1} \cdots) \ , \tag{4}$$

where S is the rpm of the spindle, F is the feedrate, D is the depth of cut, y_{n-1} is the thermal drift of the previous time period, T_i is the cutting time from the beginning, T_c is the cutting time for current cutting condition.

Foe single cutting condition, it is found that four inputs, S, F, D, T_i are sufficient for accurate prediction. Figure 4~7 show the comparison between the thermal drifts estimated by the network and those obtained from cutting experiments.

For multiple cutting conditions, two conditions are used in each experiment. It is found the four inputs as those used in the single cutting can no longer provide good prediction. Several different input combinations were tried and the one that gave the best prediction was the six-input model. In addition to the four inputs used for single cutting, the the thermal drift of the previous time period y_{n-1} and the cutting time for current cutting condition T_c are necessary for reasonable accurate predictions.

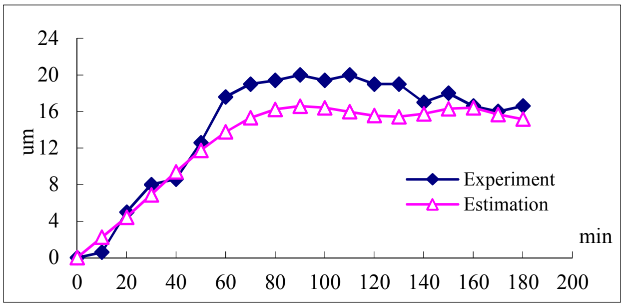

Fig. 4 Radial drift (S=700rpm F=30mm/min)

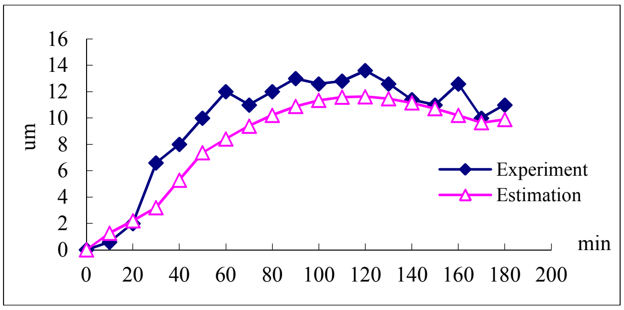

Fig. 5 Axial drift (S=700rpm F=30mm/min)

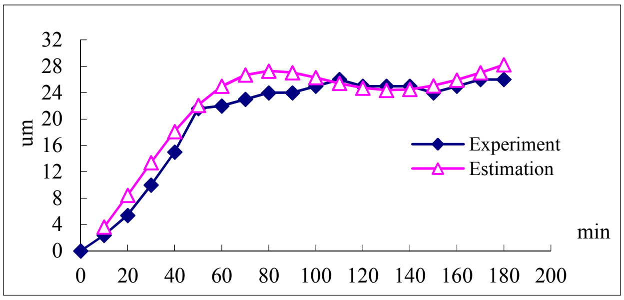

Fig. 6 Radial drift (S=1000rpm, F=50mm/min)

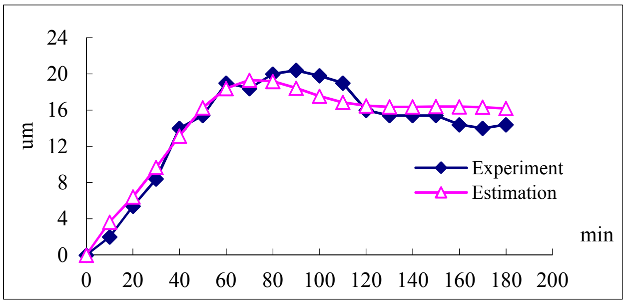

Fig. 7 Axial drift (S=1000rpm, F=50mm/min)

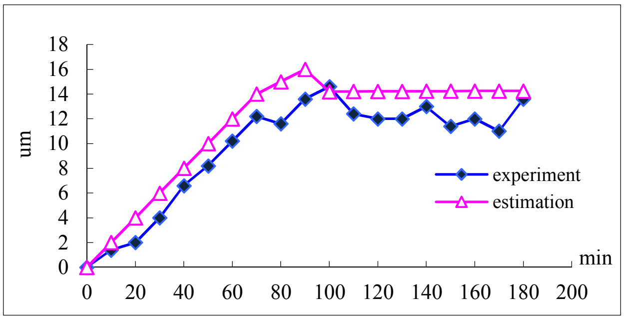

Fig. 8 Radial drift (test1 in table 2)

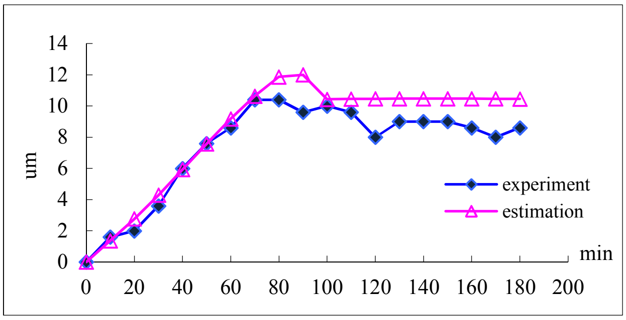

Fig. 9 Axial drift (test1 in table 2)

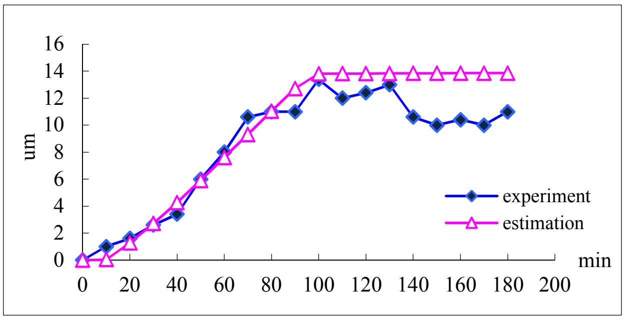

Fig. 10 Radial drift (test2 in table 2)

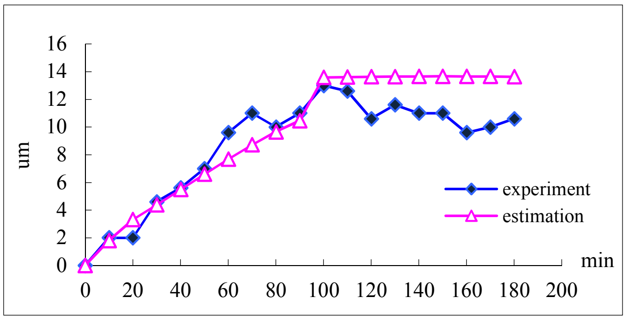

Fig. 11 Axial drift (test2 in table 2)

Concluding Remarks

Most of the thermal error compensation technologies use complicated models to predict the error. One of the reason that thermal error compensation technologies are not widely used is that they uses temperature distribution in the machine tool to predict the thermal error, yet the optimal locations and the number of thermocouples are very difficult to determine. Also the mapping model is very sensitive to faulty signals, a malfunctioned thermocouple that gives the incorrect temperature can result in incorrect predictions of thermal error. This work proposed a new approach for thermal error modeling of a CNC turning center. A new on line measurement system and a new model that predicts the thermal error are developed. The on-line measurement system uses a part inspection probing system that has been widely installed on turning centers, therefore the cost for the error measurement is kept to a minimum. The results show that, for single cutting condition, neural network using four cutting parameters as the network inputs gives accurate thermal drift estimation. However, for multiple cutting conditions, two more inputs are required for reasonable good prediction. Also, further study is required for more general cases, for instance, three or more cutting conditions.

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