The Neural-fuzzy Thermal Error Compensation Controller on CNC Machining Center*

Pai-Chung TSENG** and Shen-Len CHEN**

The geometric errors and structural thermal deformation are factors that influence the machining accuracy of Computer Numerical Control (CNC) machining center. Therefore, researchers pay attention to thermal error compensation technologies on CNC machine tools. Some real-time error compensation techniques have been successfully demonstrated in both laboratories and industrial sites. The compensation results still need to be enhanced. In this research, the neural-fuzzy theory has been conducted to derive a thermal prediction model. An IC-type thermometer has been used to detect the heat sources temperature variation. The thermal drifts are online measured by a touch triggered probe with a standard bar. A thermal prediction model is then derived by neural-fuzzy theory based on the temperature variation and the thermal drifts. A Graphic User Interface (GUI) system is also built to conduct the user-friendly operation interface with Inprise C++ Builder. The experimental results show that the thermal prediction model developed by neural-fuzzy theory methodology can improve machining accuracy from 80 μm to 3 μm. Comparison with the multi-variable linear regression analysis the compensation accuracy is increased from ±10 μm to ±3 μm.

Key Words: Thermal Drift, Compensation Technology, Neural-fuzzy Controller, Prediction

1. Introduction

In the cutting process, the tool machinery produces a side effect of friction heat from a variety of activities. Most of the work done in the cutting process is transformed into heat energy. Since various components are heated to different degrees depending on their material, structure, location and size, with additional impact of environmental temperature, the machine, components, cutting tools and clamping apparatus deform by heat to different degrees. The deformation of various parts destroys the original movement link (i.e. cutting tool path) of cutting tool and the surface of the components in process. It eventually results in the processing errors for the components to be cut. Therefore in developing precision machinery, the studies in the patterns of tool machinery’s thermal deformation and procedures to reduce the thermal deformation are significant to the improvement of processing precision.

The compensation for thermal deformation can be direct and indirect. Direct compensation is made immediately to the errors detected on-line. However, it is rather difficult to detect the errors in this way so the method is currently used only in laboratory. Indirect compensation detects the machinery’s repetitive and foreseeable errors off-line, and then builds error tables or mathematical models for errors as an error database that will be used to determine compensation in processing. Due to its low cost and practical feature, the indirect compensation becomes ever widely applied. In indirect compensation, the development of forecasting model for heat errors is most important. Therefore the reliability of the model is always the focus and goal of relevant studies. The methodologies for heat error forecasting of tool machinery usually employ the models of pre-setting machine parts and of thermal deformation, apply different theories and rules to the analysis of experi-
mental data and results, and predict the machine’s thermal deformation in processing. The error forecasting models in literature include: 1. Limited Element Methodology\(^\text{[5]}\), 2. Multiple Regression Analysis\(^\text{[8-10]}\), 3. Neural Network Analysis\(^\text{[9,10]}\). Since fuzzy theories have contributed significantly to the control and forecasting of uncertain systems in recent years, our study will adopt fuzzy theories to establish error forecasting models and study tool machinery’s thermal deformation to obtain the optimal compensation solution.

2. Theoretical Structure

This study uses questionnaire survey to build fuzzy rules library and applies neural network to modification of membership function in order to set up a thermal deformation forecasting model. The following is a brief description of the theories applied.

2.1 Questionnaire survey

To a system under control, the pair of input and output is\(^\text{[1]}\):

\[
(x^p; y^p), \quad p = 1, 2, 3, \ldots, N
\]

where \(x^p \in U = [a_n, b_n] \times \cdots \times [a_n, b_n] \subseteq \mathbb{R}^n\), \(y^p \in V = [a_n, b_n] \subseteq \mathbb{R}\). By questionnaire survey, based on \(N\) pairs of input and output mentioned above, the design of a fuzzy controller follows five steps as below.

Step 1. Define fuzzy sets of input and output

For every input range \([a_n, b_n]\), \(i = 1, 2, \ldots, N\), define \(N_i\) fuzzy sets \(A_i (j = 1, 2, \ldots, N_i)\) so as to include the range completely in the \(N_i\) fuzzy sets. The same to define \(N_p\) fuzzy sets \(B^p (j = 1, 2, \ldots, N_p)\) for output.

Step 2. Set up corresponding rules for every pair of input and output

For every pair of input and output \((x^p_0, \ldots, x^p_n; y^p_0, \ldots, y^p_n)\), calculate the value of membership function of \(x^p_i\) \((i = 1, 2, \ldots, n)\) in fuzzy set \(A_i (j = 1, 2, \ldots, N_i)\), and the value of membership function of \(y^p_i\) in fuzzy set \(B^p_i (l = 1, 2, \ldots, N_p)\); that is, \(\mu_{A_i}(x^p_i), j = 1, 2, \ldots, N_i, i = 1, 2, \ldots, n\) and \(\mu_{B^p_i}(y^p_i), l = 1, 2, \ldots, N_p\). Then, obtain the fuzzy set corresponding to the maximum value of membership function of input variable \(x^p_i\) and output variable \(y^p_i\); that is, compute \(A^p_i\) when \(\mu_{A^p_i}(x^p_i) \geq \mu_{A_i}(x^p_i), j = 1, 2, \ldots, N_i, i = 1, 2, \ldots, n\) and \(B^p_i\) when \(\mu_{B^p_i}(y^p_i) \geq \mu_{B_i}(y^p_i), l = 1, 2, \ldots, N_p\). Finally the IF-THEN rule is obtained.

IF \(x^p_i\) is \(A^p_i\) and \(\ldots\) and \(x^p_n\) is \(A^p_n\), THEN \(y^p\) is \(B^p\).

\[
(2)
\]

Step 3. Calculate the degree of every rule

The number of the input and output pair is extensive. Every pair of input and output can generate a rule. So there may coexist conflicting rules with the same front part (IF) but different posterior parts (THEN). Therefore the degree of different rules generated from Step 2 is calculated to prevent such conflicts. When a conflict appears, the rule with a greater degree is selected.

The definition of degree of rule: If rule (2) is generated for the input and output pair \((x^p; y^p)\), its degree is computed by the formula:

\[
D(\text{rule}) = \prod_{i=1}^{n} \mu_{A_i}(x^p_i) \mu_{B^p_i}(y^p_i)
\]

(3)

Step 4. Build fuzzy rule library

The fuzzy rule library consists of the following three forms:

1. Non-conflicting rule formulas generated from Step 2.
2. The rule formulas with greatest degree determined in Step 3 among the conflicting rule formulas generated from Step 2.
3. Qualitative rule formulas built on experts’ experience.

The fuzzy rule library for systems under control can be set up by sorting the rule formulas in the above three forms.

Step 5. Establish fuzzy system based on fuzzy rule library

After fuzzy rule library is set up, appropriate fuzzy inference engine, fuzzifiers and defuzzifiers are selected to develop the model for system under control based on fuzzy rule library.

2.2 The basic structure of neural fuzzy theory

Figure 1 shows the structure of neural fuzzy theory. Its biggest difference from traditional fuzzy theory is its network connection structure and learning ability. The learning ability of neural network can self adjust to appropriate membership function thus.
resolve the situation where error and trial has to be used to obtain the membership function for qualititative variables when designing fuzzy controller.

2.2.1 Network structure The neural fuzzy control system has five layers, including fuzzifying input value, calculating membership grade of front part (IF) in fuzzy inference, computing the inference of posterior part (THEN) in fuzzy inference and defuzzifying the final inference. The basic function of every node of the network is designed on the basis of artificial neuron.

In this structure, the input of the node on every layer is a layer where the input is entered, and its right subscript representing the ith input. The output of the node of every layer is designated by f, its left subscript representing at which layer the input is entered, and its right subscript representing the ith input. The output of upper layer is the input of next layer ($u_{i}^{l}:=\bar{u}_{i}^{l-1}$).

The first layer (input layer): The major function of neuron is to distribute the standardized input to next layer of neuron.

$$1^{u}_{i}=1^{f}_{i}=1^{u}_{i}, \quad i=1, \ldots, n$$

where $n$ represents the number of input variables of the controller. The neuron's connected weight is $1^{w}_{i}=1$.

The second layer (subordinate layer): This layer uses differentiable bell-shaped membership function to compute the extent of the standardized input variables being subordinate to the membership function of qualitative variables.

$$3^{f}_{i,j} := \exp \left[ -\left( \frac{2u_{i} - \nu_{i,j}}{\sigma_{i,j}} \right)^{2} \right] = 3^{u}_{i}, \quad i=1, \ldots, n \quad j=1, \ldots, m$$

where $\nu_{i,j}$ and $\sigma_{i,j}$ represent the midpoint and the width of the bell-shaped function respectively. Also, $n$ represents the number of input variables, $m$ represents the number of the membership functions, and the connected weight is $3^{w}_{i,j}=1$.

The third layer (rule layer): For the front part of inference (IF), compute the strength of corresponding rule library by using product inference engine.

$$3^{f}_{i} := \Pi_{i=1}^{n} 3^{u}_{i} = \Pi_{i=1}^{n} \exp \left[-\left( \frac{2u_{i} - \nu_{i,j}}{\sigma_{i,j}} \right)^{2} \right] = 3^{u}_{i}$$

The neuron's connected weight is $3^{w}_{i}=1$.

The fourth layer (defuzzifier layer): Use center average defuzzifier, of which connected weight $w_{i}$ represents the median of the posterior part (THEN) corresponding to a single-valued membership function. The relation is illustrated as below.

$$1^{u}_{i} = 3^{f}_{i}, \quad 1^{u}_{i} = 3^{f}_{i}, \quad \bar{w} = 1^{w}_{i}$$

$$a = \sum_{i=1}^{n} 4^{u}_{i} 3^{u}_{i}$$

$$b = \sum_{i=1}^{n} 4^{u}_{i}$$

$$4^{f} = \frac{\sum_{i=1}^{n} 4^{u}_{i}}{\sum_{i=1}^{n} 4^{u}_{i} 3^{u}_{i}}$$

The fifth layer (output layer): The final output of the fifth layer $y_{output}$ is just the output of neural fuzzy controller to the system under control.

$$4^{f} = y_{output}$$

Applying fuzzy theoretical structure in the neural network system requires three types of adjustment including a corrected value for the fourth layer of network (that is the median of the posterior part (THEN) output corresponding to a single-valued membership function), and the median and width of the input variables to corresponding Gaussian function.

2.2.2 Error correction rule for neural fuzzy controller In the learning process, error backpropagation is used to correct by approximating to the maximum variance, that is, to correct in a reverse direction from the fifth layer back to the first layer. First of all, the error function is defined as:

$$E(k) = \frac{1}{2} (y_{expected} (k) - y_{output}(k))^{2}$$

where $y_{output}$ is the actual output, $y_{expected}$ is the expected output, $k$ is the sampling time.

According to descent gradient, the adjustment rule for the fourth layer correction parameter weight $1^{w}_{i}$ is

$$1^{w}_{i}(k+1) = 1^{w}_{i}(k) + \eta_{w} \left( \frac{\partial E(k)}{\partial 1^{w}_{i}(k)} \right)$$

where $\eta_{w}$ is the learning factor of $1^{w}_{i}(k)$.

The adjustment rule for the weight $3^{w}_{i,j}$ is then computed:

$$3^{w}_{i,j}(k+1) = 3^{w}_{i,j}(k) + \eta_{w} \left( \frac{\partial E(k)}{\partial 3^{w}_{i,j}(k)} \right)$$

The adjustment rule for the median value $\nu_{i,j}(k)$ of bell-shaped membership function is

$$\nu_{i,j}(k+1) = \nu_{i,j}(k) + \eta_{\nu} \left( \frac{\partial E(k)}{\partial \nu_{i,j}(k)} \right)$$

where $\eta_{\nu}$ is the learning factor of $\nu_{i,j}(k)$.

The adjustment rule for the median value $\nu_{i,j}(k)$ of membership function is written as:

$$\nu_{i,j}(k+1) = \nu_{i,j}(k) + \eta_{\nu} \left( \frac{y_{expected}(k) - y_{output}(k)}{b(k)} \right)$$

$$\times 4^{w}(k) \left( \frac{2(\nu_{i,j}(k) - \nu_{i,j}(k))}{\sigma_{i,j}(k)} \right)^{2}$$

The adjustment rule for the width of bell-shaped membership function is
\[ \sigma_{i,j}(k+1) = \sigma_{i,j}(k) + \eta_e \left( -\frac{\delta E(k)}{\delta \sigma_{i,j}(k)} \right) \]  

where \( \eta_e \) is the learning factor of \( \sigma_{i,j}(k) \).

The adjustment rule for the width of bell-shaped membership function is computed

\[ \sigma_{i,j}(k+1) = \sigma_{i,j}(k) + \eta_e \left( \text{output}(k) - y_{\text{output}}(k) \right) \times \frac{\partial \sigma_{i,j}(k)}{\partial \sigma_{i,j}(k)} \times \left( 2\frac{\text{output}(k) - y_{\text{output}}(k)}{\sigma_{i,j}(k)} \right)^2 \]  

2.2.3 Deviate control model

In neural fuzzy theory, when correction is required for the midpoint and width of the membership function of the qualitative language variables in front part, because of the restriction by rule library, all the inferences in the rule library will lose the logic relationships as deviation happens. In order to prevent deviation, in designing a deviate control model, when a set of measuring data are read, use the correction rules to correct the input and output membership functions and then compare the median values of every input and output membership function. If deviation happens, then the median value of deviate membership function is moved towards the left to offset by a certain amount so as to avoid deviate.

\[ \nu_{i,j}(k+1) = \nu_{i,j}(k+1) - \eta_{\nu} \nu_{i,j}(k+1) \]  

After integrating the neural fuzzy network structure and deviate control model, the training process can be illustrated by Fig. 2.

3. Thermal Deformation Measuring System

3.1 Measurement unit for temperature

In this study, SMARTEC IC-type temperature sensor is used. Its internal structure contains temperature sensor, amplification circuit and A/D switch circuit. The temperature can be obtained by computing “Duty-cycle” (D.C.) signals. Measuring “Duty-cycle” signals is done by measuring analog integral voltages or digital counting. The method of digital counting is shown in Fig. 3.

3.2 Measurement unit for deformation

In the study, the length of Renishaw's cutting tool is used to set up the probe system and measure the spindle's thermal deformation in cutting. The cutting tool selects the fixed contact probe in the system, including MP4 contact probe, M15 interface module and power supply outlet. In measuring, the moment when the spindle grips the standard test rod to touch MP4 contact probe, M15 module produces trigger signals up to the Skip point of CNC after it releases debounce. When it receives this signal, the controller will place the mechanical coordinates upon trigger into variables, and then use CNC's

![Fig. 2 The training flowchart of neural fuzzy learning control system](image-url)

![Fig. 3 Digital counting flowchart](image-url)
assembly order to export the current variables via RS-232 interface. In order to ensure that using Macro program to record trigger coordinates will not be affected by the delay of tool machinery's polling skip signals, an experiment is done to continuously trigger MP4. The results of probe's repetitive good conditions prove that the delay of tool machinery's polling skip signals does not have any impact in this matter.

3.3 Integration of thermal deformation measurement system

The SMARTEC IC-type temperature sensor and the MP4 measuring probe are used to catch the temperature rise and the thermal drift. The temperatures sensors are attached to the critical points on the machine and measure the deformation with MP4 to set up different configurations of the machine by experiment as well as record the values at different temperatures. All the data about the machine related to ascent in temperature and thermal deformation can thus be gathered. The structure of the complete measurement system for ascent in temperature and thermal deformation is shown in Fig. 4.

In order to provide a more user-friendly and convenient operating interface, a Windows on-line monitoring software kit is developed in this study based on Inprise C++ Builder in Windows 95/98.

4. Experiment on Measuring Thermal Deformation

4.1 Design of the experiment on measuring thermal deformation

The vertical machining center, product of Gao Fong Machinery, is the experimental object in this study. The end milling with 6 flutes and effective surface 80 mm diameter cutter is used to conduct this experiment. The cutting parameters are set, spindle speed: 700 rpm, feed rate: 1200 mm/min, depth of cut: 3 mm, reciprocating zigzag cutting method, and cutting material medium carbon steel S45C. The attachment location of the temperature sensor significantly affects the development and precision of the model for thermal deformation. According to the studies in literature[9],[10], the optimal attachment location of temperature sensor is on the sides of spindle sleeve and on the spindle motor. It is also learned from literature[6],[7] that the environmental temperature change has crucial impact on the machinery's thermal deformation. Therefore in the experiment, SMARTEC will record the temperature of spindle sleeve's sides, spindle motor and environment. MP4 cutting tool will set the probe to measure the thermal deformation. Figure 5 illustrates the experiment flowchart.

In addition, the experiment also involves the automatic tool change (ATC) mechanism of the tool machinery. So before the experiment on deformation measurement, the precision of tool change needs to be testified. The experimental results of tool change errors within 2 μm are negligible compared to the heat errors between 50 μm and 80 μm.

4.2 Experiment results of measuring thermal deformation

Use the designed experiment parameters and conduct the cutting experiments in a factory environment. Figure 6 shows the state of ascent in temperature at different attaching temperatures. Figure 7 shows Z-axis measurement values of thermal defor-
mation. In the chart, both Z-axis error and ascent in temperature tend to approximate to a fixed value after cutting for 90 minutes when the machine is in a balanced heating state.

5. Establishment of the Thermal Deformation Model

The temperature variation range of the spindle sleeve's sides (T1) and the spindle motor (T2), and the variation of Z-axis values of thermal deformation are derived from the results from experiment on measuring thermal deformation. According to the statistics from experiment, the daytime temperature change is about 8°C. So the variation range of environmental temperature (T3) is set to be -4°C~+4°C. The ranges of all the variables are shown in Table 1.

The fuzzy sets are built for every input variable. Here every variable is equally divided into seven membership functions, as shown in Fig. 8. By the same token, the membership functions are built for

<table>
<thead>
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<th>Variables</th>
<th>Variation Range</th>
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<tr>
<td>Spindle Sleeve’s Sides (T1)</td>
<td>0°C~+15.6°C</td>
</tr>
<tr>
<td>Spindle Motor (T2)</td>
<td>0°C~+8.5°C</td>
</tr>
<tr>
<td>Environmental Temp (T3)</td>
<td>-4°C~+4°C</td>
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<td>Z-axis Deformation</td>
<td>0~79 μm</td>
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Table 1 Range of the different variables

Fig. 7 Z-axis values of thermal deformation in real cutting

Fig. 8 Membership functions of input variables T1, T2 and T3
output variables, as shown in Fig. 9.

Using the questionnaire survey mentioned previously to establish fuzzy rule library for thermal deformation, the input variables are the temperatures of T1, T2 and T3, and the Z-axis values are the corresponding output variables. This is a pair of three inputs to one output. Its fuzzy rule library is a three-dimensional (3D) arrangement $7 \times 7 \times 7$, where environmental temperature T3 is determined by the change of weather, and both the temperatures of spindle sleeve's sides T1 and spindle motor T2 depend on the thermal features. Consequently, T1 and T2 are related to certain extent while T3 is of little relevance to T1 and T2. There are 13 rules with respect to T1, T2 and T3 concluded from the analysis of experimental data. The rule library is shown in Table 2.

After the rule library is established, use the measurement data for different temperatures obtained from thermal deformation experiment as inputs to get the corresponding Z-axis positioning error values. The output value is the compensation value for thermal deformation. Compute the error between output value and expected value and modify the input and output membership functions using the error correction rules of adjustable fuzzy theory. The

<table>
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Table 2  Fuzzy rule library for thermal deformation

Fig. 9 Membership functions of output variable Z

Fig. 10 The membership functions of input variables T1, T2 and T3 after modification
learning factors of all the membership functions are designated as 0.001 and the error tolerance is ±2 μm. The convergence results are obtained after 193 epochs. The input and output membership functions after modification are shown in Figs. 10 and 11.

6. Testing Results

In order to test the feasibility of the compensation theory in this study, the conclusions from the analysis mentioned previously are used for compensation test. Z-axis uses the regression model of cutting as compensation basis. MP4 measures the error of a fixed point from origin. Let a fixed point in working space be origin, whose coordinates are \( X = -50, Y = -200, Z = -300 \). The temperature information read by SMARTEC temperature IC is sent to temperature management program in the personal computer. The compensation value computed is transmitted to I/O B2 card (FANUC I/O extension card) via 8255 Card.

The compensation value is testified in the notchal cutting experiment for 8 hours with the fixed measuring point coordinates (mechanic coordinates) of \( X = -640, Y = -400, Z = -300 \). It has proved that this adjustable fuzzy theoretical model can provide comparatively accurate compensation. The comparison of the thermal deformation prediction results from the adjustable fuzzy theory with the ones from multiple regression analysis, as shown in Fig. 12, has proved that the prediction and simulated control results of thermal deformation obtained from adjustable fuzzy theory are better than those from multiple regression analysis.

7. Conclusions

This study is focused on the methodology to establish thermal deformation forecasting model out of the compensation technologies related to tool machinery’s thermal deformation. By experiment, it selects the temperatures largely related to Z-axis values of thermal deformation and measures the thermal deformation in notional cutting. The adjustable fuzzy control theory is then introduced. It applies questionnaire survey to the establishment of fuzzy rule library, modifies all the membership functions by descending gradient method and sets up the thermal deformation forecasting model. The experiment on measuring thermal deformation in notional cutting uses, based on industry experience, face-milling cutter to cut carbon steel, which produces a larger quantity of heat from spindle than ending milling cutter. As shown in experiment, the temperature and error can reach a preliminary balance in one and half an hours. This allows further development of the heat error measurement method in a short period of time. Using the data to build a thermal deformation forecasting model, as proved by experiment, can significantly reduce Z-axis value of thermal deformation from 80 μm to below 3 μm, which is better than 10 μm resulted from the forecasting model built on the basis of multiple regression analysis. Moreover, fast modeling can also benefit the development of the machine’s heat error compensation model before the tool machines are released from manufacturing factories.

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