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# Comparative study of ANN and ANFIS prediction models for thermal error compensation on CNC machine tools

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## Abstract

Thermal errors can have significant effects on CNC machine tool accuracy. The errors usually come from thermal deformations of the machine elements created by heat sources within the machine structure or from ambient change. The performance of a thermal error compensation system inherently depends on the accuracy and robustness of the thermal error model. In this paper, Adaptive Neuro Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) techniques were employed to design four thermal prediction models: ANFIS by dividing the data space into rule patches (ANFIS-Scatter partition model); ANFIS by dividing the data space into rectangular sub-spaces (ANFIS-Grid partition model); ANN with a back-propagation algorithm (ANN-BP model) and ANN with a PSO algorithm (ANN-PSO model). Grey system theory was also used to obtain the influence ranking of the input sensors on the thermal drift of the machine structure. Four different models were designed, based on the higher-ranked sensors on thermal drift of the spindle. According to the results, the ANFIS models are superior in terms of the accuracy of their predictive ability; the results also show ANN-BP to have a relatively good level of accuracy. In all the models used in this study, the accuracy of the results produced by the ANFIS models was higher than that produced by the ANN models.

## 1. Introduction

Errors due to the changes in the temperature of the machine tool elements create relative movement between the tool and the workpiece during the machining process, which affects the accuracy of the part being produced, these are known as the thermal errors [1]. According to various publications [2-4], thermal errors represent approximately 70% of the total positioning error of the

CNC machine tool. With improvements of machine tool positioning accuracy, tooling, and enhanced machining performance improved, thermal errors have become more significant. As a result, a reduction of thermal errors is needed for high-precision manufacturing systems [5].

Two different ways have been used to reduce the thermal errors of machine tools: Thermal error avoidance and thermal error compensation [1]. In thermal error avoidance, heat-source isolation, structural improvement and materials that have a low thermal expansion coefficient are used to reduce the thermal errors. Although, this can improve basic machine accuracy, it is neither cost-effective nor applicable to the renewal of existing machine tools [1]. Thermal error compensation attempts to forecast the thermal errors and then compensate for them with software. Extensive research has been carried out in the area of thermal error compensation [2]. There are two main research areas in relation to this: Numerical analysis techniques such as the finite-element method [6] and the Newton-Raphson method [7] are utilized for thermal error compensation. These methods are restricted to qualitative analysis because of the complexity of machine tool structures, such as geometrical dimensions and machine joints. The second area uses empirical modelling, which is based on the measurement of temperature changes and thermal drift of the machine tools. Examples include multiple regression analysis [8], types of Artificial Neural Networks [9], fuzzy logic [10], adaptive network fuzzy inference system [11] and a combination of several different modelling methods [2].

Among these error compensation methods, the Adaptive Neuro-Fuzzy Inference System and Artificial Neural Network models were the most promising methods: They showed satisfactory predictive accuracy in many real-world applications. These models have their own advantages, and disadvantages. Experiments show that neither of them needs a proper selection of thermal sensors and their locations, in order to ensure the prediction accuracy and robustness of these models. Further exploration regarding the selection of thermal sensors for thermal error compensation models is needed.

The motivations behind this paper are to develop a method competent in determining the key temperature sensors for modelling using grey system theory and also to determine the empirical relationships for the estimation of thermal errors. Adaptive Neuro Fuzzy Inference System (ANFIS) and traditional Artificial Neural Network (ANN) techniques were used to design four thermal prediction models: ANFIS by dividing the data space into rule patches (ANFIS-Scatter partition model); ANFIS by dividing the data space into rectangular sub-spaces (ANFIS-Grid partition model); ANN with a back-propagation algorithm (ANN-BP model) and ANN with a PSO algorithm (ANN-PSO model), and compare the versatility, the robustness and their prediction accuracy.

## 2. Material and methods

An artificial intelligence system is a system that can make decisions which would be considered intelligent if they were made by a human being. They adjust themselves using some conditions (input data), and they improve decisions automatically for future conditions. Artificial Neural Networks, fuzzy logic systems, particle swarm optimisation, and neuro-fuzzy systems are the most common artificial intelligence system types. In this part of the paper, the theory behind and structures for artificial intelligence systems will be described. Furthermore, proper selection of thermal sensors and their locations will be introduced using the grey system theory.

## 2.1 Artificial Neural Networks (ANNs)

Artificial Neural Networks, especially the Multi-Layer Perceptron networks (MLP) are an extension of perceptron neural networks, which have one or more hidden layers. A group of the neurons which are connected with each other through the environment form the whole ANN. Figure 1 shows the basic structure of the ANN. The learning algorithm is defined as a mathematical tool that sketches the methodology and the speed for the network, to obtain the steady state of network parameters successfully. There are many optimization methods which can be used to train the ANN, such as the back-propagation algorithm (BP) and particle swarm optimization (PSO). The choice of the error function and the optimization techniques are significant, because they may increase the stability of the ANN. The back-propagation algorithm is the basic learning mechanism: In this algorithm, the ANN output on presentation of input data is matched with the desired output to obtain the error. The error is used to incrementally adjust appropriate weights in the connection matrices to reduce it. Following many presentations of training data, the error value of the ANN is expected to be decreased to a satisfactory level, and the ANN will have then learned how to resolve the task modelled by training data. Particle swarm optimization (proposed by Eberhart and Kennedy [12]) is also an optimization technique. Researchers have applied it to train ANN and have found that ANN with PSO has a good training performance, a faster convergence rate and a better predicting ability than ANN with BP [13]. In this paper, in order to enhance the ability of ANN to make predictions it is adjusted with the PSO technique.

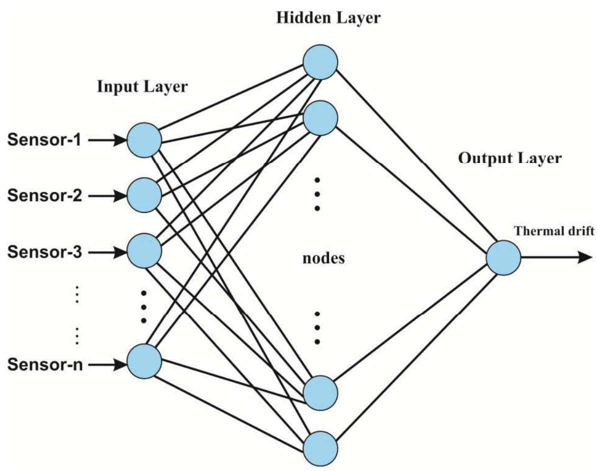


Figure 1: Basic structure of ANN model.

## 2.2 The Adaptive Neuro-Fuzzy System (ANFIS)

The architecture and learning procedure of the Adaptive Neuro-Fuzzy System (ANFIS), have both been described by Jang [14]. According to Jang, the ANFIS is a neural network that is functionally the same as a Takagi-Sugeno type inference model. The ANFIS is a hybrid intelligent system that takes the advantages of ANN and the fuzzy logic theory into a single system. By employing the ANN technique to update the parameters of the Takagi-Sugeno type inference model, the ANFIS is given the ability to learn from given training data, the same as ANN. The solutions mapped out onto the Takagi-Sugeno type inference model can therefore be described in linguistic terms.

The efficiency of any ANFIS model depends on the success in partitioning the input and output variables space correctly. This can be achieved by using a number of methods such as grid partitioning (ANFIS-Grid partition model), the subtractive clustering method (ANFIS-Scatter partition model) and fuzzy c-means clustering [15]. The equivalent ANFIS network with two variables is shown in Figure 2:The first layer implements a fuzzification, the second layer executes the T-norm of the antecedent part of the fuzzy rules, the third layer normalizes the membership functions (MF), the fourth layer computes the consequent parameters, and finally the last layer calculates the overall output as the summation of all incoming signals [14].

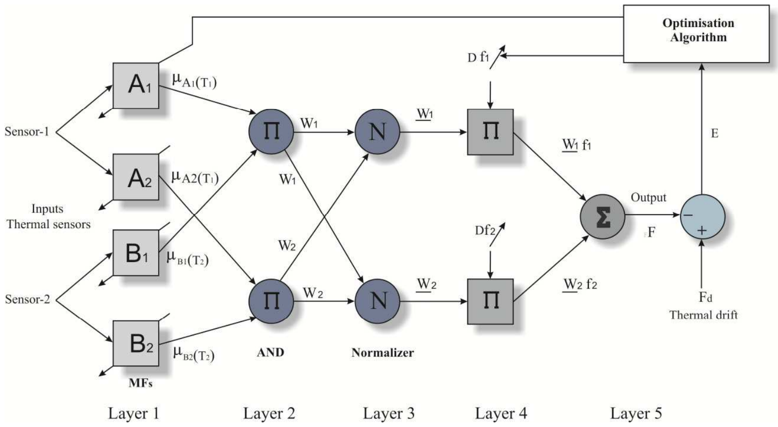


Figure 2: Basic structure of ANFIS.

## 2.3 GM (h, N) Model

In grey system theory, the main function of the GM (h, N) model is a way to acquire a calculation of the measurement between the discrete sequences and to compensate the shortcomings in the traditional methodology [16]. Assume that the original data with a number of samples (N) is described in sequences $x_i^{(0)}(k),\ i = 1,2, \ldots\ldots, N$.

$x_1^{(0)}(k)$, and sequences $x_2^{(0)}(k), x_3^{(0)}(k), x_4^{(0)}(k), \ldots .\, x_N^{(0)}(k)$ are the influential factors of the system, then the GM (h, N) model is described as [16]:

$$\sum_{i=0}^{h} a_i \frac{d^{(i)} x_1^{(1)}}{dt^{(i)}} = \sum_{j=2}^{N} b_j\, x_1^{(1)}(k) \qquad (1)$$

Where, (i) $a$:Is the developing coefficient. (ii) $b$: Is defined as the grey input. (iii) $x_1^{(1)}(k)$: The major sequence. (iv) The accumulation generating operation AGO $x^{(0)} = x^{(1)}$

$$= [\sum_{k=1}^{1} x^{(0)}(k), \sum_{k=1}^{2} x^{(0)}(k), \sum_{k=1}^{3} x^{(0)}(k), \ldots \sum_{k=1}^{n} x^{(0)}(k)]$$

According to the previous definition of GM (h, N), the GM (0, N) is a zero order grey system, which can be described as follows:

$$az_1^{(1)}(k) = \sum_{j=2}^{N} b_j x_j^{(1)}(k) = b_2 x_2^{(1)}(k) + b_3 x_3^{(1)}(k) + \cdots + b_N x_N^{(1)}(k) \qquad (2)$$

Where, $z_1^{(1)}(k) = 0.5x_1^{(1)}(k-1) + 0.5x_1^{(1)}(k)k = 2,3,4, \ldots, n$.

The analytical steps are shown below.

1- Substituting the AGO value, we can write.

$$az_1^{(1)}(2) = b_2 x_2^{(1)}(2) + \cdots + b_N x_N^{(1)}(2)$$
$$az_1^{(1)}(3) = b_2 x_2^{(1)}(3) + \cdots + b_N x_N^{(1)}(3)$$
$$\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$$
$$az_1^{(1)}(n) = b_2 x_2^{(1)}(n) + \cdots + b_N x_N^{(1)}(n) \qquad (3)$$

2- Dividing $a_1$ in both sides, then the equations (3) can be written as

$$\begin{bmatrix} 0.5x_1^{(1)}(1) + 0.5x_1^{(1)}(2) \\ 0.5x_1^{(1)}(2) + 0.5x_1^{(1)}(3) \\ \vdots \\ 0.5x_1^{(1)}(n-1) + 0.5x_1^{(1)}(n) \end{bmatrix} = \begin{bmatrix} x_2^{(1)}(2) & \cdots & x_N^{(1)}(2) \\ x_2^{(1)}(3) & \cdots & x_N^{(1)}(3) \\ \vdots & \cdots & \vdots \\ x_2^{(1)}(n) & \cdots & x_N^{(1)}(n) \end{bmatrix} \begin{bmatrix} \frac{b_2}{a_1} \\ \frac{b_3}{a_1} \\ \vdots \\ \frac{b_N}{a_1} \end{bmatrix} \qquad (4)$$

Assume $\theta_m = \frac{b_j}{a_1}$, where $m$=2,3,…,$N$, then equation(4) can be rearranged into:

$$\begin{bmatrix} 0.5x_1^{(1)}(1) + 0.5x_1^{(1)}(2) \\ 0.5x_1^{(1)}(2) + 0.5x_1^{(1)}(3) \\ \vdots \\ 0.5x_1^{(1)}(n-1) + 0.5x_1^{(1)}(n) \end{bmatrix} = \begin{bmatrix} x_2^{(1)}(2) & \cdots & x_N^{(1)}(2) \\ x_2^{(1)}(3) & \cdots & x_N^{(1)}(3) \\ \vdots & \cdots & \vdots \\ x_2^{(1)}(n) & \cdots & x_N^{(1)}(n) \end{bmatrix} \begin{bmatrix} \theta_2 \\ \theta_3 \\ \vdots \\ \theta_N \end{bmatrix} \qquad (5)$$

3- The coefficients of the model can be obtained by solving this equation:

$$\hat{\theta} = (B^T B)^{-1} B^T Y \qquad (6)$$

Where,

$$Y = \begin{bmatrix} 0.5x_1^{(1)}(1) + 0.5x_1^{(1)}(2) \\ 0.5x_1^{(1)}(2) + 0.5x_1^{(1)}(3) \\ \vdots \\ 0.5x_1^{(1)}(n-1) + 0.5x_1^{(1)}(n) \end{bmatrix}, \quad B = \begin{bmatrix} x_2^{(1)}(2) & \cdots & x_N^{(1)}(2) \\ x_2^{(1)}(3) & \cdots & x_N^{(1)}(3) \\ \vdots & \cdots & \vdots \\ x_2^{(1)}(n) & \cdots & x_N^{(1)}(n) \end{bmatrix} \quad \hat{\theta} = \begin{bmatrix} \theta_2 \\ \theta_3 \\ \vdots \\ \theta_N \end{bmatrix}$$

Therefore, the influence ranking of the major sequences (thermal sensors) on the output sequences (thermal drift) can be known by comparing the model values of ($\theta_2 \sim \theta_N$).

## 3. Experimental work

In this study, experiments were performed on a small vertical milling centre (VMC). Three non-contact displacement transducers (NCDTs) were used to measure the drift of the tool in the X, Y and Z axes. The thermal data was measured using 58 temperature sensors placed in strips at the carrier and spindle boss surfaces as explained by White et al [3], other eleven ambient temperature sensors were placed around the machine to pick up the ambient temperature [6]. A general overview of the experimental setup is shown in Figure 3.

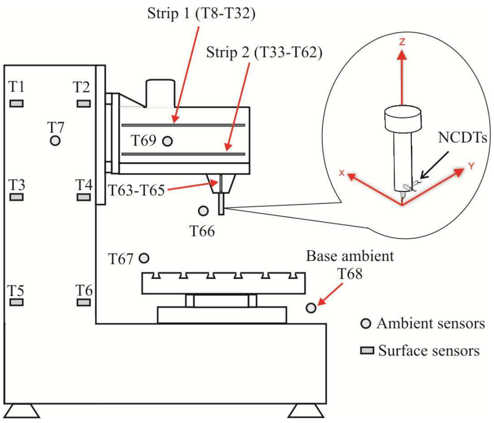


Figure 3: A general overview of the experimental setup.

The machine was examined by running the spindle at its highest speed of 8000 rpm for 60 minutes to excite the largest thermal behaviour. It was then stopped for 60 minutes for cooling. The temperature sensors at the selected points on the machine tool and the thermal drift of the spindle were measured simultaneously; the thermal drift of the machine is shown in Figure 4. The maximum drift of the X-axis is 2 µm, the Y-axis is 60 µm, and the Z-axis is 22 µm. In this paper, the X-axis thermal drift is much smaller than that of Y-axis and Z-axis due to mechanical symmetry and therefore can be ignored [3]: Only the Y-axis and Z-axis are considered.

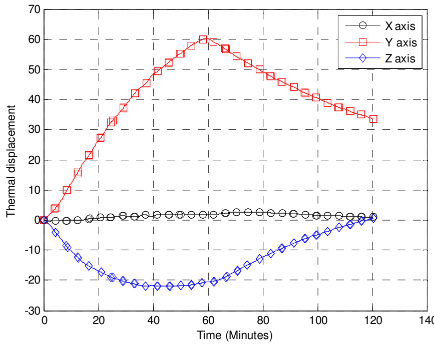


Figure 4: Thermal drift of the machine spindle.

The influence coefficient between the thermal error in the Y direction and the temperature sensors are calculated using the GM (0, N) model. The representative temperature sensors for modelling are selected from each group (Surface sensors and ambient sensors) according to their influence coefficient value. The representative thermal sensors T2, T16, T29, T55, T63 and T71 (which are located on the column, carrier, spindle boss, and base) are used as the thermal key sensors for modelling.

### 3.1 ANN Models

Six temperature sensors (T2, T16, T29, T55, T63 and T71) were selected as input for models, and the thermal drift in Y direction was chosen as a target variable. Usually ANN models have three layers: Input, hidden and output layers. Although, for common engineering problems, one hidden layer is sufficient for model training, two or more hidden layers may be needed for very complex phenomena. An ANN models with three layers was used in this study. According to ANN models, the input layer has six sensors and the output layer has one sensor (the thermal drift in Y direction). The test (60 minutes heating and 60 minutes cooling) was used for training the models.

In order to examine the performance of the ANN models on non-training data, another test was carried out on the same machine in an operational cycle as follows: It was allowed to run at spindle speed 4000 rpm for 120 minutes, and then paused for 60 minutes before running for another 120 minutes; and then stopped for 180 minutes. During the experiment, the thermal errors were measured by the NCDTs, and the predicted displacements were obtained using ANN models. A validation test on the ANN-PB model and ANN-PSO model for thermal error prediction have shown satisfactory results (see Figure 5).

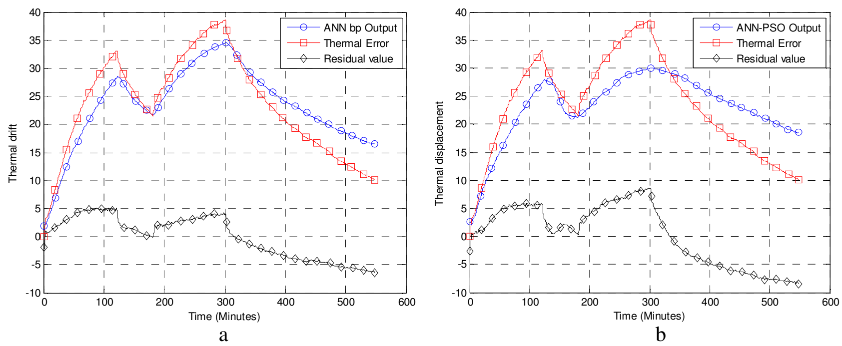


Figure 5: (a) ANN-BP model output vs. the actual thermal drift. (b) ANN-PSO model output vs. the actual thermal drift.

### 3.2 ANFIS Models

Similar procedures (ANN models) were carried out on the ANFIS models. The construction of two models (ANFIS-Grid and ANFIS-Scatter) is described as follows: The number of the membership function is (2×3×2×2×3×2 and 5×5×5×5×5×5) and in total (144 and 5) rules can be obtained to define their relationship with thermal displacement. The same test (60 minutes heating and 60 minutes cooling) was used for training the models. The Gaussian functions were used to describe the membership degree of these variables. After setting the initial parameter values in the ANFIS models, the input membership functions were adjusted using a hybrid learning scheme. The error between the output and expected values can be computed.

Simulation results show that the ANFIS models can provide a good prediction result with the validation data. Figure 6 presents the comparison between thermal drift from the actual measured data and the output of the models.

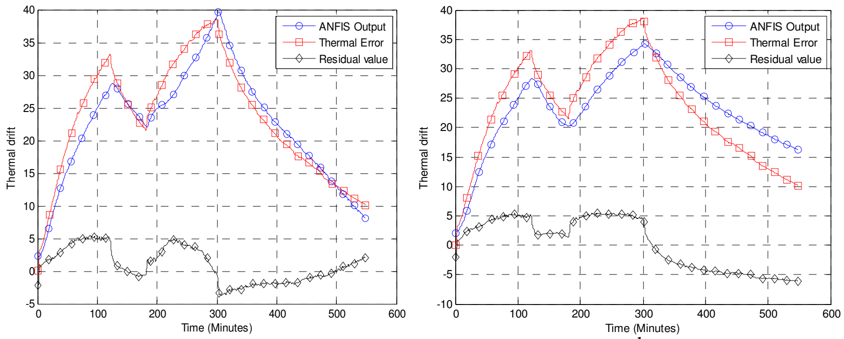


Figure 6: (a) ANFIS-Grid model output vs. the actual thermal drift. (b) ANFIS-Scatter model output vs. the actual thermal drift.

### 3.3 Results

The results of the GM (0, N) model can determine which sensors on the machine structure contribute most significantly to the total thermal drift. The models of ANFIS and ANN for the prediction of thermal drift were then constructed using six selected inputs and one output.

The results of this paper are as follows:

- The ANFIS models for the prediction of thermal drift revealed a more reliable prediction when compared with ANN models.
- The model prediction of thermal drift showed that the ANFIS-Grid partition model has a high prediction performance. The residual value of the model is smaller than ± 5 µm.

Three performance criteria including root mean square error (RMSE), Nash-Sutcliffe efficiency coefficient (E) and correlation coefficient (R) were used to judge the most optimum model. From the Table 1 (as a result of the comparison of RMSE, E and R indices for predicting thermal drift) it was revealed that the prediction performance of the ANFIS-Grid model is higher than those of ANFIS-Scatter, ANN-BP and ANN-PSO models, respectively. Thus, the accuracy of outputs decreases gradually from the ANFIS to the ANN models.

Table 1: Performance calculation of the used models.

| Model | Training stage | | Validation stage | | |
|---|---|---|---|---|---|
| | E | RMSE | E | RMSE | R |
| ANFIS-Grid partition | 0.990 | 0.225 | 0.89 | 2.8125 | 0.9530 |
| ANFIS-Scatter partition | 0.990 | 0.213 | 0.86 | 3.2057 | 0.9343 |
| ANN-BP | 0.990 | 0.3578 | 0.8098 | 3.7684 | 0.9287 |
| ANN-PSO | 0.980 | 0.4207 | 0.6158 | 5.3557 | 0.7567 |

## 4. Conclusions

In this paper, various traditional ANN and hybrid ANFIS models were proposed for the prediction of the thermal errors on a CNC machine tool, and the following conclusions can be drawn:

- The new technique GM (0, N) model is able to find the optimal temperature sensors for thermal error modelling. The advantage of using key temperature sensors is greater economic efficiency and reduces modelling time. In addition, the robustness of the models can be increased and the predicting precision of the models using the optimal combination of the temperature sensors are enhanced.
- Experimental results show that the thermal error in the Y direction can be significantly reduced to less than ±5 µm using ANFIS models with validation data (different conditions of rotational speeds on the machine tool). The results also show that the ANN models can reduce the thermal error to less than ±10 µm. However, BP algorithms are limited during the training procedure, in that they are sensitive to the weight's initial values. If the weights are not correctly chosen, the training process might be cornered in a local minimum or maximum. In contrast, while a PSO algorithm gives unsatisfying results, further investigation is necessary in order to overcome some of the limitations of BP. A PSO algorithm also gives fast convergence during the training stage.

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