euspen's 22nd International Conference & Exhibition, Geneva, CH, May/June 2022
www.euspen.eu

Study on environmental thermal induced error modelling of a stage based on artificial neural network

Seung-Han Yang[1], Sung-Hwan Kweon[2], Kibum Jung[1], Kwang-il Lee[3]

[1]*School of Mechanical Engineering, Kyungpook National University*
[2]*Institute of Mechanical Engineering Technology, Kyungpook National University*
[3]*School of Mechanical and Automotive Engineering, Kyungil University*

syang@knu.ac.kr

Abstract
There are many studies on the displacement error of a stage caused by the internal heat source, but only few studies have been done on the error caused by the external heat source. The displacement error caused by the external heat source called environmental thermal induced error occurs when the stage is affected by the temperature change of the environment due to the external heat source. In order to reduce that error, a method of maintaining a constant environmental temperature has been proposed, but in general working environment, it is difficult to completely control the environmental temperature and error due to various external heat sources. Therefore, the effect of the environmental temperature change on the error of the stage should be analysed first. In this study, we propose a method to model and analyse the environmental thermal induced error of the stage using the artificial neural network(ANN). Several thermal sensors are used to measure the temperature of environment and stage, and a measurement system is used to measure the displacement error of the stage. The above-mentioned measurement process is performed according to the time interval, and an artificial neural network-based error model is established using the measurement data. The proposed model can be applied to evaluate the precision of various stages.

Neural Network, Thermal Error, Precision, Evaluation

1. Introduction

Among the various source of machine tool errors, thermal induced errors make up 40-70% followed by geometric errors.[1] To reduce thermal induced error of the machine tool, various methods such as thermo symmetric design, separation of the heat source from the machine body, cooling method, correction of errors, and operating in a constant temperature chamber were proposed and research for these have been continued.[2-7] However, in general, the machines are used in an environment where the temperature is not in constant, and it is difficult to find out the exact location of the external heat source.[8] The machine tool generates heat on the stage due to the cutting process, etc. This causes the stage to deform under the influence of heat in a general working environment where constant temperature and humidity are difficult to achieve. In addition, although various studies have been proposed on the internal heat source of the machine tool, research on thermal induced error by the environmental temperature caused by external heat source is still ingoing. Since the location and the amount of heat generated by the internal heat source can be known, thermal induced error can be corrected through methods such as thermo symmetric design, but in the case of the external heat source, it is difficult to predict and correct thermal induced error because the location and the amount of heat source are hard to calculate. The need for a model that can effectively solve these problems and can be easily applied in the field has been raised. There are methods that have been used to correct thermal induced error, the finite element method and engineering empirical model. The finite element method is useful when the exact location, size, and boundary conditions of heat sources are known.[9] The empirical model using multiple regression analysis has a high-order term variable, so there is a problem in robustness, and a lot of effort and knowledge are required. In addition, there is a limit to modeling and calculating all heat sources outside the machine tool. Therefore, the thermal induced error of the stage on the machine tool by the environmental temperature is modeled using ANN (Artificial Neural Network). By measuring the temperature of the stage, the thermal induced error can be predicted by ANN model, and using this, the thermal induced error of the stage can be corrected afterwards.

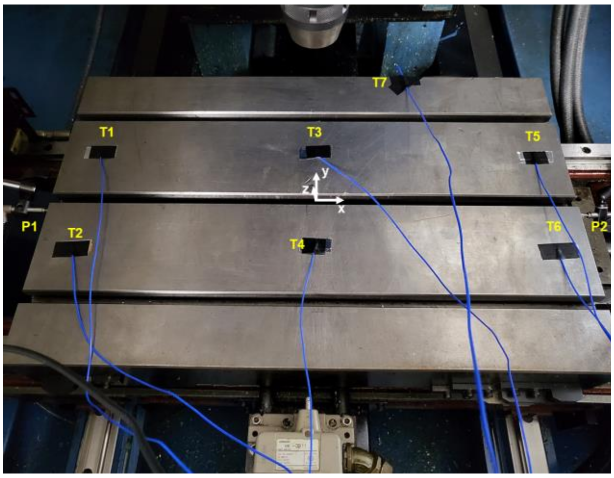


Figure 1. Sensors on the Stage

2. Pre-experiment and ANN modeling

Table 1 Specification of T-30 Stage

Material	S45C	**Length**	0.6m
Thermal Property	14µm/m-℃	**Width**	0.38m

Table 2 Specification of Thermocouple

Thermocouple Type	K
Ambient Temperature Min	-50℃
Ambient Temperature Max	200℃
Ambient Temperature Error Max	±0.75℃

Table 3 Specification of LVDT

Name	DK802LR
Measuring Range	2 mm
Resolution	0.1 µm
Operating Temperature	0℃ - 50℃
Output	Voltage

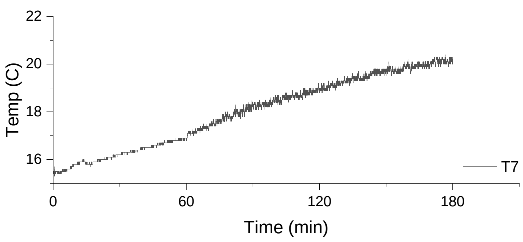
The machine tool used for measurement is komatec's SPT-T-30. Table 1 shows the material of the stage used for the T-30.

Seven thermocouples were placed to measure the temperature of the stage. Six of them(T1 – T6) were attached to the stage to measure the temperature of the stage, and one(T7) was attached outside the stage to measure the environmental temperature as shown in Figure 1. Two LVDTs (Linear Variable Displacement Transducers) were used to measure the displacement of the stage. The stage of the T-30 has two slides at the bottom, so main thermal expansion is expected in the slide direction, so one LVDT was placed on the left and the other was placed on the right in the slide direction. K-type thermocouples were used for the thermal sensor, and Sony's DK802LR was used for the LVDTs. The performance of Thermocouple is shown in Table 2 and the performance of LVDT is shown in Table 3.

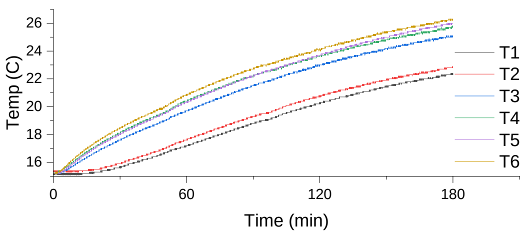
As an external heat source, heat was applied to the stage by placing a heater at an arbitrary position. The initial temperature was 15 degrees Celsius in equilibrium both the environment and the stage. The experiment was conducted for about 3 hours, it was confirmed that when the external temperature changed to 20 degrees as shown in Figure 2-(a), the stage also showed a change in temperature up to 26.3 degrees as shown in Figure 2-(b). The displacement of the stage was 14 µm in the P1 direction and 43 µm in the P2 direction as shown in Figure 2-(c).

Error prediction model was generated using an ANN to train, validate and predict the displacement of the stage using the measured temperature. When determining the structure of the ANN, hyper-parameters such as the number of hidden layers and the number of units must be determined. Hyper-parameters affect accuracy and loss value among parameters constituting ANN. Therefore, to get minimum loss value without falling into overfitting, the hyper-parameter should be optimized. However, since there is no general rule in determining hyper-parameters, it must be followed by the designer's intuition using the grid search method or the random search method. [10,11] In this study, the epoch, the number of hidden layers, the number of units, and the optimizer type were set using the grid search method to have the minimum loss value.

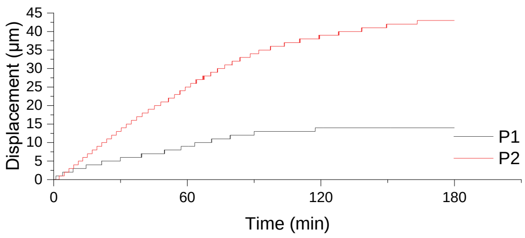
11665 data set was obtained through the experiment which includes the temperature of the stage measured by six thermocouples and the displacement obtained from two LVDTs as one data set. Data set was divided into training data and validation data in a 7:3 ratio. As shown in Figure 3, the hyper-parameters of the model using the training data were set to 3 hidden layers, 200 units, Adam for the optimizer, and 50 epochs by the grid search method. The generated model showed a loss value of 0.13 for the validation data.



(a) Temperature of Air



(b) Temperature of Stage



(c) Deformation of Stage

Figure 2. Thermal Effect of Stage

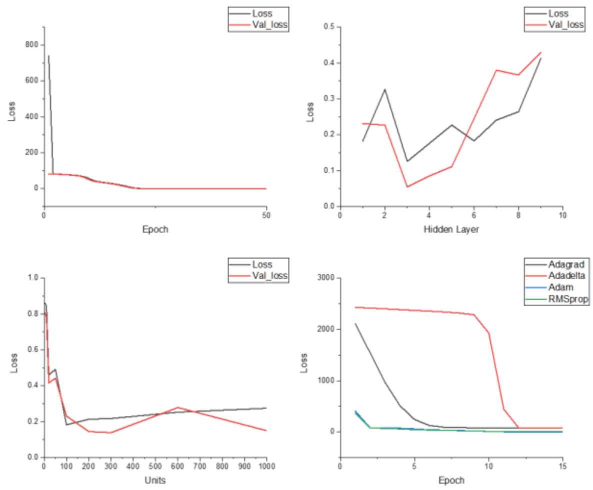
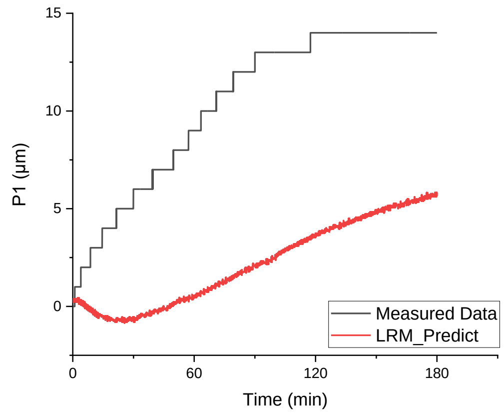


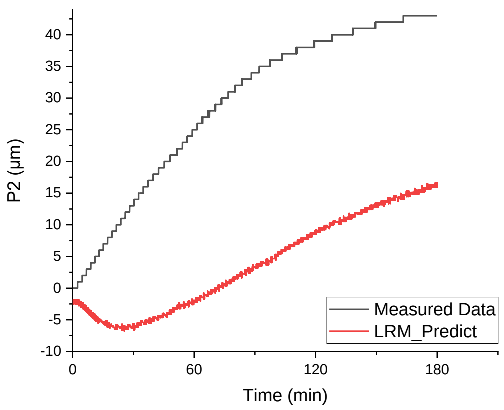
Figure 3. Hyper-parameters of ANN

3. Performance evaluation of generated ANN model

In order to evaluate the performance of the generated model, the data obtained from three temperature sensors at arbitrary positions on the stage were applied to models generated by

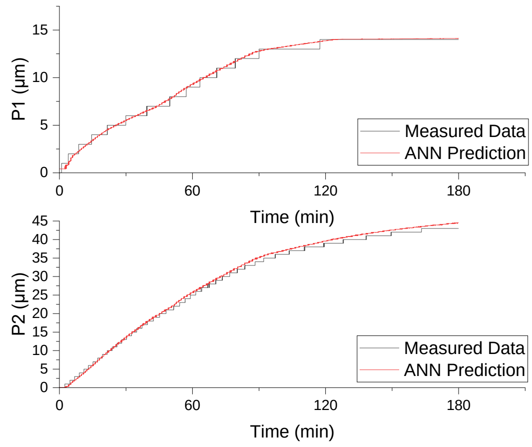


(a) Deformation at P1

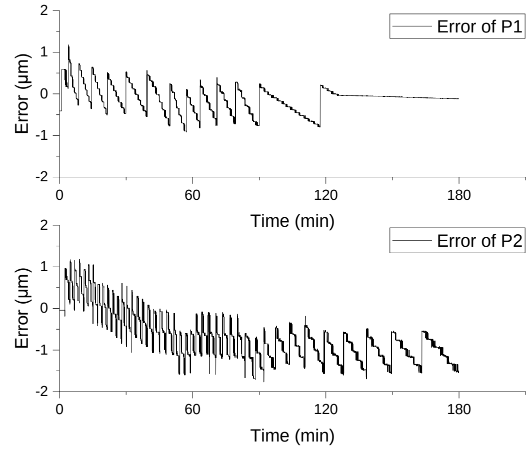


(b) Deformation at P2

Figure 4. Prediction result using LRM



(a) Deformation at P1 and P2



(b) Error of P1 and P2

Figure 5. Prediction result using ANN

linear regression analysis and ANN. To check whether the thermal induced error can be predicted using the temperature measured at arbitrary positions, three of the sensors were chosen randomly for the training data and the others were used for testing data. The ANN model is compared with linear regression model to verify its accuracy of error prediction.

Regression analysis is a method of calculating and evaluating the relevance of each obtained or given data. The multiple linear regression equation with k independent variables is formulated as Equation (1) by the least squares method that minimizes the sum of squared errors. [12,13]

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \qquad (1)$$

In the Equation (1), β_k means a k-th coefficient, X_k is a k-th independent variable and Y_i is dependent variable. When a linear regression model(LRM) was made with the data of the experiment performed in this study, P1 and P2 were expressed as Equation (2) and (3), shown as Figure 4.

$$P_1 = -14.61774704 - 1.0816478T_1 + 1.64223143T_2 + 0.53484341T_3 \qquad (2)$$

$$P_2 = -54.11475207 - 2.54939173T_1 + 6.2839985T_2 + 0.07861386T_3 \qquad (3)$$

The LRM was optimized with the gradient descent optimizer, and the results predicted by the LRM were compared with the experimental data.

On the other hand, the error of the stage predicted by the ANN model is as shown in Figure 5. This indicates that the model made with ANN can predict more accurately compared to LRM when predicting the heat induced error using the temperature data measured on the stage.

Table 4 Prediction Result

		LRM	ANN
P1	Mean	8.2015μm	0.2403μm
	Max	11.0085μm	1.1767μm
P2	Mean	25.2303μm	0.8057μm
	Max	31.9598μm	1.7692μm

4. Conclusion

An ANN model was generated to predict the thermal induced error of the stage caused by the influence of the environmental temperature. The temperature of arbitrary positions on the stage was measured using thermocouples, and the displacement was measured using LVDTs. Hyper-parameters for the model were set using the grid search method to get minimum loss value. To test the prediction accuracy, ANN model was compared with the linear regression analysis model, which is a commonly used as prediction model. As a result of comparison, it was found that both the maximum error value and the average error value were decreased in the ANN model. Compared with the experimental data, the linear regression analysis model was able to predict the thermal induced error with an error of up to

31.9598µm, and the ANN model was able to predict the thermal induced error with an error of up to 1.7692µm.

Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2019R1A2C2088683, 2020R1C1C100330011).

References

[1] Bryan J 1990 International Status of Thermal Error Research *Annals of CIRP* **39** 645-656

[2] Chen J S, Yuan J X, Ni J and Wu S M 1993 Real-time Compensation for Time-variant Volumetric Errors on a Machining Center *Transactions of the ASME Journal of Engineering for Industry* **115** 472-279

[3] Kurtoglu A 1990 The Accuracy Improvement of Machine Tools *Annals of CIRP* **39** 417-419

[4] Hatamura Y, Nagao T, Mitsuishi M, Kato K, Taguchi S and Okumura T 1993 Development of an Intelligent Machining Center Incorporating Active Compensation for Thermal Distortion *Annals of the CIRP* **42** 549-552

[5] Chen J S 1995 Computer-aided accuracy enhancement for multi-axis CNC machine tool *Int. J. Mach. Tools Manufact* **35** 593-605

[6] Veldhuis S C and Elbestawi M A 1995 A Strategy for the Compensation of Errors in Five-Axis Machining *Annals of the CIRP* **44** 373-377

[7] Weck M 1995 Reduction and Compensation of Thermal Errors in Machine tools *Annals of the CIRP* **44** 589-598

[8] Moriwaki T and Zhao C 1992 Neural network Approach to Identify Thermal Deformation of Machining Center *Proceedings of 8th International IFIP WG5.3 Conference*

[9] Weck M and Zangs L 1975 Computing the Thermal Behavior of Machine Tools Using the Finite Element Method – Possibilities and Limitations *16th MTDR* **16** 185-193

[10] Krizhevsky A, Sutskever I and Hinton G E 2012 Imagenet classification with deep convolutional neural networks *In Advances in neural information processing systems* 1097-1105

[11] Zeiler M D and Fergus R 2014 Visualizing and understanding convolutional networks *In European conference on computer vision* 818-833

[12] Kim S 2015 A study on prediction of blood donation number using multiple linear regression analysis *M.S. dissertation, Sungkyunkwan University*

[13] Cha Y M and Ahn J B 2005 A comparison study of corrections using artificial neural network and multiple linear regression for dynamically downscaled winter temperature over South Korea *Asia-Pacific Journal of Atmospheric Sciences* **41** 401-413