Construction and Operation of a Knowledge Base on Intelligent Machine Tools

SEUNG WOO LEE, JUN YEOB SONG
Intelligent Manufacturing Systems Division
Korea Institute of Machinery & Materials
171 Jangdong Yusunggu, Daejeon
KOREA
lsw673@kimm.re.kr and sjy658@kimm.re.kr http://www.kimm.re.kr

HWA KI LEE
Department of Industrial Engineering, College of Engineering
INHA University
253 Younghyundong Namgu, Incheon
KOREA
hwakilee@inha.ac.kr http://www.inha.ac.kr

Abstract: - Machine tools lie at the heart of almost all manufacturing systems, and their performance has a massive influence on both the performance and productivity of systems. In accordance with the development of computer systems, intelligent technologies have been applied to manufacturing systems, thereby raising the need for more intelligent machine tools. Intelligent machines respond to external environments on the basis of decisions that are made by sensing the changes in the environment and analyzing the obtained information. This study focuses on the construction of a knowledge base which enables decision making with that information. Approximately 70% of all errors that occur in machine tools are caused by thermal errors. In order to proactively deal with these errors, a system which measures the temperatures of each part and predicts and compensates the displacement of each axis has been developed. The system was built in an open- type controller to enable machine tools to measure temperature changes and compensate the displacement. The construction of a machining knowledge base is important for the implementation of intelligent machine tools, and is expected to be applicable to the network-based, intelligent machine tools which look set to appear sooner or later.

Key-Words: Machining Knowledge Base, Intelligent Machine Tools, Thermal errors, Offset compensation, Open controller, Multiple linear regression models, Neural Network

1 Introduction

A manufacturing system consists of hardware and software, the two elements that construct and operate such a system respectively. Machine tools, as the hardware, have been recognized as an important factor exercising considerable influence on the performance and productivity of manufacturing systems. Accordingly, many manufacturing system integration engineers have studied intelligent machine tools, shifting the machine tools technologies from hardware to software.

A typical study on the implementation of intelligent machine tools is that of Hatamura, whose study was based on sensors [1]. On the various parts of machine tools, temperature, sound, torque, and stress sensors were installed to support various functionalities including status monitoring and control. However, such an application failed due to the complicated sensor structure and the weakness of the closed-loop NC. According to the development of the functionalities of the NC, machine tools with built-in adaptive control and cutting simulation functions using the NC code have been developed. Recently, machine tools, which can be worked automatically by using knowledge base, have been developed.

The most recent trend in machine tool development involves intelligent machines that can actively recognize environmental changes, make judgments, and respond to the changes. Intelligent machine tools incorporate a sensing or monitoring function which senses external environmental changes, a knowledge processing function which makes judgments with the obtained information, and an action implementing part which responds to the environmental changes on the basis of a judgment [2, 3]. While such expert systems are being studied in order to implement a knowledge processor, most of the systems are operated on an off-line basis, resulting in slow knowledge information processing and various problems in the interfacing with the controllers of machine tools.

To solve such problems, many studies are being conducted on intelligent machine tools which have PC-NC, which is an open controller based on PC, for implementation with the various software developed for intelligence and connected with the open controller.

Intelligent machine tools require a knowledge base in order to recognize the environment and respond positively to environmental changes. For this study, a knowledge base which can compensate and minimize thermal errors in machine tools was constructed. Thermal errors are the most important cause of error in machine tools; therefore, the knowledge base presented in this study will be able to help with the implementation of intelligent machine tools. The developed knowledge base was installed on the numerical controller of real machine tools to test its efficiency in the automatic replacement of thermal errors with compensated value.

2 Building a Knowledge Base

2.1 Knowledge expression

Since the 1990s, the open CNC (Computerized Numerical Control) has become intelligent through the use of STEP-NC technologies, which enable data communication with the CAD system and software, thereby allowing machine tools to make use of various types of process information, on the basis of the introduction of high performance PCs to the open-type controller [4].

Many studies are being conducted on distributed control and autonomous intelligent machines with the aim of implementing an efficient system structure. To this end, human action is a good example for structural analysis [5, 6].

As shown in Fig. 1, external environments are recognized by the senses and the information is sent to the brain through the nerves; the brain then makes decisions on the basis of the obtained information. The decision making process depends on the knowledge accumulated in the brain, which responds to the external environment in accordance with the decision made.

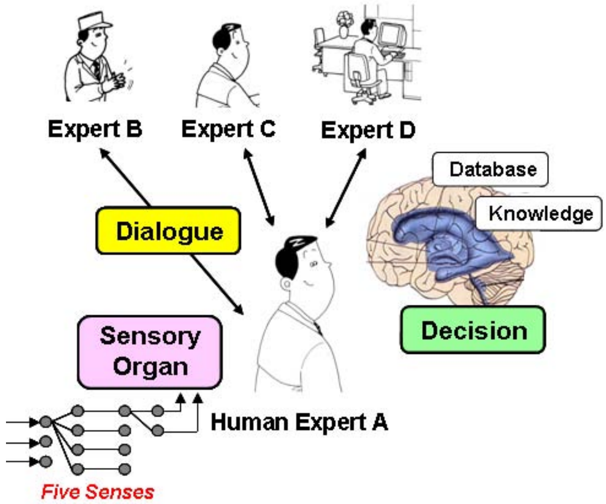

Fig. 1 Process of intelligence of a human expert

The knowledge processor, which is the brain of a machine tool, builds a knowledge base with the information required for machining in order to make decisions that respond to the status data taken from the sensors [2]. Fig. 2 shows the structure of a knowledge base in an intelligent machine tool. It is based on the rule basis, having functions which are implemented independently or dependently. Partial knowledge in each part can be used by integration [7].

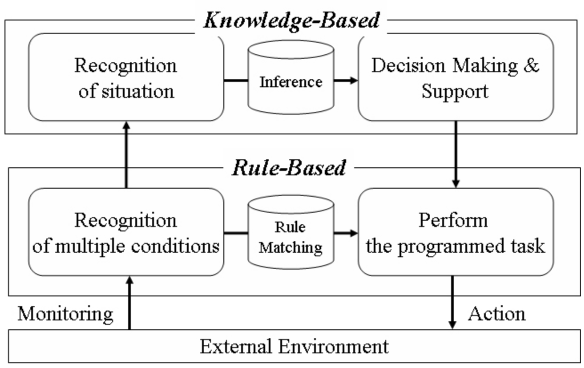

Fig. 2 Structure of a knowledge base

The methods of utilizing the built-up knowledge base efficiently can be classified into the bottom-up and top-down approaches. The top-down approach, which is also known as 'divide and conquer', consists of dividing a problem into sub-problems and then solving them, in order to solve the parent problem. The knowledge for solving problems can be classified into four categories: equations; rules; decision making; and experience data, as shown in Figure 3 [8].

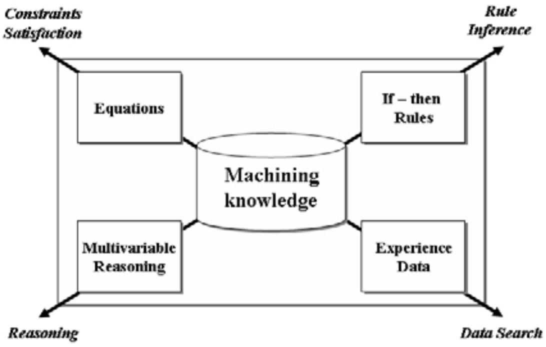

Fig. 3 Classification of four categories in the knowledge base

As for the methodologies for utilizing the knowledge in such categories, the following constraints must be taken into account: satisfaction, rule inference, reasoning, and data search.

Table 1. Classification and examples of rules

Term		Definition	Example
Term		Definition of term	Compensative value
Fact		The fact that inter-links one term with another	Compensative values are calculated with temperature
Rule	Constraints	Conditional statement judged as True/False	If temp. is 50℃, the compensative value is 2 *um*
	Guideline	Recommending conditional statements including judgment as True/False	Temp. exceeding 100℃ is not recommended
	Action Enabler	Judge as True/False, execute event, message or action	Start-up oil cooler when temp. exceeds 70℃
	Workflow	Control flow between Rule Sets	Go to Rule Set to reset cutting condition if temp. exceeds 70℃
	Computation	Rule including calculation algorithm	Compensative Value = F (temp. Xdxdy)
	Inference	Judge the condition to set up new factor and influence on the inference	No application of compensative value if temp. is below 25℃. Stop oil cooler if there is no compensative value application.

Knowledge can be expressed in numerous ways; however, the application of a methodology that uses rules to express knowledge is one of the most common ways. A rule-based knowledge expression should enable the easy ordering of the results obtained from preceding research and support the user in correct decision-making by making possible the easy modification of the constructed rules whenever necessary. Table 1 presents the classification and examples of the rules.

Knowledge can provide more flexible and diverse decision making functionalities than an algorithm method, which gives results in accordance with predefined rules and sequences. The knowledge developed exclusively for the machine tools in this study can automatically provide the values for compensating thermal deformation errors. A knowledge base, which is the collection of such knowledge, was built with the model equation obtained from the thermal deformation experiment as its building rule. A rule is a definition of a certain fact, so structured as to execute the following clause when the preceding clauses have been satisfied. In this study, the model equation obtained was used as the calculation rule.

2.2 Prediction models

A variety of machining information is present in machine tools. Various information types, including high-speed machining techniques such as machining conditions, the automatic decision of the tool path which can be applied commonly to all machine tools, and operation techniques such as status monitoring, fault cause analysis and compensation of thermal errors, are used by specific devices.

Thermal errors account for approximately 70% of all the errors that arise in machine tools [9]. In this study, a prediction model capable of compensating the thermal error to minimize it was developed and implemented in the knowledge base in equation form.

To build a thermal displacement prediction model, experiments were conducted on thermal displacement, and the temperature and displacement were recorded. The prediction model provides the displacement values in 3-axes, with the input of the temperature values at the 4 measurement points. Multiple linear regression analysis and neural network analysis methods were used for the model.

The multiple linear regression method is used for prediction and analysis through model estimation by building a mathematical model which represents the relations between the variables, and then entering the observed values of the variables into the model [10]. To this end, 3 linear regression equations are required, as shown in Fig. 4, because 4 independent variables including X, Y, Z, and the atmosphere to explain the relations among the 1 response variable and several explanatory variables, and the 3 displacements in the x, y, and z axes are produced.

$$Y_1 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$
$$Y_2 = \beta_5 + \beta_6 X_1 + \beta_7 X_2 + \beta_8 X_3 + \beta_9 X_4$$
$$Y_3 = \beta_{10} + \beta_{11} X_1 + \beta_{12} X_2 + \beta_{13} X_3 + \beta_{14} X_4$$

Y_1: X axis displacement, Y_2: Y axis displacement, Y_3: Z axis displacement
X_1: X axis temperature, X_2: Y axis temperature, X_3: Z axis temperature
X_4: atmosphere temperature, $\beta_{0\text{-}14}$: regression constant

Fig. 4 Equations of regression model

While various prediction models utilize neural networks, including the Hopfield neural network, the multi-layer percept theory, the competitive learning neural network, the self-organizing neural network, and the adaptive resonance theory neural network, a neural network using a multi-layer percept theory was established to build the prediction model for thermal displacement [11].

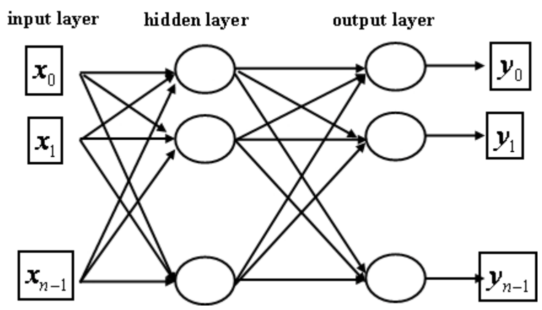

Fig.5 Multi-layer percept theory of a Neural Network

The multi-layer percept theory model, which is suitable for pattern recognition and function approximation, has one or more hidden layers between the input and output layers, as shown in Fig. 5. The learning algorithm is the error back propagation method, which adjusts the weight(s) of the hidden layer(s) and the output layer. This method minimizes error - on the basis of the said adjustment - by varying the weights of the input layer and the hidden layer(s).

The neural network in this study has a 2-layer structure. The numbers of the neurons in the input layer, hidden layer, and output layer are 4, 6, and 1, respectively. To reduce errors, the combined strengths and critical values of each axis were measured with the back propagation algorithm using the gradient descent method.

3 Implementation

3.1 Open-type controller

Since the 1990s, the trend in CNC technology has been shifting from hardware to intelligent, knowledge-based software, in accordance with the application of open-type controllers (PC-NC) using high performance PCs and the related technologies [1]. Since open-type controllers can enhance user convenience and implement the wide functionalities of the PC in NC devices, their advantages have been widely recognized and they are now used for various purposes.

The 2 prediction models described above were constructed in the knowledge base in order to compensate the thermal errors. The knowledge base basically controls the rule and is programmed using JAVA.

The open-type controller technology has solved various problems in the closed-type controller. The open-type controller enables the addition of appropriate NC functions as required, and is not restricted to the NC functions provided by the NC developers. It maximizes user convenience in conjunction with other application programs and can increase work efficiency.

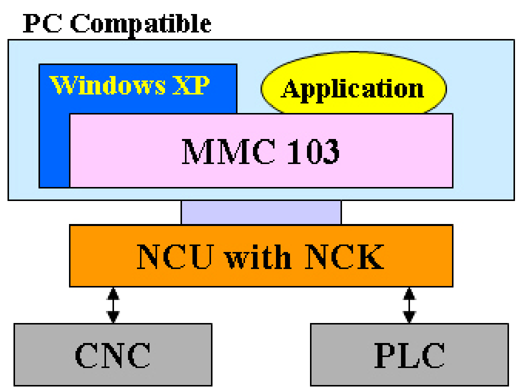

Fig. 6 Software structure of the open controller

Fig. 6 shows the software structure of the open-type controller used in this study. The NC Kernel can send the commands created in the application by MMC (Man Machine Control) to the CNC and PLC. The knowledge base, including the developed prediction model, can be installed in the application area too.

In this study, the open-type controller for a machining center was an 840D, SIEMENS, which can execute user software on the basis of the software structure described earlier. Fig. 7 shows a screen shot of the MMC (Man Machine Control) of the 840D open-type controller. The software allows the construction of an interface by importing user defined software such as compensation software.

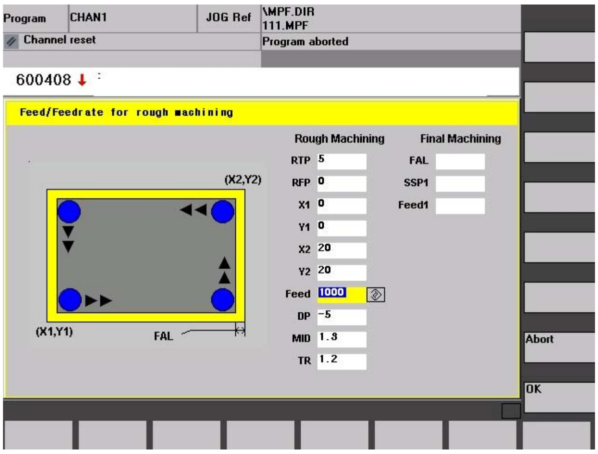

Fig. 7 MMC of the 840D open-type controller

3.2 Offset compensation using a knowledge base

The errors that occur in machine tools can be classified into dynamic and static errors. The former are caused by vibration and/or chatter of the machine or vibration of the spindle, while the latter are caused by geometric errors in the assembly characteristics of the structural system – such as guide ways, column, and ball screw – and thermal errors.

Studies related with thermal compensation of machine have been conducted with regard to the improvement of structural design, the cutting off heat sources using an oil cooler, and so forth as well as model-type compensation. However, since structural improvement and heat source cooling methods are still liable to thermal deformation, the compensation method of offset values is widely used in workshops in order to improve the precision of machine tools.

The accuracy of the developed prediction model was tested with a '3-axes milling machine' installed with an open-type controller. Thermocouples were installed in order to measure the temperature. A gap sensor of the eddy current-type was installed for comparison with the actual displacement. The thermal displacement test complied with the ISO/DIS 230-3, BS3800: part3: 1900 and ASME B5.54-1992 specifications [12].

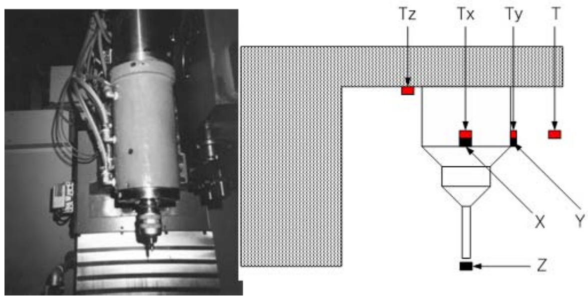

Fig. 8 Test environment for creating thermal errors

As shown in Fig. 8, for the test environment aimed at creating the thermal displacement prediction model, the temperature changes that occurred during the operation of the machining center were measured using the isolated thermocouple input modules installed around the vertical machining center [13]. The temperature was measured at least once every 10 minutes. The measurement data have to be obtained for at least 4 to 6 hours in order to secure reliability. In this test, the thermal displacement was measured, together with the temperature changes, with a gap sensor in the operational range of 4000 to 6000 rpm (which is the most common working range in vertical machining centers) without a load. The measurements were obtained for application to the actual operational conditions of the machine tool.

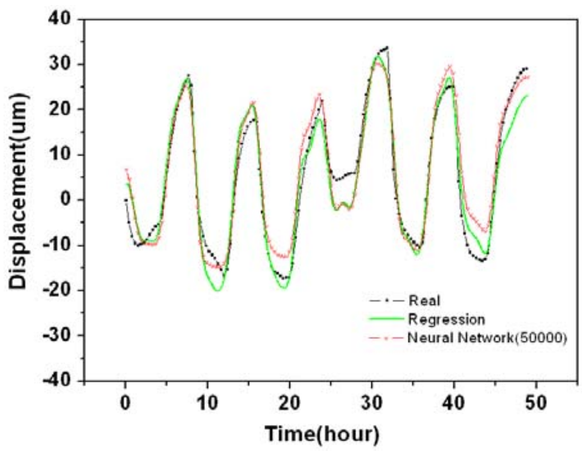

Fig. 9 Comparison between actual value and predicted value using model (z-axis)

Through the test, it was analyzed that the thermal displacement in a vertical machining center was larger in the z and y axes than that in the x-axis. Fig. 9 shows the comparison of the z axis between the actual displacement value and the value predicted by the linear regression model and the neural network model. The neural network model is learned 50000 times.

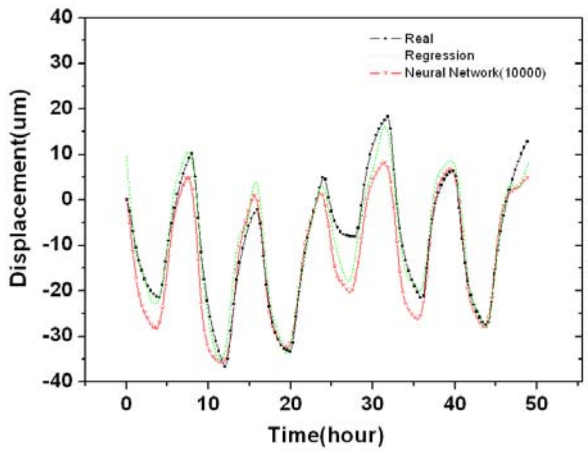

Fig. 10 Comparison between actual value and predicted value using model (y-axis)

Fig. 10 shows thermal error in the y-axis. The analysis results showed that the neural network method had better accuracy than the multi-linear regression model, as was the case with the z-axis. The results in the y-axis were obtained by 10,000 cycles of learning with the neural network.

Considering the analysis results, the thermal errors occurring in machine tools are substantial. In a vertical-type machining center, the largest deformation occurred in the z-axis, requiring the compensation of thermal errors for precision machining.

It was analyzed that the neural network model has better accuracy than the regression analysis model because neural network model have learning algorithms and can separate nonlinearity such as exclusive-or unlike regression analysis model; however, the linear regression model was used for the operation of the actual open-type controller because it is simple. Using the model equation thus analyzed, the compensation value was estimated in the computation rule form in the rule base.

In the Fig. 11, only the regression constant of the linear regression model installed in the NC was changed in accordance with the change in the environment in order to carry out the compensation of the thermal displacement with the modified regression model equation. With this method, the open controller can carry out the compensation by calculating the displacement of the machine with the temperature data obtained on a real-time basis.

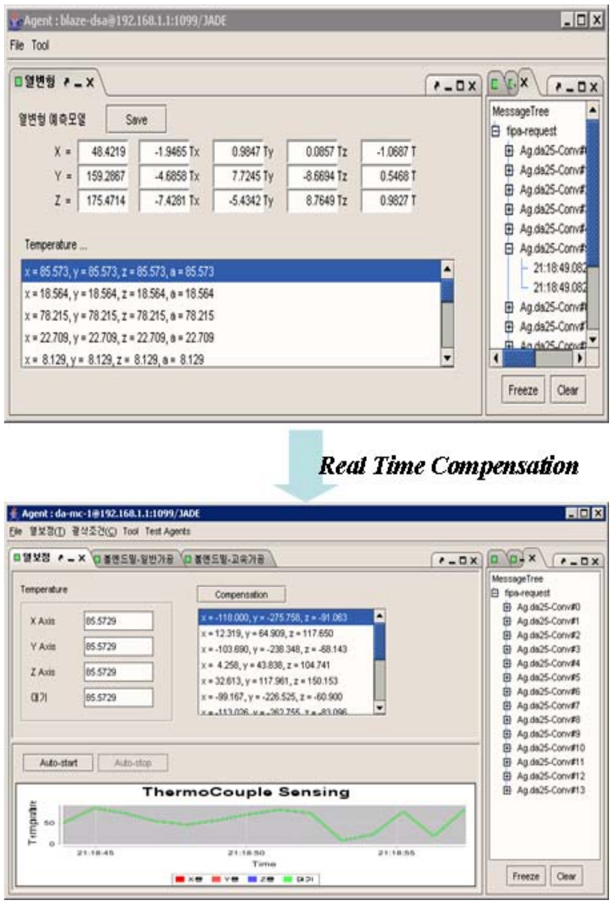

Fig. 11 Real-time compensation using the multi-linear regression model

The available compensation methods are NC code correction command, analog compensation, which inserts the analog voltage to the position feedback signal of the servo system, digital compensation, which compensates the position values of the servo system by transmitting digital values to the open controller via a communication port, and the offset compensation. The offset value compensation is the easiest method for operators. Fig. 12 shows a window of the automatic compensation of the offset value in an open controller.

As shown in Fig. 12, the offset value is modified by the NC programs, which is enabled by calling the offset value modification NC program during the operation of the machining NC programs. The most common method is to call the M code (M98 and M99), which is a sub-NC program; to shift the reference coordinate by the value calculated using thermal deformation prediction software.

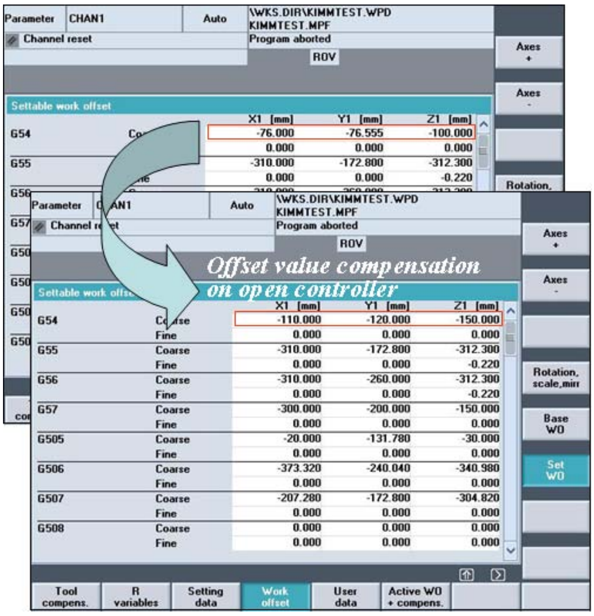

Fig. 12 Offset values compensation by open controller

4 Conclusion

Intelligent machine tools can be detect environmental changes and respond autonomously. This ability is determined by the volume of the process knowledge in the CNC of the machine. This study is focused on the construction and operation of a knowledge base which can compensate thermal error, which is the most important cause of errors in machine tools. To this end, thermal deformation experiments were conduced to create two prediction models of linear regression analysis and neural network models. Considering the accuracy with the actual deformation and the applicability with the open controller, the regression analysis model was used to construct the knowledge base for the offset compensation in real machine tools. In the actual process, precision was improved by approximately 23% compared with that achieved by manual compensation of the offset values. This is due to the faster collection of the temperature of the axis and automatic offset compensation. Precision was measured with a 3D measured machine (CMM). Productivity could also be improved by automatic compensation, leading to a shorter process cycle. Further studies will be conducted to build an infrastructure for the implementation of intelligent machine tools by constructing a knowledge base containing more machining information.

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