AN UPDATE OF THERMAL ERROR COMPENSATION MODEL VIA ON-MACHINE MEASUREMENT

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Software compensation is state-of-the-art technology used to reduce CNC machine tool thermal errors, and it belongs to a key intelligent functions of modern machine tools. However, a pretrained and nonadaptive model may not be accurate and robust enough for long-term application. This research presents a transfer function based thermal error compensation model updated via on-machine measurement. A mathematical model is implemented into the machine management software of a large horizontal machining centre to compensate for thermal errors in real time using C#/C++ programming language. The results show that after the thermal error compensation model is updated via on-machine measurement, the prediction accuracy, measured as peak-to-peak values, and the normalized root mean squared error are significantly improved. The prediction accuracy of the compensation model updated via on-machine measurement strongly depends on the sampling interval of the on-machine measurements.

KEYWORDS

Thermal errors, Compensation, Accuracy, On-Machine measurement, Probing, Machine tool

1 INTRODUCTION

In the context of Industry 4.0 and other national policies, intelligent functions of computer numerical control (CNC) machine tools are becoming a crucial part of contemporary technological development in the manufacturing industry. One of the most challenging issues is continuous part quality maintenance through reduction of machine tool thermal errors. The state-of-the-art technology to reduce CNC machine tool thermal errors is online error compensation based on thermal error estimation models [Mayr 2012].

To develop a thermal error compensation system, the positional errors of a cutting tool relative to a workpiece should be estimated based on a mathematical model. Then, thermal error compensation is achieved by inserting the compensation signal generated from the thermal error model into the feedback loop of the servo system.

Many error compensation models have proven capable of mitigating thermally induced errors using temperature sensor measurements. An overview of the thermal error modelling methods that have been researched and applied is presented in [Li 2021]. In these methods, the predicted accuracy and robustness of the thermal error model play an important role in the compensation effect. Robustness reflects the holding capacity of predicted accuracy under various external conditions. It is an important indicator of the thermal error compensation effect of machine tools [Liu 2017].

However, the low prediction accuracy and poor robustness of these models under varying manufacturing conditions and the thermally varying surrounding environment (changing boundary conditions) have also been recognised [Mares 2013], [Miao 2013]. These accuracy and robustness issues emerge because thermal error compensation models strongly depend on the characteristics of the training (calibration) data. However, model training conditions cannot typically cover all of the machine working conditions that are necessary to derive an accurate and robust model due to limited resources and limited availability of machine time for testing. In addition, potential users of thermal error compensation technology (typically machine tool manufacturers) hesitate because of the lengthy period of time required to characterize the thermal behaviour of a machine tool. It takes many hours for a machine structure to reach its thermal steady state and then to cool it down to its original state. As a result, thermal error compensation models represent physics incompletely and the robustness in the prediction performance of thermal behaviour that differs from the training phase may be poor. Therefore, various model update mechanisms and updates of model inputs have been developed to refine the prediction accuracy and model robustness according to continuous changes in machine operation status. This is especially essential in the case of small batch production, where the manufacturing processes change frequently and the pretrained thermal error model is usually not robust enough.

One strategy for improving robustness has been to update the model parameters periodically using process intermittent probing to identify any changes in thermal errors at the tool centre point (TCP). Numerous on-machine measurement methods can be employed to provide thermally induced displacements as feedbacks for the compensation model. State-of-the-art on-machine and inprocess measurement systems and sensor technologies were presented by Gao et al. [Gao 2019]. As on-machine touch probe systems have become common accessories in a wide variety of precision machine tools, their application seems a logical and promising solution for updating thermal error models.

One challenge with the implementation of this approach is the reduction in machine productivity, since the machining cycle may be unnecessarily interrupted during probing. Early approaches employed process intermittent probing to constantly update the model. Mou [Mou 1997] developed an adaptive error correction method using feature-based analysis techniques for error correction of machine tools. Process intermittent gauging and state observation techniques were integrated to track the thermal effect in real time and fine tune the error model coefficients as the cutting process proceeds. A multiple linear regression model was derived to identify the time-varying thermally induced errors and form the state observer model. These techniques, however, were based on the conventional static thermal error model. As a result, the thermal error model thus developed may not accurately reveal the dynamic nature of the thermoelastic system.

Yang and Ni [Yang 2005] developed an adaptive model for thermal error estimation based on a recursive dynamic modelling strategy. This approach significantly improved the accuracy and robustness of the thermal error model by considering the dynamic effects of machine thermoelastic systems. The intermittent probing was carried out periodically using a sampling time of 3.5 minutes. This means that the probing may occur when not required and consequently it decreases machine productivity.

Blaser et al. [Blaser 2017] proposed thermal error compensation of 5-axis machine tools that is extended by on-machine measurements. The information gained by the process intermittent probing is used to adaptively update the model parameters. During the compensation phase, periodic on-machine measurements are essential to control the required precision of the compensation model. However, periodic on-machine measurements significantly reduce the obtainable machine tool productivity. Furthermore, Zimmermann et al. [Zimmermann 2021] replaced the periodically performed on-machine measurements with adaptive on-machine measurements, which are triggered based on temperature measurements when unknown thermal conditions occur, to optimize the trade-off between the precision and productivity of the proposed compensation model.

Another approach to increasing the robustness of thermal error compensation models is to update the model inputs.

In most cases, this approach entails using temperature values of representative points of the machine structure to calculate the resulting displacements at the TCP by thermal error models. However, even data from a numerical control (NC) system (such as spindle speed or spindle load) are possible model inputs, e.g. [Brecher 2004]. Furthermore, this method can be combined with adaptive models by updating the model parameters mentioned above.

Ariaga et al. [Ariaga 2022] introduced an approach for informing the model update scheme by making use of proper orthogonal decomposition (POD) to perform subspace clustering of temperature measurement data. Probing cycles are then performed to update the model if the observed clusters differ significantly from those observed in the training data. A similar adaptive compensation approach was employed by Inigo et al. [Inigo 2022]. POD-based compensation models were tested via a finite element model of a milling machine column as a case study. The proposed method is capable of identifying thermal behaviour that differs from the training phase of the compensation model. Thus, its inputs can be adapted according to the temperature behaviour. Zimmermann et al. [Zimmermann 2021] developed an adaptive input selection method for data-based thermal error compensation models, which enables automated and adaptive selection of the optimal model inputs even after the initial model training. Adaptive input selection was applied to the thermal error compensation of 5-axis machine tools presented by Blaser et al. [Blaser 2017].

The purpose of the presented research is to examine how the compensation model update via on-machine measurement affects prediction accuracy and long-term stability. A compensation model of thermally induced relative displacements in the Z-direction between the TCP and the table of the large horizontal machining centre caused by spindle activity based on transfer function (TF) was selected. The modelling approach, which uses TFs, presents an established dynamic method with a physical basis, see [Yang 2005], [Mares 2013], [Blaser 2017] and its modelling and calculation speed are suitable for online applications. TF-based compensation methods significantly improve the accuracy and robustness of thermal error models by considering the dynamic effects of machine thermoelastic systems, as shown in previous studies, e.g., [Brecher 2004], [Mares 2013].

However, the structures of compensation models using TFs for prediction of thermally induced displacements in previous research papers differ. Despite the fact that different heat sources are permanently combined in real machining conditions, which cause complex thermal errors at the TCP, much of the research has focused on approximation of only one active heat source in the total machine tool thermal error, e.g., spindle [Yang 2005], rotary table [Blaser 2017].

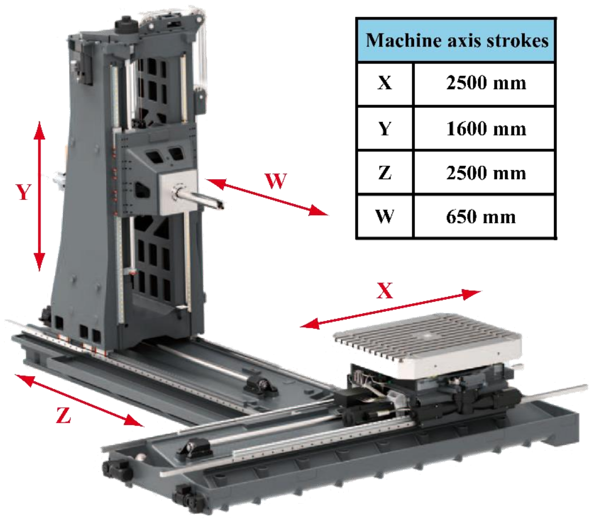
Mares et al. [Mares 2020] proposed a comprehensive model concept which is based on the partial linearisation of the issue. This means isolating particular thermal elements, solving them separately, and building an approximation model with their subsequent superposition. This model concept can be extended by updating the model parameters via on-machine measurement, as shown in Section 4.

The simplicity of the calibration and application of the compensation model to the machine tool control system, along with the minimization of the number of measured model inputs, are advantageously employed. The model may be applied without installing additional external gauges (see [Brecher 2004]), and the model is easily extensible and modifiable in real time (which is advantageous for machine learning principles and intelligent solutions within the machine tool).

2 EXPERIMENTAL SETUP

2.1 Machine tool

The tested machine tool is a large horizontal machining centre with table dimensions of 1250 x 1250 mm, and a retractable spindle with a diameter of 112 mm was used to demonstrate the method. The machine tool has a spindle with 31 kW power, and the maximal spindle speed is 6000 rpm. The machine tool structure and strokes of the movable axes are presented in Fig. 1.



Machine axis strokes	
X	2500 mm
Y	1600 mm
Z	2500 mm
W	650 mm

Figure 1. Structure of the tested horizontal machining centre.

The large horizontal machining centre is equipped with indigenous temperature sensors (Pt100, Class A, 3850 ppm/K) placed close to the main heat sources by the machine tool manufacturer. Today, almost every spindle is equipped with sensors to monitor the bearing temperature, including the tested machine centre. Since the thermal error compensation model will focus on spindle activity, the key model input is the temperature measured close to the spindle front bearing (ΔT_{in}). Tests for thermal distortion caused by rotating spindles were carried out according to the ISO 230-3 international standard [ISO 230-3 2020]. Eddy current sensors (sensor type: PR6423, produced by Emerson [Emerson 2013]) supported by a magnetic stand were used for noncontact sensing of relative displacements in the X, Y, and Z directions between the TCP represented by a test mandrel (length, 125 mm; diameter, 40 mm) and the working table of the horizontal machining centre. Displacements were sensed in micrometre resolution. The experimental setup on the horizontal machining centre per ISO 230-3 is shown in Fig. 2. The measurement point is placed at the side of the table to sense thermally induced displacements at the zero position of the retractable spindle position (W = 0 mm).

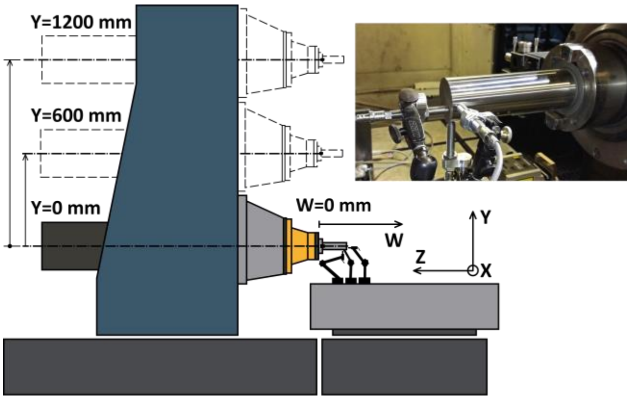


Figure 2. Experimental setup.

Data were acquired using a cRIO 9024 programmable automation controller (PAC) [National Instruments 2015] with LABVIEW software (the sampling rate was 1 s). Temperatures installed by the machine tool manufacturer and other NC data such as effective power, electric current, torque, feed rate and motor temperatures were logged using OPC UA (Open Platform Communications United Architecture) communication between the machine controller and the PAC cRIO 9024.

2.2 *Measurement cycle*

A one-dimensional network of spindle excitation points was proposed for the Y-axis (the vertical position of the spindle stock on the column) with a constant W-axis position (retractable spindle position W = 0 mm). The spindle excitation was performed in 3 different linear Y-axis positions in total (Fig. 2).

Tests with a constant spindle speed, along with a spindle speed spectrum test, were designed to verify the validity of the thermal error compensation model updated via on-machine measurement (Tab. 1).

Measurement n.	Spindle speed [min^{-1}]	Y [mm]
1	4000	0
2	2000	600
3	4000	1200
4	4000	600
5	4000	0-1200

Table 1. Spindle speed and the vertical Y-position of the spindle stock on the column during the tests.

Each measurement in Tab. 1 was followed by a cooling phase until the machine tool was close to a steady state with the surrounding environment, which took several hours. As a result, one measurement was conducted per day. Data acquisition was only realized during the heating phase.

The heating phase of measurement no. 1 was employed for a calibration test to identify a thermal error compensation model (see Section 3.1). Verification tests (measurements no. 2 to no. 5) were carried out under different conditions than the calibration (training) test. The spindle speed and the position of the heat source (the vertical position of the spindle stock on the column) varied during the verification tests; see Tab. 1.

3 COMPENSATION MODEL FOR THERMAL ERRORS

A discrete TF is used to describe the link between the excitation and its response as mentioned in Section 1

$$y(t) = u(t) \cdot \varepsilon + e(t), \tag{1}$$

$$y(t) = \frac{(a_n Z^{-n} + \ldots + a_1 Z^{-1} + a_0 Z^0)}{(b_m Z^{-m} + \ldots + b_1 Z^{-1} + b_0 Z^0)} u(t);\ m > n. \tag{2}$$

The vector *u(t)* in equations (1) - (2) is the TF input in the time domain, *y(t)* is the output vector in the time domain, ε represents the TF in the time domain, *e(t)* is the disturbance value (further neglected), a_n is the calibration coefficient of the TF input, b_m is the calibration coefficient of the TF output, *n* is the order of the TF numerator, *m* is the order of the TF denominator and *Z* is the complex number.

The differential form of the TF (generally suitable for programming languages like Python or C#/C++) is introduced in Eq. (3) as

$$y(k) = \frac{u(k-n)a_n + \ldots + u(k-1)a_1 + u(k)a_0}{b_0} - \frac{y(k-m)b_m + \ldots + y(k-1)b_1}{b_0}, \tag{3}$$

where *k-n* (*k-m*) signifies the *n*-multiple (*m*-multiple) delay in sampling frequency.

Linear parametric models of autoregressive with external input (ARX) or outputs error (OE) identifying structures are used with the help of Matlab Identification Toolbox [Ljung 2020]. The linear parametric model ARX as an optimal model structure (with the best fitting quality and robustness) is discussed in [Mayr 2018] where MISO (multiple input single output) models handling with arbitrary TCP measurements are introduced.

Excitations in the case of the employed TFs mean temperatures measured close to heat sinks or sources, and the responses stand for the linear deflections in the examined directions.

The approximation quality of the simulated behaviour is expressed by a local peak-to-peak approach

$$p2p = |\max(\delta Z_{mea} - \delta Z_{sim})| + |\min(\delta Z_{mea} - \delta Z_{sim})|, \tag{4}$$

where *p2p* is the abbreviation for a peak-to-peak evaluation method, δZ_{mea} in Eq. (4) represents the measured output (thermal displacement at the TCP in the Z-direction) and δZ_{sim} is the simulated (predicted) thermal displacement obtained by applying the thermal error compensation model.

In this paper, the approximation quality of the identified models is also expressed by the *fit* value, the normalized root mean squared error expressed as a percentage, see [Ljung 2020], defined as follows

$$fit = \left(1 - \frac{\| \delta Z_{mea} - \delta Z_{sim} \|}{\| \delta Z_{mea} - \overline{\delta Z}_{mea} \|}\right) \cdot 100. \tag{5}$$

The $\overline{\delta Z_{mea}}$ stands for the arithmetic mean of the measured output (thermal displacement) over time.

The *fit* represents a global approach to express the approximation quality of the compensation model, it is a percentage value where 100% would equal a perfect match of measured and simulated behaviours.

3.1 Model identification

To reduce the major thermal error of the machine tool (in the Z-axis direction), a compensation ARX model was calibrated on measurement no. 1 (see Tab. 1). The input is the temperature measured on the spindle front bearing (ΔT_{in}) and the output is the displacement measured in the Z-axis direction (δZ_{mea}).

The TF-based model of thermal displacement in the Z-axis direction depending on the measured temperature is expressed by Eq. (6) as

$$\delta Z_{sim} = \Delta T_{in} \cdot \varepsilon, \tag{6}$$

where δZ_{sim} is the simulated output from the thermomechanical system (thermal displacement) and ε is the TF identified in the time domain.

Measured input (ΔT_{in}), output (δZ_{mea}) and simulated output (δZ_{sim}) employed in the TF model identification process are shown in Fig. 3 (all quantities are expressed in relative coordinates). The approximation quality is *fit* = 89% and *p2p* = 16.6 µm.

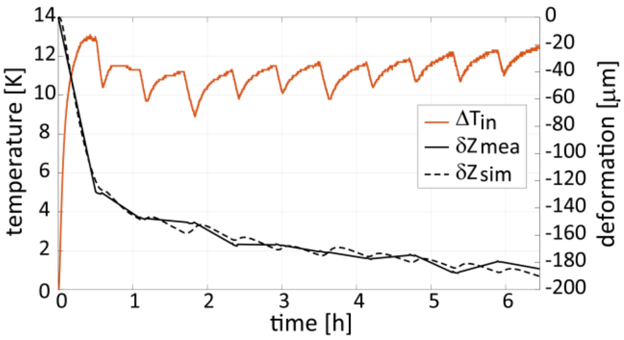


Figure 3. Calibration test setup for spindle rotation impact on large horizontal machining centre (measurement no. 1 at the position Y = 0 mm).

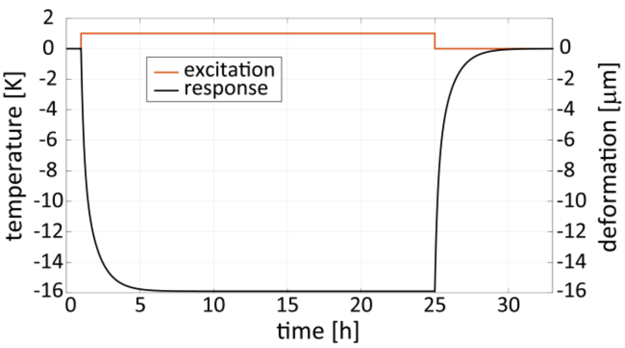


Figure 4. LTI step response of the identified TF.

The stability of the identified TF model is expressed by the LTI step response test shown in Fig. 4.

System excitation represents the sudden change of the key temperature equal to 1 K (red curve in the graph in Fig. 4), and system response is the predicted displacement at the TCP given by Eq. (6), see black curve in Fig. 4.

The established calibration coefficients a_n and b_m of the identified TF are summarised in Tab. 2. The order of the TF was selected based on the best *fit* value, see Eq. (5).

TF	Coefficients		
ε	a_0 (µm·K^{-1})	a_1 (µm·s^1·K^{-1})	a_2 (µm·s^2·K^{-1})
	-0.0130427	0.0130361	0
	b_0 (–)	b_1 (s^{-1})	b_2 (s^{-2})
	1	-1.9982716	0.998272

Table 2. Coefficients of the identified TF describing the influence of spindle rotation on thermal error at the TCP in the Z-axis direction.

3.2 Industrial implementation of the compensation algorithm in the machine tool controller

Recently, machine tool control systems have been used not only to control the movement of machine tools in order to execute NC programs and interpolation but also to implement other functionalities (e.g. diagnostic systems, software compensations, measurement applications, technological modules, etc.) and to communicate with other systems (MES, ERP, other production machines, measuring equipment, etc.). To fulfil these requirements, standard machine control systems can be extended with an additional programming environment (management software).

The tested large horizontal machining centre, produced by the TOS VARNSDORF company, is equipped with a standard Siemens SINUMERIK 840D sl CNC controller and a unique programming environment (TOS Control management software) developed by CTU in Prague in collaboration with TOS VARNSDORF.

TOS Control integrates a standard machine control system (Siemens Sinumerik 840D sl or Heidenhain TNC640) and additional functions through applications which further extend the range of machine use and facilitate its full integration with the Industry 4.0 concept. The management software consists of a start screen with the system main menu and the application modules (applications which can represent various intelligent machine tool functions, including software thermal compensation).

Applications are developed in C#/C++ programming language and use a unified communication interface within the TOS control system. This infrastructure enables easy expansion of the system with additional applications from both the operators' and developers' points of view, as well as expansion with additional control systems.

Thus, the thermal error model in Section 3.1 is implemented in the TOS Control programming environment as an independent application developed in C#/C++ programming language to compensate for thermal errors at the TCP in real time.

3.3 Application of the compensation model in verification tests

The model identified in Section 3.1 was applied to the heating phase of measurements no. 2 to no. 5 (see Tab. 1).

Fig. 5 shows the behaviour of the front bearing temperature ΔT_{in}, ambient temperature ΔT_{amb} behaviour over time, the position of the TCP in the Y-axis direction and the spindle speed during verification tests on the large horizontal machining centre.

The data measured during the heating phases (active heat source represented by spindle rotation) of measurements no. 2, 3, 4, 5 according to Tab. 1 are presented in Fig. 5.

The cooling phases of each measurement are omitted as the data acquisition was not realized during the cooling phases. Moreover, the heating phases of measurements no. 2 to no. 5 are linked together in order to present the measured data in a single graph in Fig. 5. This data representation is in accordance with the intended compensation model update via on-machine measurement presented in Section 4.

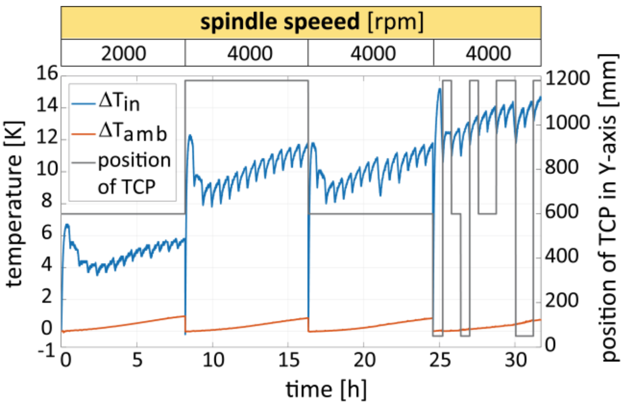


Figure 5. Measured temperature at the spindle front bearing, ambient temperature, spindle speed, and position on the Y-axis during verification tests (measurements no. 2, 3, 4, 5).

On-machine measurement (typically by touch probe) represents the common practice of using a machine tool to measure the workpiece while it is still on the machine rather than moving the workpiece to the metrology room. It significantly rectifies geometric errors on the part before the part is removed from the machine tool. Consequently, it decreases the scrap machined parts.

In principle, on-machine probing can be used for direct compensation of thermal error at the TCP (besides other errors) thanks to intermittently measured resulting displacements at the machine tool TCP (e.g. a test mandrel clamped in the spindle with noncontact displacement sensors placed on the working table as shown in Section 2.1 or a touch probe in combination with a datum sphere mounted on the working table).

Subsequently, the measured displacements can be superposed to the desired position of the particular axis. The significant benefit of the on-machine probing approach is that the thermal displacements which have to be compensated are directly available. Nevertheless, a sufficient sampling rate of the on-machine measurement has to be selected, as interruptions to the process lead to lower machine tool productivity.

Moreover, the resulting displacements at the TCP obtained by on-machine measurement can be employed as feedbacks for the compensation model to refine its prediction accuracy. Consequently, it leads to a lower sampling rate of the on-machine measurement. Since a manufacturing process is basically started from an initial workpiece alignment, the on-machine measurement is often the first task that must be conducted. Subsequently the compensation model is supposed to be always updated at the beginning of each work shift (see Section 4).

Fig. 6 depicts the thermal displacement measured at the TCP in the Z-direction (solid blue curve) and the predicted thermal displacement (solid red curve) of the large horizontal machining centre obtained from the TF model calculated by Eq. (6) for the verification tests (measurements no. 2 to no. 5). The data in Fig. 6 are presented analogously to Fig. 5 (linked heating phases of the verification tests without the cooling phases).

The approximation quality expressed by the *fit* value given by Eq. (5) is only 41.5%. The approximation quality expressed by the *p2p* value of the thermal error compensation model according to Eq. (4) is 64 µm for the verification tests.

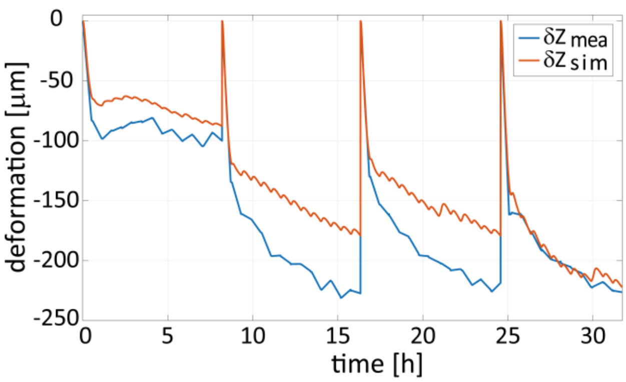


Figure 6. Measured and simulated thermal displacement in the Z-direction during verification tests (measurements no. 2, 3, 4, 5).

The identification of the TF-based model is derived from measurement no. 1 which was set at the zero position of the linear Y-axis (the lowest vertical position of the spindle stock on the column, Y=0 mm). The model training conditions applied in Section 3.1 evidently differ from the machine tool working conditions during the verification tests (measurements no. 2 to no. 5, see Tab. 1).

Firstly, the position of the heat sources (the vertical position of the spindle stock on the column) varied during the verification tests.

Secondly, the spindle speed also varied during the tests. Previous studies (e.g., [Mares 2020], [Horejs 2022]) showed that a TF-based compensation model is capable of sustaining the high approximation quality (stability in prediction performance) in the event of a changeable spindle speed that differs from the training phase. However, in the previous studies mentioned above, the compensation model of a medium-sized CNC machining centre was investigated only in one spindle excitation position.

On the contrary, the verification tests on a large horizontal machining centre (see Section 2) were intended to excite the heat source, represented by the spindle, in various machining centre positions. It results in low compensation model prediction accuracy of thermal errors at the TCP in the Z-direction, as shown in Fig. 6 (*fit* = 41.5%, *p2p* = 64 µm).

4 COMPENSATION MODEL UPDATED VIA ON-MACHINE MEASUREMENT

Due to the complexities of manufacturing processes, real machining conditions may not be identical to the experimental conditions used for the compensation model derivations shown in Section 3.3.

Consequently, the pretrained and nonadaptive thermal error model may not be accurate or robust enough for long-term application. A model update mechanism needs to be developed to refine the thermal error model according to continuous changes in operation status.

Therefore, to increase the robustness of the prediction performance of thermal error Z-direction displacement, the TF model was updated using on-machine measurement with eddy current type displacement sensors and the test mandrel (see Section 2.1).

4.1 *Principle of the compensation model update*

The principle of the proposed model update consists in using the gain $gain_{UP}^{\tau}$ to improve the approximation quality of the thermal error model. The gain is defined as follows

$$gain_{UP}^{\tau} = \frac{\delta Z_{mea}(t_u)}{\delta Z_{sim}(t_u)}, \tag{7}$$

where $\delta Z_{mea}(t_U)$ represents the measured thermal displacement in the Z-axis direction at times t_U, $\delta Z_{sim}(t_U)$ is the simulated thermal displacement obtained by the thermal error compensation model according to Eq. (6), see Section 3.1, τ is the on-machine measurement sampling interval.

The adjustable parameter of the model update is the sampling interval τ. The TF-based compensation model is always updated via on-machine measurement of the actual TCP displacements after time τ has elapsed. Therefore, the model will be updated only at times $t_u = \tau \cdot k$ (k=1, 2, 3, …).

The initial value of $gain_{UP}^{\tau}$ is equal to 1 and the gain value is periodically updated at the sampling interval τ. The simulated displacement calculated by the updated compensation model $\delta Z^{\tau}_{sim\ UP}$ is then given by Eq. (8) as

$$\delta Z^{\tau}_{sim\ UP} = \delta Z_{sim} \cdot gain_{UP}^{\tau}. \tag{8}$$

This approach enables rapid updating of the original thermal error compensation models with minimal additional modelling effort. The substantial advantage of the proposed solution is that the original compensation model parameters can remain unaffected, thus preserving model transparency. Instead the gain is modified to multiply the original compensation model.

Moreover, this method also provides insight into the required sampling frequency of the on-machine measurement and its effect on the resulting approximation quality of the updated model, which is discussed in Section 4.2.

4.2 *Analysis and comparison of prediction results*

The model update method was tested for various values of the sampling interval τ. Specifically, the parameter τ was set as τ = {30, 60, 90, 120, 150, 180} minutes.

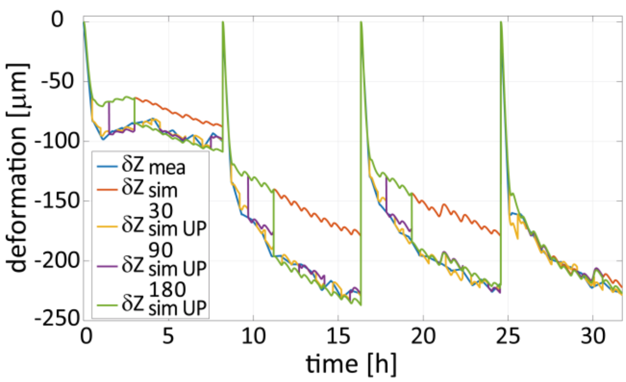


Figure 7. Comparison of prediction results using the model update method (for selected parameter τ values) with the original compensation and the thermal displacement measured in the Z-axis direction.

Fig. 7 shows the measured, simulated displacement in the Z-axis direction (using the compensation model identified in Section 3.1) and the predicted displacements by the updated compensation model according to Eq. (8) using sampling interval values τ = {30, 90, 180} minutes. Compensation results for the other sampling interval values of the on-machine measurement τ are shown in Fig. 9.

Fig. 8 depicts the residuals for the simulated displacement in the Z-axis direction using the model identified in Section 3.1 (Eq. (6)), residuals for the compensation model updated via on-machine measurement according to Eq. (8) for set values of the sampling interval τ = {30, 90, 180} minutes.

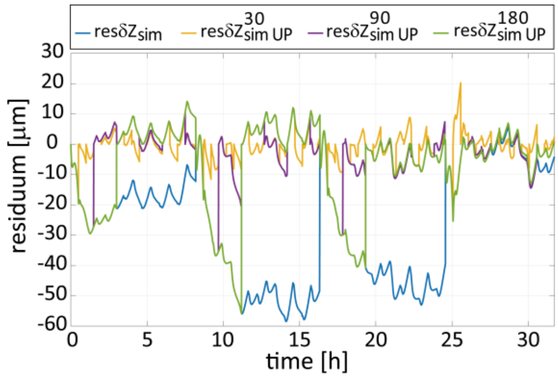


Figure 8. Comparison of residual errors using the model update method (for selected parameter τ values) with the original compensation.

The residual value is expressed as

$$res = \delta Z_{mea} - \delta Z_{sim}. \tag{9}$$

The approximation quality (*p2p, fit*) of simulated displacements in the Z-axis direction using the compensation model identified in Section 3.1 (dashed lines) and the approximation quality (*p2p, fit*) of the compensation model updated via on-machine measurement (see Section 4.1) depending on the selected value of the sampling interval parameter τ are shown in Fig. 9.

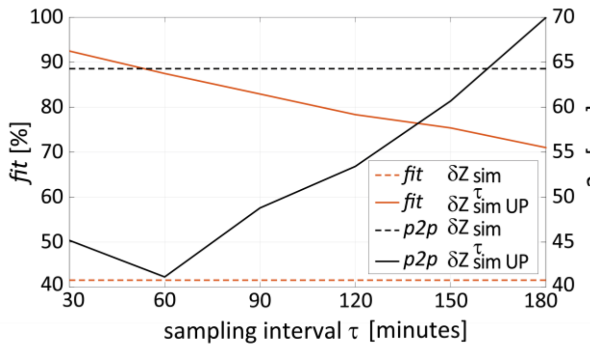


Figure 9. Approximation quality assessment for the compensation model with the model update method for different values of the parameter τ.

As mentioned in Section 3.3, the approximation quality of thermal behaviour during the verification tests expressed by the *p2p* value of the thermal error compensation model according to Eq. (6) is 64 μm (see black dashed line in Fig. 9) and the *fit* value is only 41.5% (see red dashed line in Fig. 9).

The *fit* value for the model updated via on-machine measurement (see Eq. (8)) increases from 56% to 92% (solid red line in Fig. 9) depending on the sampling interval τ (from 180 minutes to 30 minutes). The dependence of the *fit* value on the sampling interval τ is almost linear, as shown in Fig. 9. Thus, the prediction accuracy of the updated thermal error model by on-machine measurement is significantly improved.

The *p2p* value for the model updated by on-machine measurement is decreased from 70 μm to 43 μm depending on the sampling interval τ (from 180 minutes to 30 minutes). Updating the thermal error model via on-machine measurement generally has a positive effect on the resulting *p2p* value, as expected. However, the value of *p2p* is locally affected by the sampling interval τ, e.g. in the case of the sampling interval τ = 180 minutes the *p2p* value is even higher (70 µm) than the *p2p* value obtained using the original compensation model without updating via on-machine measurement (64 µm). Contrary to expectations, the best *p2p* value was obtained for the sampling interval τ = 60 minutes (*p2p* = 43 µm) and not for the shortest tested sampling interval (30 minutes) of on-machine measurements (*p2p* = 50 µm).

5 CONCLUSIONS

At present, thermal error software compensation is a fundamental part of intelligent modern machine tool functions to minimise thermally induced errors. To achieve effective control of the thermal error compensation of CNC machine tools, the prediction accuracy and robustness of the compensation model are particularly important. Furthermore, on-machine probing systems have become common accessories in a wide variety of precision machine tools. Thus, their application seems to be a logical and promising solution for thermal error model updates.

This paper provides new insight into the updating of thermal error compensation models using on-machine measurements to improve the prediction performance of the compensation algorithm.

First, experiments for thermal distortion caused by rotating spindles were carried out on a large horizontal machining centre according to the ISO 230-3 international standard. The main objective was to investigate the effects of the model update via on-machine measurement on the compensation results. Spindle excitation was realized in 3 different linear Y-axis positions.

Subsequently, a TF-based model was built to compensate for the thermal errors of the large horizontal machining centre. The modelling approach uses TFs, presents an established dynamic method, and its modelling and calculation speed are suitable for online applications. TF-based model identification is derived from measurement at the lowest linear Y-axis position. Furthermore, the compensation algorithm is implemented into the machine management software of the machining centre using C#/C++ programming language.

The developed model was applied in verification tests with the excitation of the spindle in different linear Y-axis positions. Thus, the model training conditions differed significantly from the machine tool working conditions during the verification tests. This resulted in low prediction accuracy of thermal errors at the TCP in the Z-axis direction using the developed compensation model.

Consequently, a model update approach was proposed via on-machine measurement. The substantial advantages of the proposed solution are simplicity and model transparency; the original compensation model parameters can remain unaffected.

The model update method was tested for various values of the on-machine measurement sampling interval. The presented findings confirm that the prediction accuracy measured as peak-to-peak values and the normalized root mean squared error of the thermal error compensation model updated via on-machine measurement are significantly improved. The prediction accuracy of the compensation model updated via on-machine measurement strongly depends on the sampling interval of the on-machine measurements (the peak-to-peak value is decreased from 70 µm to 43 µm and the normalized root mean squared error is increased from 56% to 92% depending on the sampling interval τ, from 180 minutes to 30 minutes).

The research showed that the prediction accuracy and robustness of thermal error compensation modelling of CNC machine tools can be significantly increased by a model update via on-machine measurement. The on-machine measurement method represents a suitable approach for thermal error compensation model updates.

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