Special Interest Group Meeting on Thermal Issues
ETH, Zurich, Switzerland, March 2022
www.euspen.eu

Statistical analysis of self-optimizing thermal error compensation models for machine tools

Nico Zimmermann[1,2], Josef Mayr[1] and Konrad Wegener[2]

[1]*inspire AG, Technoparkstrasse 1, 8805 Zurich, Switzerland*
[2]*Institute of Machine Tools and Manufacturing (IWF), ETH Zürich, Leonhardstrasse 21, 8092 Zurich, Switzerland*

zimmermann@inspire.ethz.ch

Abstract

Model-based thermal error compensation strategies are a sustainable and cost-effective way to reduce thermal errors of machine tools. Especially, the application of self-optimizing compensation strategies enables an almost autonomous reduction of thermal errors of machine tools. The implementation of self-optimizing thermal error compensation models often requires statistical optimization algorithms, which do not necessarily find the global optimum of the analysed optimization problem. Therefore, this paper presents a statistical analysis of a self-optimizing thermal error compensation strategy based on the Thermal Adaptive Learning Control (TALC), the autonomous selection and recalibration of the optimal model inputs and adaptively triggered on-machine measurements, so-called state updates. The state updates verify the current prediction accuracy of the thermal error compensation models. The simulated statistical analysis particularly concentrates on the comparison of the compensation results when adaptively instead of periodically triggered state updates are applied in the TALC. Adaptive state updates, which are triggered based on a novelty detection model, have two advantages. Firstly, a more precise and robust compensation and secondly the repeatability of the peak-to-peak error reduction of the considered thermal errors can be improved by up to 77%.

Thermal error, Compensation, Machine tool, Adaptive Control

1. Introduction

Thermal error compensation strategies are a sustainable and cost-efficient tool to improve the machining accuracy of five-axis machine tools, because the energy-intensive tempering of the machine tools and the workshop can be replaced by a control-based procedure. This enables a transformation from resource-based towards intelligence-based countermeasures to reduce the thermal errors of machine tools which cause a large fraction of inaccuracies on produced workpieces as discussed by Mayr et al. [1]. Thermal errors of machine tools are strongly influenced by various internal and external heat sources as described by Bryan [2]. This includes for example environmental influences, drives, bearings, process heat and the influence of the relevant fluidic media. So far, particularly phenomenological models have been integrated into the compensation strategies for thermal errors of machine tools to describe the relationship between the resulting thermal errors and their origin. Phenomenological models are for example applied by Brecher et al. [3], Gebhardt et al. [4], Mayr et al. [5] and Mareš et al. [6] to compensate thermal errors of machine tools. They can be extended to a self-learning system to empower the adaptation of thermal error compensation models towards changing boundary conditions. These self-learning systems are increasingly integrated into machine tools as shown by Möhring et al. [7].

Therefore, Blaser et al. [8] developed the Thermal Adaptive Learning Control (TALC) which combines phenomenological models and on-machine measurements to realize robust long-term compensation results. Mayr et al. [9] advance the TALC by introducing recalibration of the model parameters using the weighted least square algorithm for ARX models. To further improve the robustness of data-based thermal error compensation models, Zimmermann et al. [10] developed the adaptive input selection, which enables autonomous selection and recalibration of the optimal model inputs even after the initial model training. A further improvement of the self-learning ability and the productivity is achieved by Zimmermann et al. [11] who introduced on-demand triggered on-machine measurements to check the accuracy of the thermal error compensation models selectively. The results show that the on-demand triggered on-machine measurements drastically reduce the number of on-machine measurements compared to periodically triggered on-machine measurements. However, these results do not encompass a statistical analysis regarding the repeatability of the presented method. This analysis is especially important because the integrated statistical optimization algorithms do not imperatively result in the global optimum. Therefore, this paper analyses the statistical repeatability of the compensation results when adaptively instead of periodically triggered on-machine measurements are applied.

Section 2 describes in detail the TALC und the method for the on-demand triggered on-machine measurements. In Section 3 the experimental results which are used for the statistical analysis are described. Section 4 summarizes the results of the conducted statistical comparison and Section 5 gives a conclusion.

2. Self-optimizing thermal error compensation models

2.1. Thermal adaptive learning control (TALC)

The TALC, introduced by Blaser et al. [8], comprises a calibration and a compensation phase. In the calibration phase,

the considered thermal error and the available temperatures are measured to enable the creation of the data-based compensation models. At the end of the calibration phase, the optimal inputs, the model structure and the model parameters are automatically estimated by applying the Group LASSO method for ARX-models, developed by Zimmermann et al. [12]. After the model setup, the compensation phase starts and on-machine measurements with a reduced frequency called state updates check the possible exceedances of the Action Control Limits (ACL). When an ACL exceedance of a residual error is detected, a No-Good (NG) mode starts with the same measurement frequency as in the calibration phase to trace the data containing the previously unknown thermal load cases. After the NG mode, the model parameters as well as the model inputs are updated, and the frequency of the on-machine measurements is reduced again. However, estimating the optimal frequency of the state updates is a crucial challenge, because too few measurements can result in a limited accuracy of the compensation results and too many measurements result in a poor productivity of machine tools using the TALC. Therefore, Zimmermann et al. [11] introduced on-demand state updates, when so far unknown thermal conditions occur. Figure 1 summarizes the concept of self-learning thermal error compensation models by combining the TALC with the adaptive input selection and on-demand triggered state updates.

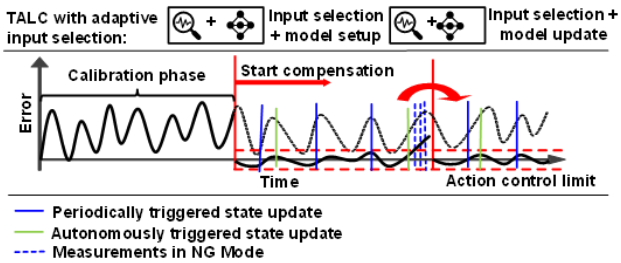

Figure 1. Concept of the TALC in combination with the adaptive input selection and the autonomously triggered state updates adapted from [12]

2.2. Adaptively triggered on-machine measurements

The autonomously triggered state updates are realized by integrating a novelty detection model into the TALC. The novelty detection model aims at identifying data which differ in some aspect from the previously acquired training data of the compensation models. The temperature data are particularly suitable to trigger the on-machine measurements because they can be gathered without an interruption of the manufacturing process. Consequently, the productivity of the machine tool is only decreased by a measurement when the probability of an exceedance of the ACL is relatively high. Figure 2 illustrates the resulting integration of the novelty detection into the concept of the TALC. In parallel to the prediction of the current thermal errors, the novelty detection model, which is based on a one-class support vector machine, analyses the current temperature measurements in comparison to the used training data of the compensation models. The detailed description of the mathematical method is given by Zimmermann et al. [11]. An exceedance of the novelty detection threshold triggers an on-machine measurement to check a possible exceedance of the defined ACLs, because the current thermal state is not represented in the already available temperature data. When no exceedance of the ACL is detected by the conducted on-machine measurement, only the novelty detection model is updated with the current thermal state, because the data-based models are able to represent the corresponding thermal errors correctly. On the other hand, a detected exceedance of the ACL results in a NG mode and after the NG-model the compensation models as well as the novelty detection model is adapted. Consequently, the self-learning ability of the novelty detection model is realized by its updates and enables a decreasing frequency of the conducted state updates, because an increasing number of thermal boundary conditions are considered in the novelty detection model.

Consequently, the compensation results are also directly influenced by the triggering of the state updates which can be followed by a NG-mode and a model update.

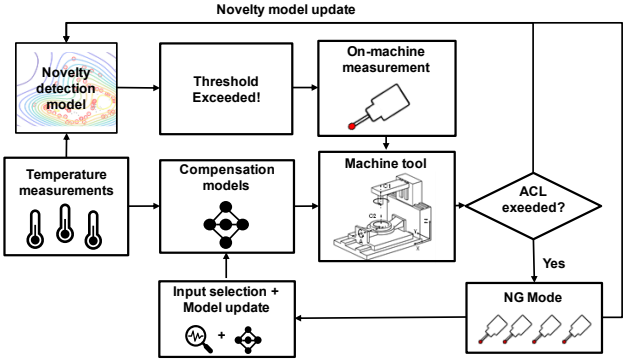

Figure 2. Method of the automatically triggered on-machine measurements adapted from [11]

3. Experimental setup

The statistical analysis regarding the repeatability of the autonomously triggered state updates is conducted by using measurements from a five-axis machine tool. The kinematic chain of the analysed machine tool can be described according to ISO 10791-1:2015 [13] as follows:

V [w – C' – A' – X' – b – Y – Z – S – t].

In total 20 temperature sensors measure the temperatures of the different components of the machine tool. Another four temperature sensors are placed around the machine tool to measure the environmental temperatures and two sensors are placed in the working space. The temperature of the inlet and outlet of the machine cooling and the temperature of the metalworking fluid are also measured. Furthermore, one eddy current sensor which is mounted in the spindle measures the elongation at the spindle nose.

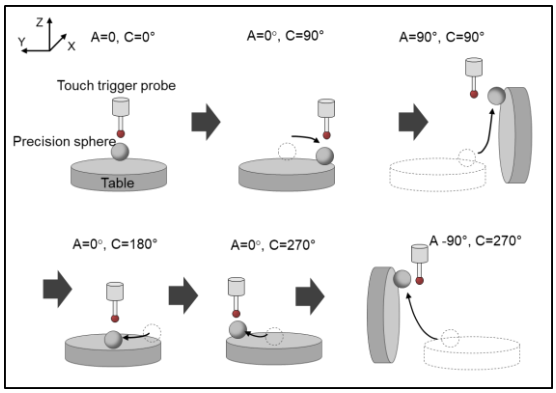

Figure 3. Procedure of the extended R-Test adapted from [12,14]

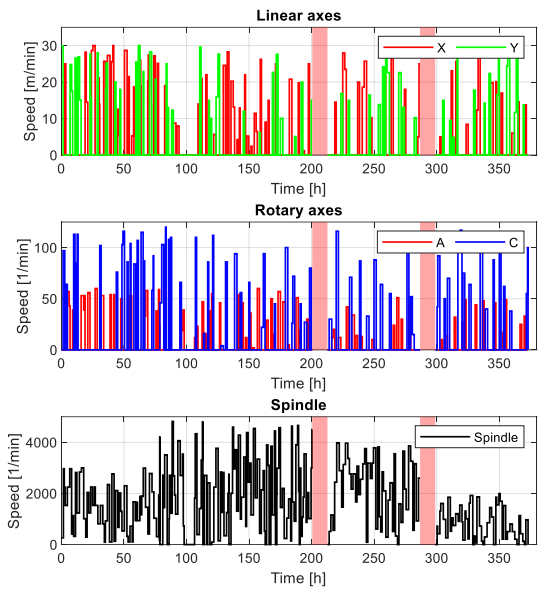

Figure 4. Speed profile of the conducted long-term experiment for the linear and rotary axes as well as for the spindle adapted from [12]

The thermal position errors of A-axis (E_{Z0A},E_{Y0A}) and the thermal position and orientation errors of the C-axis (E_{X0C}, E_{Y0C}, E_{Z0T}, E_{R0T}, E_{A0C}, E_{B0C}, E_{C0C}) are measured by applying a slightly adapted version of the on-machine measurement cycle presented by Zimmermann et al. [14], shown in Figure 3. The measurement cycle is based on a touch trigger probe and a precision sphere, which is mounted on the machine table. In total six measurement positions with different inclination angles of the swiveling and the rotary axis are included in the measurement cycle. The speed profile for the linear and rotary axes and the spindle of the used long-term experiment is shown in Figure 4.

To realize the statistical comparison between periodically and adaptively triggered state updates, the evaluated compensation strategies are repeatedly applied to the presented long-term measurement. To analyse the effectiveness and the repeatability of the compensation strategy with autonomously triggered state updates, it is 25 times applied on the presented experimental data. Furthermore, the compensation strategy with the periodical state updates is applied with five different state update frequencies on the presented experimental data. In this analysis state updates with an interval of one, two, three, four and five hours are analysed, and the compensation of every considered case is repeated 25 times to realize an overall statistical comparison of the state update triggering methods. The other parameters of the TALC are identical for both compensation strategies and are summarized in Table 1.

Table 1. Predefined parameters of the TALC (CP: calibration phase, NG: MT out of precision)

Parameter	Value
Calibration phase	24 h
Measurement interval	5 min
Measurement interval (post CP)	Adaptive
Measurement interval (NG)	5 min
Action control limit (ACL)	Adaptive
NG mode duration	16 measurements
Measurement cycle duration	120 s
Max. n_a	5
Max. n_b	5

4. Results

The compensation results for the thermal error E_{Z0A} with hourly and adaptive state updates are presented in Figure 5. The results indicate that the thermal error is significantly reduced by applying the TALC with hourly as well as with adaptive state updates and the resulting residuals are similar. However, the number of state updates can be significantly reduced by applying the adaptive state updates to the TALC. Compared to the hourly triggered state updates, the number of state updates is reduced from 275 to 81. This corresponds to a reduction of 71%.

The corresponding results of the statistical analysis for the thermal error E_{Z0A} are illustrated in Figure 6. These results also indicate that the average reduction of the peak-to-peak error for E_{Z0A}, which is approximately 67%, is almost identical for hourly and adaptively triggered state updates. However, the comparison of the peak-to-peak error reduction shows that the adaptively triggered state updates result in more precise compensation results than periodically triggered state updates with an interval of four hours which approximately exhibits the same number of state updates. Furthermore, the results of the statistical analysis show that the adaptive state updates result in a significantly reduced standard deviation of the compensation results compared to the periodically triggered state updates with a similar number of state updates. The standard deviation (k=2) of the peak-to-peak error reduction for periodically triggered state updates between the 25 simulations is 27.9%. On the other hand, the standard deviation (k=2) of the conducted simulations is only 6.3% for the adaptively triggered state updates. Consequently, the standard deviation of the peak-to-peak error reduction is 77% smaller when the on-demand state updates are used and the number of the conducted state updates is almost identical. This indicates that the increased self-learning ability of the TALC due to the adaptively triggered state updates results in precise and repeatable compensation results.

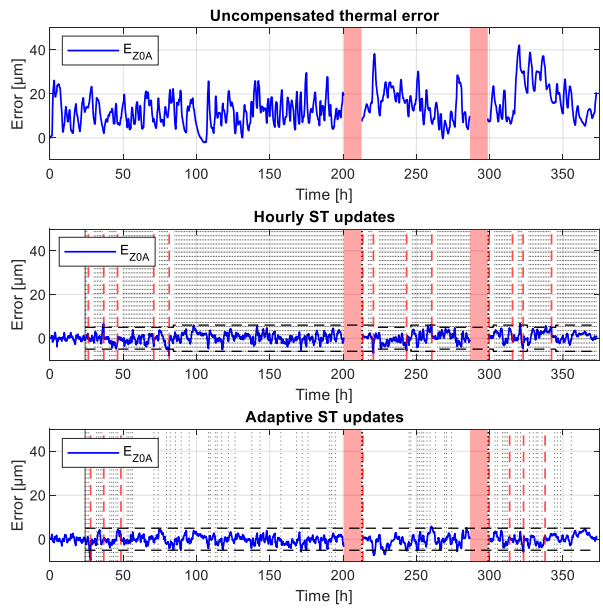

Figure 5. Uncompensated and compensated thermal error E_{Z0A} for hourly and adaptive state updates for the speed profile shown in Figure 4. The horizontal black dashed lines represent the ACL. The black vertical line shows the model setup and the red dashed line the exceedance of the ACL of any considered thermal error. The black dash-dotted lines indicate the triggered state updates. The red area is a not-true-to-scale representation of the interruption between the measurements.

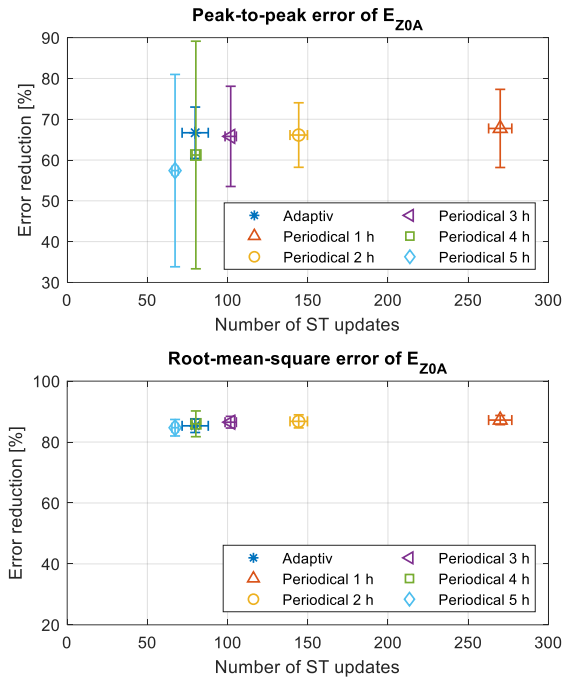

Figure 6. Statistical analysis of the peak-to-peak error reduction and the root-mean-square error reduction in relation to the number of conducted state updates for the thermal error E_{Z0A} using periodical and autonomously triggered state updates. The presented values represent the mean, and the error bars represent the double standard deviations resulting from 25 repeated simulations.

The comparison of the root-mean square error of E_{Z0A} with different state update strategies shows that the root-mean-square error is significantly reduced by the TALC, and the reduction does not strongly depend on the applied state update strategy. Consequently, the on-demand triggered state updates particularly improve the reduction of the peak-to-peak error which can directly be influenced by individual thermal boundary conditions that are not correctly represented by the previous compensation model. Table 2 summarizes the mean and the corresponding standard deviation of the peak-to-peak-reduction for all considered thermal errors.

Table 2. Mean peak-to-peak error reduction and the corresponding double standard deviation (Std) for the considered thermal errors obtained from the TALC with adaptively and periodically triggered state updates.

	Adaptive		Periodical 1h		Periodical 4h	
Error	Mean [%]	Std [%]	Mean [%]	Std [%]	Mean [%]	Std [%]
E_{Y0A}	3	18	1	25	0	16
E_{Z0A}	67	6	68	10	61	28
E_{X0C}	71	6	73	6	68	7
E_{Y0C}	5	14	3	15	-2	16
E_{Z0T}	64	15	67	5	62	12
E_{R0T}	67	9	64	6	62	7
E_{A0C}	37	16	36	26	33	20
E_{B0C}	31	19	39	5	30	17
E_{C0C}	25	27	26	38	29	28

5. Conclusion

This paper presents a statistical analysis of the compensation results of self-optimizing thermal error compensation models which are based on the TALC, the adaptive input selection and on-demand triggered state updates. In the conducted statistical analysis particularly the effect of adaptively triggered state updates in comparison to periodically triggered state updates on the compensation results is analysed. For every considered state update strategy 25 simulations are conducted on a long-term measurement containing various thermal conditions. The results show, that the repeatability of the peak-to-peak error reduction can be improved by up to 77% when adaptively triggered state updates are used instead of periodically triggered state updates with the same number of on-machine measurements. Consequently, completely self-optimizing models realise a precise and reliable compensation of thermal errors although they also rely on a statistical optimization algorithm.

References

[1] Mayr, J., Jedrzejewski, J., Uhlmann, E., Alkan Donmez, M., Knapp, W., Härtig, F., Wendt, K., Moriwaki, T., Shore, P., Schmitt, R., Brecher, C., Würz, T., Wegener, K., 2012, Thermal issues in machine tools, CIRP Annals - Manufacturing Technology, 61/2:771–791.

[2] Bryan, J., 1990, International Status of Thermal Error Research (1990), CIRP Annals - Manufacturing Technology, 39/2:645–656.

[3] Brecher, C., Hirsch, P., Weck, M., 2004, Compensation of thermo-elastic machine tool deformation based on control internal data, CIRP Annals - Manufacturing Technology, 53/1:299–304.

[4] Gebhardt, M., Mayr, J., Furrer, N., Widmer, T., Weikert, S., Knapp, W., 2014, High precision grey-box model for compensation of thermal errors on five-axis machines, CIRP Annals - Manufacturing Technology, 63/1:509–512.

[5] Mayr, J., Müller, M., Weikert, S., 2016, Automated thermal main spindle & B-axis error compensation of 5-axis machine tools, CIRP Annals - Manufacturing Technology, 65/1:479–482.

[6] Mareš, M., Horejš, O., Havlík, L., 2020, Thermal error compensation of a 5-axis machine tool using indigenous temperature sensors and CNC integrated Python code validated with a machined test piece, 66/June:21–30.

[7] Möhring, H. C., Wiederkehr, P., Erkorkmaz, K., Kakinuma, Y., 2020, Self-optimizing machining systems, CIRP Annals, 69/2:740–763.

[8] Blaser, P., Pavliček, F., Mori, K., Mayr, J., Weikert, S., Wegener, K., 2017, Adaptive learning control for thermal error compensation of 5-axis machine tools, Journal of Manufacturing Systems, 44:302–309.

[9] Mayr, J., Blaser, P., Ryser, A., Hernandez-Becerro, P., 2018, An adaptive self-learning compensation approach for thermal errors on 5-axis machine tools handling an arbitrary set of sample rates, CIRP Annals, 67/1:551–554.

[10] Zimmermann, N., Lang, S., Blaser, P., Mayr, J., 2020, Adaptive input selection for thermal error compensation models, CIRP Annals, 69/1.

[11] Zimmermann, N., Breu, M., Mayr, J., Wegener, K., 2021, Autonomously triggered model updates for self-learning thermal error compensation, CIRP Annals, 00:4–7.

[12] Zimmermann, N., Büchi, T., Mayr, J., Wegener, K., 2022, Self-optimizing thermal error compensation models with adaptive inputs using Group-LASSO for ARX-models, 50th SME North American Manufacturing Research Conference (under review).

[13] ISO 10791-1:2015, Test Conditions for Machining Centres – Part 1: Geometric tests for machines with horizontal spindle (horizontal Z-axis), International Organization for Standardization ISO,Geneva, Switzerland.

[14] Zimmermann, N., Mayr, J., Wegener, K., 2020, Extended discrete R-Test as on-machine measurement cycle to separate the thermal errors in Z-direction, in *Euspen Special Interest Group Meeting on Thermal Issues*.