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Hybrid thermal error compensation model using mixed targeted assembly error models

Christian Naumann[1], Philipp Klimant[1,2], Sebastian Lang[3,4], Josef Mayr[3,4], Evgenii Oborin[5], Christoph Einspieler[5], Friedrich Bleicher[5], Konrad Wegener[4]

[1]*Fraunhofer institute for machine tools and forming technology IWU Chemnitz*
[2]*University of Applied Science Mittweida, Virtual Technologies*
[3]*ETH Zurich, Institute of machine tools and manufacturing IWF*
[4]*inspire AG*
[5]*Vienna University of Technology, Institute of production engineering and photonic technologies IFT*

Christian.naumann@iwu.fraunhofer.de *office: +49-371-5397-1144*

Abstract
Thermal errors present a major hurdle in maintaining positioning accuracy in cutting machine tools. Model based compensation methods can predict the thermal error and reduce it via control-internal offsets. There are numerous such compensation models. For complex machine tool designs and under realistic working conditions, however, all of these methods still have not eliminated the thermal error reliably. The GeoComp project attempts to improve the accuracy of thermal error predictions by breaking down the error into individual assemblies along the kinematic chain and using the best suited compensation model for each error component. To demonstrate this on the DMU 80 evo, the kinematic chain for the z-direction of the column error was set up. Using three simulated load cases, the thermal error of this kinematic chain was examined and a compensation model for the dominant Z-slide error component was computed using a characteristic diagram. Once the training database has been extended, similar compensation models will be created for all assemblies and the resulting hybrid model will be tested and evaluated.

Machine tools, thermal error, compensation, hybrid method, kinematic chain

1. Introduction

Thermal errors in cutting machine tools refer to relative displacements between cutting tool (TCP) and workpiece as a result of thermal influences. Thermal influences may, e.g. be waste heat from the machine or the cutting process (electric losses, friction, etc.) or ambient temperature changes. Even after decades of research, thermal errors continue to reduce the machining precision and can lead to reduced productivity or even scrap.

An effective method for reducing thermal errors during machining is thermal error compensation, which involves the measurement or model-based prediction of the thermal error with a subsequent application of a corresponding positioning offset in the machine tool control. There are four main types of compensation methods.

The first type uses correlative compensation models. They use correlations between input data (mostly temperatures sensors) and output data (relative TCP displacement) to predict the current thermal error based on these measured sensor values.

One recent example is the compensation model based on Gaussian process regression developed by Miao et al. [1], which proved to be superior to ridge regression, principle component regression (PCR), thermal autoregressive with exogenous input (ARX) and long short-term memory (LSTM) neural network models when tested under different working conditions in an investigation on a Vcenter-55 three-axis machine tool. In another work by Chen et al. a standard neural network with hyperparameter optimization and correlation based input variable selection to minimize collinearity was successfully employed to reduce the thermal error of an AWEA VP-2012 gantry machine tool by between 30 and 90 % [2].

The second type uses characteristic/phenomenological models to map the transfer function between input/excitation (waste heat, ambient temperature, etc.) and output/response (displacement). One of the early examples of this is the use of first and second order time-delay transfer functions. Brecher et al. have used such a model to deal with both internal heat sources from spindle and three kinematic axes and from the ambient temperature via measurement based model training and thereby achieved an error reduction of more than 80% [3].

The adaptive learning control using ARX models (TALC) developed by Blaser also falls into this category [4]. It uses a specially developed on-machine measurement cycle to achieve self-adaptability of the compensation model parameters.

Horej et al. used a similar ARX model as a basis and updated it for untrained thermal load cases by adding transfer functions. In their investigation, this improved the prediction accuracy as measured by RMSE from 56% to 92% without needing to change the original model parameters [5].

The third type uses online-capable simulation models, which are most often model order reduced (MOR) FEM simulations. This requires the accurate modelling of the geometry the prevailing boundary conditions along with a good parametrization of the model parameters, as is described by Ess [6]. Ihlenfeldt et al. use such models in what they call structure model based correction and have developed a method for updating the model parameters to account for changing ambient conditions or machine tool wear [7].

The fourth type uses direct TCP measurements of the full TCP displacement or of local component deformations. Brecher et al. use integrated deformation sensors (IDS), essentially long CFRP

bars with a 1D displacement sensor, to measure the lengthening and bending of large machine assemblies combined with a geometric-kinematic model to compute the corresponding TCP displacement [8]. In an investigation on a three-axis vertical machining center, this enabled them to reduce the thermal error by over 85% in the most critical direction.

Overall, there are numerous highly effective compensation methods for reducing the thermal error of machine tools under variable working and ambient conditions. Most of them are, however, still limited in their prediction accuracy when several more complex scenarios overlap. Correlative models, e.g., usually have trouble extrapolating beyond the trained thermal load cases. Phenomenological models have difficulties when internal heat sources / sinks with changing loads overlap with changing ambient conditions. Methods such as TALC can then use measurements to recalibrate the model, but this is still limited and it interrupts the production process. Simulation based methods require a great effort to correctly parametrize them and many heat transfer and convection parameters can only be estimated roughly, which limits the overall accuracy of these models. Using IDS is a very robust method but not all machine assemblies allow for their usage. Aside from these general considerations, there are many different types of machine tools in terms of heat sources and sinks, kinematics, operating conditions, etc. which make some compensation strategies more effective than others.

There is thus not yet a catch-all solution for thermal error compensation. The GeoComp project attemps to fill some of these gaps by combining several of the above-mentioned methods and reducing the complexity of the task by evaluating the thermal error at the assembly level. GeoComp and its goals are described briefly in chapter 2. This chapter also contains some information on the machine tool DMU 80 evo, which is used in the subsequent sections. One major part of the GeoComp approach requires the separation of error components along the kinematic chain. Chapter 3 determines the elements of this kinematic chain for the DMU 80 evo and describes the simulations used here. One important assembly on this machine in terms of thermal behaviour is the Z-slide. Therefore, chapter 4 presents a compensation model for the Z-slide based on regression analysis. Finally, chapter 5 gives a brief summary and an outlook on future work within GeoComp.

2. Project GeoComp

The project GeoComp – "Compensation of geometrical errors of kinematic chains caused by thermal deformations" consists of two ideas:

1) a thermo-physical model that describes the transformation from power consumption via heat transfer in the machine tool kinematic and imposes temperature changes causing lateral and angular geometrical errors. A reduced thermal model of the machine tool for a real-time application and HMI interface.

2) a self-learning methodology that recalibrates the described links between measured model inputs, temperatures and power consumption, as well as geometrical errors

A new compensation method of thermally-induced TCP errors will be developed and implemented in the closed-loop CNC position control. This can be done by an optional CNC software or an additional edged device. The solution will be validated on a demonstration machine tool for parameter optimization. External measurements will assess the geometrical error compensation between TCP and workpiece. The expected outcome is a CNC software or an edge device, applicable to different machine tools and resulting in a significantly increased machine tool and workpiece accuracy over its lifetime.

GeoComp separates the thermal error along the kinematic chain into individual error components for the major assemblies in order to make the error prediction of each assembly much simpler and more targeted than the entire machine tool would allow. In a hybrid approach, each assembly receives the most suitable error model from the four compensation types mentioned in section one.

The demonstration machines in the project are the DMG Mori DMU 80 evo, the KrauseCo-Mauser FLEX-Module and the Mori Seiki NMV 5000 DCG.

2.1. Demonstration machine DMU 80 evo

For this initial investigation, the DMU 80 evo was chosen since it has demonstrated a very complex thermal behaviour in previous studies [9]. For the DMU 80 evo, there is already a parametrized and validated FEM simulation model which agrees well with measurements [10]. Figure 1 shows the simplified CAD model used for the simulations in Ansys Mechanical. The housing was omitted here.

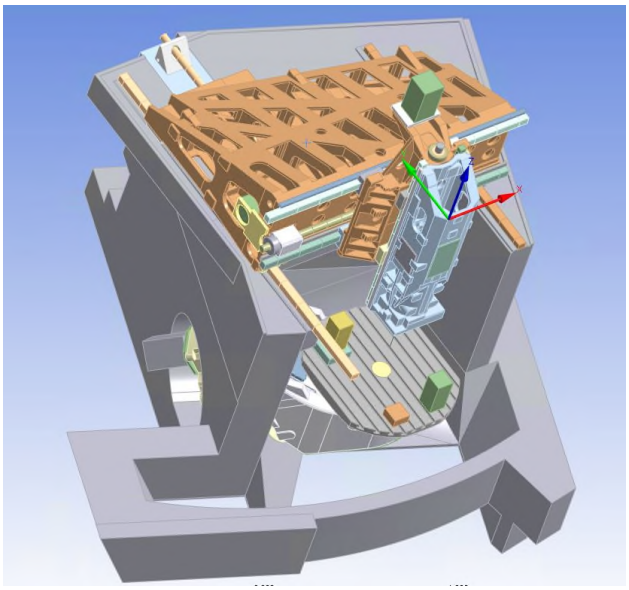

Figure 1. CAD model of the DMU 80 evo without housing

For the DMU 80 evo, several different compensation approaches have been tested and despite some promising partial results, none of the individual compensation methods was fully successful. Correlative approaches require an extended, more suitable temperature sensor placement. Phenomenological models have trouble with the interaction of internal heat sources, cooling system and ambient effects. Finally, simulation based approaches have difficulties with the cooling system, the machine table and the complex conditions within the workspace during machining. So far, the best solution was a hybrid model combining IDS for the machine column and a regression based method for the machine table [10]. In practice, however, this solution is not so useful, since no IDS are actually installed in the DMU 80 evo series.

2.2. Compensation approach for the DMU 80 evo

The solution pursued in GeoComp is to first break down the thermal error into individual components for the main assemblies along the kinematic chain. These components are machine bed, Y-slide, X-slide, Z-slide and machine table. Depending on the direction of error, measurement systems and component bending or tilting are also considered and modelled, particularly for the machine bed and the Y- and Z-slide. In order to obtain these error components, FEM simulations are used.

The simulations provide training data for correlative and phenomenological models. Currently, these simulations are performed in Ansys Mechanical but in the future, the training data will be generated more efficiently by using model order reduced simulations obtained from the MORe software [11]. Since the error components for the assemblies have a much simpler thermo-elastic behaviour, correlative models using the temperature sensors are expected to be more successful. Where temperature sensors are too sparse, transfer functions are employed using motor currents, axis movements or more distant temperature sensors as inputs.
For the machine table, where the simulations are less accurate because the existing CAD models lack some relevant details and strong, transient heat exchange occurs with the ambient air and the cutting fluid, thermal adaptive learning control (TALC) will be used and trained using on-machine measurements [4].

3. Kinematic chain of thermal error components

The kinematic chain of the DMU 80 evo for the z-direction of the thermal error contains the machine bed, Y-slide, X-slide, Z-scale, Z-slide and tool. The tool has been ignored here, since it needs to be modelled separately and requires both the tool specifications and either an additional temperature sensor or detailed data on the cutting process. The Z-slide includes the spindle drift. The linear measurement system (scale) of the Z-axis is attached to the X-slide and ensures position-independent accuracy for the Z-axis movement. Due to design restrictions in the Z-slide, the scale itself does not actually remove much of the thermal error in z-direction. Since the scale does not contribute to the thermal error, it needs no compensation model.

Figure 4 shows the kinematic chain in z-direction for three simulated load cases. Figure 2 shows the corresponding simulated temperature sensor values, whose locations are shown in figure 3. The simulated load cases in figures 2 and 4 were pasted together, they are not one long sequence.

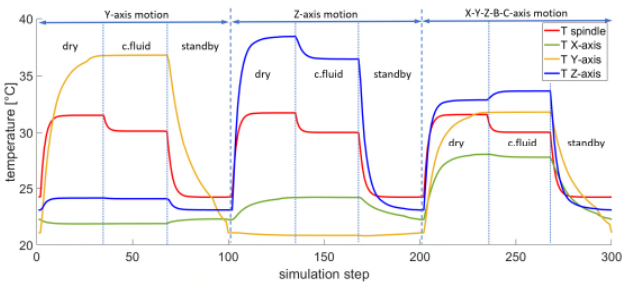

Figure 2. simulated temperature sensor values of DMU 80 evo column

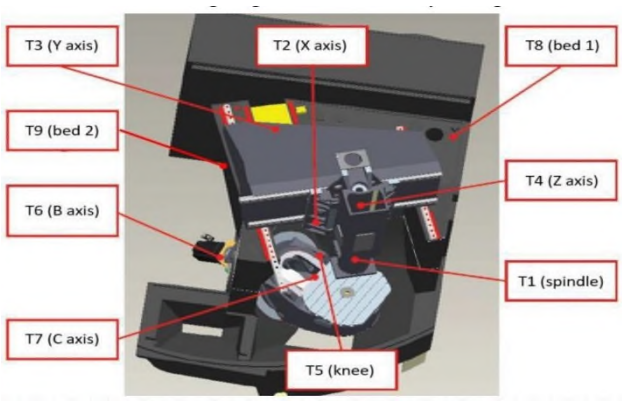

Figure 3. temperature sensor locations of DMU 80 evo [9]

The three load cases are described in table 1. They are each preceded by another load case modelling the machine tool warmup in standby, which is necessary to create realistic thermal starting conditions that can later be reproduced in measurements. All sections with axis movements were done with the spindle running at max. load.

Table 1 simulation load cases

Load case		
1 Y-axis movement	**A** dry heating by cyclic Y-axis motion	G1 Y 75% S 100%
	B heating by cyclic Y-axis motion with cutting fluid	G1 Y 75% S 100%
	C cool-down in standby	-
2 Z-axis movement	**A** dry heating by cyclic Z-axis motion	G1 Z 75% S 100%
	B heating by cyclic Z-axis motion with cutting fluid	G1 Z 75% S 100%
	C cool-down in standby	-
3 all-axis movement	**A** dry heating by cyclic sequential motion of all 5 axes	G1 X 75% S 100%
	B heating by cyclic sequential 5-axis motion with cutting fluid	G1 X 75% S 100%
	C cool-down in standby	-

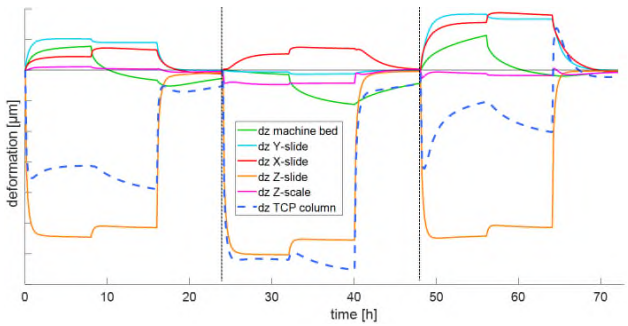

Figure 4. simulated thermal z-error of relevant column assemblies

4. Usecase: thermal z-error estimation of Z-slide

As figure 4 shows, the z-TCP error of the entire column from bed to tool tip is very difficult to map using regression or phenomenological model types even though these load cases are not yet very complex. Mapping the individual error components, especially the dominant Z-slide, however, is much more feasible. Using only the two sensors on spindle and Z-axis shown in figure 2, a regression based model using a characteristic diagram achieved good prediction accuracy with a coarse 3x3 grid, see figure 5. A similar model for the entire TCP displacement, even with all four column sensors as inputs and a finer grid only reached a very rough approximation of the simulated curves.

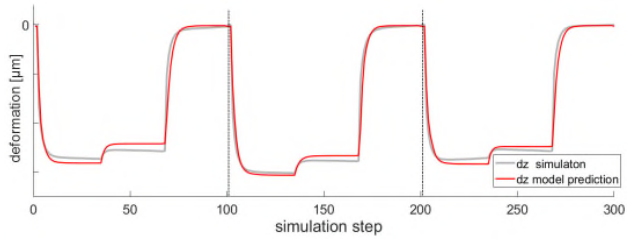

Figure 5. simulated vs. predicted thermal z-error of the Z-slide

This initial work is meant to demonstrate the feasibility of the GeoComp approach. The next steps, which are currently in progress, will lead to the complete hybrid compensation model and finally its validation using machine tool measurements. Once the Ansys simulation model has been ported to the more efficient MORe simulation software, a larger set of load cases will be computed to obtain as many operating scenarios in the

training data as possible. With this large training database, the optimal compensation models for each of the column assemblies will be selected and computed. Then, the TALC model for the machine table will be created from measurement data. Finally, all compensation models are combined and tested jointly.

5. Summary

Thermal errors present a major hurdle in maintaining positioning accuracy in cutting machine tools. Model based compensation methods can predict the thermal error and reduce it via control-internal offsets. There are numerous such compensation models. For complex machine tool designs and under realistic working conditions, however, all of these methods still have not eliminated the thermal error reliably.

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