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

Thermal monitoring and adaptive compensation model based on proper orthogonal decomposition and optimal sensor placement.

Beñat Iñigo[1], Natalia Colinas-Armijo[1], Gorka Aguirre[1], Luis Norberto López de Lacalle[2], Harkaitz Urreta[1]

[1] *IDEKO member of Basque Research and Technology Alliance, Elgoibar (Basque Country), Spain*

binigo@ideko.es

Abstract
Thermal errors represent one of the most important error sources regarding the volumetric accuracy of machine tools. Thermal error compensations are a relatively low-cost solution to improve the accuracy of machine tools. The estimation is usually based on temperatures measured on certain points in the machine and a compensation model that is obtained from some training tests where temperatures and thermal errors are measured. After the initial test is done, the model is verified by periodic measurements throughout the machine working life. Such measurements should be kept to a minimum, as they affect the productivity of the machine. In this work, a thermal monitoring system is presented based on the Proper Orthogonal Decomposition reduction of an initial thermal test. This surveillance system proved to be useful to detect erratic thermal behavior or the apparition of new uncharacterized heat sources. An adaptive compensation approach was presented capable of adapting its inputs according to the temperature behavior.

Keywords: Thermal error compensation, Optimal sensor position; Proper Orthogonal Decomposition, Adaptive Model, Machine Tool

1. Introduction

Thermal errors are one of the main contributors to the volumetric error of machine tools [1], causing relative displacement between workpiece and Tool Center Point (TCP). Numerical compensation relies on model-based prediction of the thermoelastic deformation of the machine and it is a relatively low-cost solution to improve the accuracy of machine tools once they are placed on the shopfloor.

Due to the necessity to minimize machine occupation time, the compensation model has to be able to predict thermal behaviour beyond training phase with none or limited displacement measurements. Yet, developing such a robust model would need long training tests and excitation of all possible heat sources, which is not always possible. Furthermore, conditions in or around the machine tool can change. These changes should be detected so that the model can be retrained. Several works have been focused on adaptive models and varying measuring frequencies to overcome this problem [2].

When large amount of temperature data is available (either from simulation or actual on-machine measurements) reduction techniques, such as Proper Orthogonal Decomposition (POD) based approaches, allow to identify dominant trends in the thermal field. They are usually combined with optimal sensor placement procedures in order to select the optimal location and number of sensors needed to compensate certain thermal behaviors [3].

In [4], a thermal error compensation solution for local and distributed thermal effects was proposed, based on POD and stablished optimal sensor placement procedures. The model showed good prediction capability, even when the amplitude and frequency of the characterized heat sources changed. In this work a modification of this approach is presented, capable of monitoring the thermal state of the machine and detect temperature behaviors that differ from those of the training phase. Furthermore, an adaptive compensation model is developed, that changes according to these outliers detected in the temperature data.

2. Temperature monitoring and adaptive compensation

POD based compensation models usually require to select certain nodes in order to predict the thermal modes. The number of nodes s needs to equal the number of modes selected to reduce temperature field. If the selected number of nodes is bigger than the number of modes an overdetermined system is obtained when predicting the thermal states. When expanding again to the full temperature field, the self-prediction of the s temperatures will be interdependent and will only hold if the thermal behavior of the machine going on is similar to the interval where the original temperature matrix was recorded. Self-prediction errors can be monitored in order to detect thermal phenomena that was not adequately captured in the training test.

Furthermore, outlier temperatures (i.e. the ones that are not behaving as expected), can be detected by by observing the highest self-prediction errors. Nodes with self-predicting errors over certain tolerance are eliminated and the model is recalculated. This will always be possible as long as the number of nodes s is still higher than the number of modes r. Temperature prediction of eliminated nodes is still computed so that they can be reincorporated to the model when the error falls below the tolerance again. The functioning of this adaptive compensation system is illustrated in Figure 1.

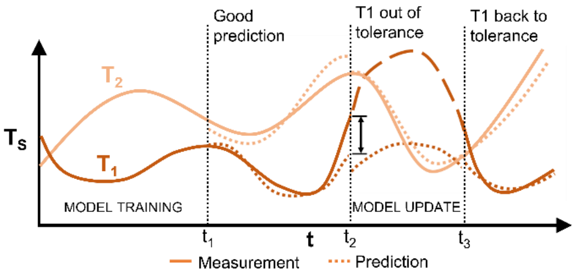

Figure 1. Illustrative example of the adaptive thermal model. At t_1 model starts predicting, after training is done. At t_2, T1 gets out of tolerance, so the model is updated ignoring it. At t_3, it is incorporated again.

3. Case study

3.1. Column model

A milling machine column Finite Element (FE) model has been developed and it is used as a case study. The FE model, as well as the main heat sources affecting the column, are shown in Figure 2. A local heat source Q1 (e.g. heat generated by a motor or an auxiliary system located in this area) has been defined at a fixed location. A moving heat source Q2 (e.g. heat being conducted from the ram to the column as the vertical axis moves) is defined near the theorical location of the vertical guideways. An additional local source Q3 has been defined for validation purposes (see section 3.3) External surfaces exchange heat with the varying ambient by convection.

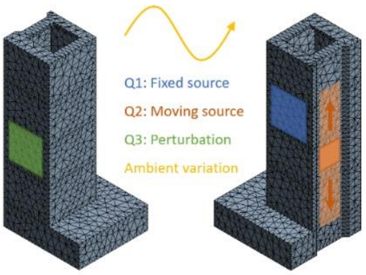

Figure 2. Finite Element model of the column and main heat sources.

3.2. Model training

In order to obtain a compensation model, the temperature of the machine has to be registered during a training test and arranged as a snapshot matrix. In this case, a transient thermoelastic simulation is carried out, where all heat sources defined in section 3.1 are varied. Step inputs in Q1 and Q2 are introduced with amplitudes of 200W and 250W respectively, as well as sinusoidal variation of ±2ºC and 24h period in the ambient. Position of Q2 is also varied at two different speeds. Details of the amplitude and position variation of the heat sources are shown in Figure 3.

The temperature of each node is registered every 100 seconds and stored in the snapshot matrix T. A snapshot of the thermal field at a given instant is plotted in Figure 4, where the effects of the heat sources are clearly appreciated.

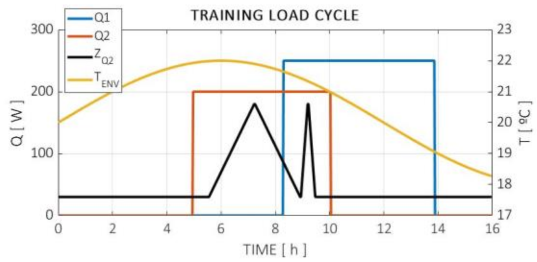

Figure 3. Training load cycle for the of the compensation model. Approximate vertical movement of Q2 (in black) is also represented.

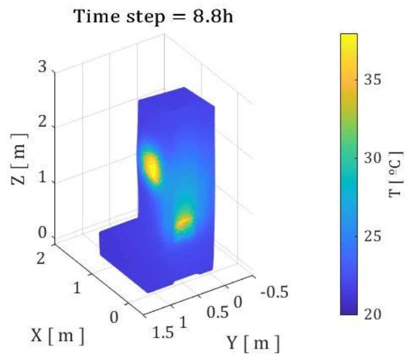

Figure 4. Snapshot of the temperature of the machine at t=8.8h

Following the procedure described in [4], the snapshot matrix of temperatures is decomposed using SVD, and reduced by selecting the first dominant r modes. In this case, selecting $r = 15$ modes was enough to capture the 99% of the information in T. This suggests that, as long as the thermal field varies in a similar way to the testing cycle, 15 modes will be enough to predict the behavior of the full temperature field.

3.3. Model testing

In order to validate the compensation model a testing cycle is defined. For this purpose, load sources present in the training cycle are varied in a different way: Warm-up cycle of varying amplitudes is defined for local source Q1, trajectory in Z is changed with 3 different velocities for Q2 and ambient temperature phase and amplitude is varied. Additionally, a third heat source Q3 is introduced at the second half of the testing cycle, in order to prove the temperature monitoring ang adaptive model. Details of the amplitude and position variation of the heat sources are shown in Figure 6.

Figure 6. Testing load cycle with an extra heat source (in green).

4. Thermal monitoring and adaptive model

In this section the performance of the thermal monitoring and the adaptive compensation model are evaluated using the testing cycle defined in section 3.3.

First of all, the performance of the temperature prediction model M is evaluated by computing the Root Mean Square (RMS) error of the overall temperature field at each time step. Figure 7 shows the error throughout the testing cycle.

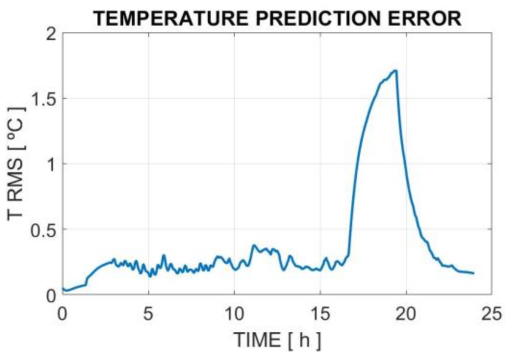

Figure 7. RMS error of the full temperature prediction throughout the testing cycle.

As it can be seen, the model predicts the temperature field with relatively good accuracy as long as thermal conditions remain similar to the training test, even if the amplitudes, frequencies and feed rates of the loads are varied (see Figure 6). However, when Q3 is turned on, the model loses accuracy as expected and it comes back when the effects of Q3 dissipate.

In real on-machine implementation the full temperature field will not be available, but only a few sensor measurements in the selected spots (n_s). However, by observing the self-prediction error, disturbance introduced by Q3 can also be observed. The evolution the error is shown in Figure 8 for each of the sensors.

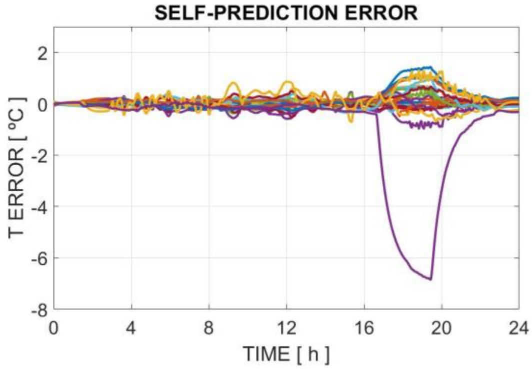

Figure 8. Self-prediction error Es of the selected temperature sensors.

As expected, sensors near the heat source Q3 show the largest deviation from its predicted value. By stablishing tolerance thresholds, a temperature surveillance system can be implemented. To avoid large data storage, prediction error is only calculated in a moving window of the las 10 time steps. To illustrate the functioning of the system Figure 9 shows the state of the temperature prediction at t=17h. Sensors out of ±0.8ºC tolerance are shown in red, those between ±0.4ºC and ±0.8ºC are shown in yellow and the ones inside ±0.4ºC in green.

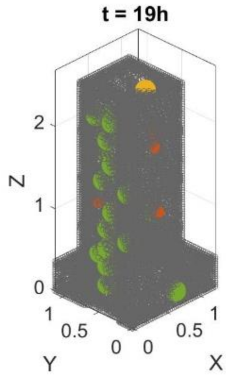

Figure 9. Temperature prediction state at t=19h

Though, predicted values are interdependent through the self-prediction model, and therefore, other sensors located further away from heat source are also affected by the values of the erratic sensors. This problem is faced by detecting and eliminating the outliers and updating the compensation model with the remaining sensors (see section 2.2). Simulation from 3.3 is carried out again, but this time allowing the adaptive modelling. Figure 10 shows the self-prediction error of the measured temperatures for adaptive compensation.

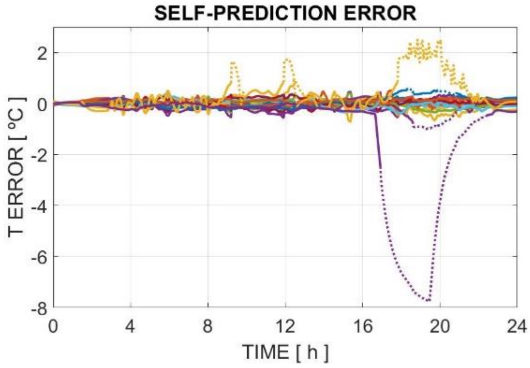

Figure 10. Self-prediction error with adapting compensation model. Nodes eliminated from the model are plotted with dot lines.

With the perturbation of Q3, the temperature near the heat source (purple outlier in Figure 10) got out of tolerance at t=17h, and therefore, was eliminated from the compensation model. A temperature near the moving source (yellow outlier in Figure 10) also showed an erratic behavior and was eliminated from the model at several points throughout the test. Comparison between Figure 8 and Figure 10 shows that several temperature predictions were being affected by the outlier temperature. Once the outlier temperatures were eliminated from the model, the remaining ones were again in accordance with the prediction inside the stablished tolerance. When Q3 was shut down, the erratic temperatures slowly returned to tolerance and were finally reincorporated to the model.

5. Conclusions

Compensation model was presented that proves to work properly when amplitude, phase and position of the heat sources vary, as long as they had been excited in training test.

Temperature monitoring system was implemented, a surveillance system that allows to easily identify thermal behavior that differs from training phase. This allows to take corrective actions like restarting model training under new thermal conditions or checking faulty machine elements that may be causing the thermal distortion.

An adaptive compensation model was also implemented. Responding to the information of the surveillance system, nodes were eliminated or incorporated to the model in order to eliminate unknown phenomena from the prediction but still compensate expected behavior.

References

[1] J. Mayr, J. Jedrzejewski, E. Uhlmann, M. Alkan Donmez, W. Knapp, F. Härtig, K. Wendt, T. Moriwaki, P. Shore, R. Schmitt, C. Brecher, T. Würz and K. Wegener, "Thermal issues in machine tools," *CIRP Annals,* vol. 61, p. 771–791, 1 2012.

[2] N. Zimmermann, M. Breu, J. Mayr and K. Wegener, "Autonomously triggered model updates for self-learning thermal error compensation," *CIRP Annals,* 5 2021.

[5] P. Benner, R. Herzog, N. Lang, I. Riedel eta J. Saak, «Comparison of model order reduction methods for optimal sensor placement for thermo-elastic models,» Engineering Optimization, %1. bol.51, p. 465–483, 3 2019.

[4] N. Colinas-Armijo, B. Iñigo, L. Lacalle eta G. Aguirre, «Optimal temperature sensor placement for error compensation of distributed thermal effects,» in *International Conference on Thermal Issues in Machine Tools*, 2021.