euspen's 19th International Conference & Exhibition, Bilbao, ES, June 2019
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Thermal characterization and modelling of a gantry-type machine tool linear axis

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Abstract
The thermal behaviour of precision 5-axis machine tools is one of the main sources of geometric inaccuracy on machined workpieces. For better finishing results thermal error motions can be compensated by the numerical control of the machine tool. This approach requires a deeper understanding of the machine tools thermal response. To prevent the need for implementing complex physical models for each machine tool type an input-output approach for thermal error motion compensation is developed. The error motions are characterized by conducting displacement and temperature measurements for different thermal load cases, where displacements are measured using a linear comparator system. System identification, namely an **A**uto **R**egressive model with e**X**ogenous input (ARX), is used to model the thermal positioning errors of a gantry-type linear axis. Determining the time and position dependent component errors is the challenge addressed in this paper. Using a set of measured position dependent errors on a particular 5-axis machine tool, the modelling approach is extensively tested and validated. Additionally, problems concerning the optimal input selection for the model are analysed. Using linear correlation coefficients, the input sets are investigated. In order to reduce the effect of input correlation, regularization is applied to the ARX model structure. The conducted examinations suggest that the ARX structure provides a good dynamic model for thermal errors. Comparative tests show that regularization and the usage of optimal inputs can improve the prediction accuracy significantly.

Thermal errors, modelling, measurement, compensation

1. Introduction

Precision manufacturing is strongly connected to the accuracy of the used machine tools (MTs). Driven by accuracy requirements of MT applications the required efforts to develop advanced design measures becomes more expensive and time consuming. This requires a paradigm change which was attempted in several attempts starting decades ago, namely to enable the control system to compensate for erroneous movements of the machine. These errors occur due to the fact that the movement of the tool centre point (TCP) and position measurement of MT axes takes place far away from each other. This leads to an insufficient controlled movement of the TCP relative to the workpiece. According to Wegener et al. [1] compensation, as kinematic, thermal, gravitational or dynamic compensation is one of the achievements in recent times towards accuracy, reliability and robustness. The physical modelling behind is highly complicated, if all the influential effects within a MT are taken into account. The currently used compensation strategies range from models describing the physical effects to phenomenological models identifying the thermal system behaviour from empirical data. Physical models tend to be complex and unmasterable while phenomenological models are based on a simple description requiring higher experimental efforts. Wegener et al. [2] summarize that compensation requires thorough understanding of the machine behaviour and its underlying causes.

According to Mayr et al. [3], thermal influences on MTs are still one of the largest contributors to errors on machined workpieces. In the past decades, research has been conducted to minimize the thermal effects on the machining accuracy, including error measurement, modelling, prediction and heat generation reduction. Of all factors that contribute to the thermal error of a MT, thermal errors of ball screw systems play a very important role, thus this issue is addressed in this paper.

Error compensation is the final objective of thermal research, and various compensation methods are proposed by researchers. Most of these methods use a certain correlation between structural temperatures and the thermally induced TCP deviations. Other inputs can be the environmental temperature and, as mentioned in several studies (for instance Moriwaki [4], Brecher et al. [5] and Gebhardt et al.[6]), data such as feed rate, spindle speed, effective power, electric current, torque or strain gauge measurements. The primary idea is to have an input to the model which is easy to measure during the ongoing production process. Shi et al. [7] investigated the relationship between thermally induced errors of feed drive systems and the axial thermal expansion as well as ball screw temperatures. They estimated a thermal expansion based modelling method for thermal error calculation. Additionally they performed a regression analysis of the heat generation influence on the thermal error with the corresponding modelling method. They conclude that the resulting equations are highly non-linear. Additionally, when the thermal expansion is taken as an implicit variable, the relationship between temperature rise and thermal error can be formulated as a multiple linear regression model.

The focus of this research is to apply a more diverse measurement procedure to investigate the thermal error propagation in a gantry-type linear axis under different thermal load cases. Based on these results an error prediction model is developed, which is able to capture the thermal behaviour based on present and past effects. Additionally it is shown that the input selection of such models has a great influence on the prediction quality and the robustness, especially under varying thermal loads.

2. Experimental setup

The enabling technology to compensate thermal errors of linear axes with a phenomenological model approach is the capability to measure the most dominant deviations in a short time, with a reasonable accuracy and in a repeatable way. Due to the fact that most measurement devices do not guarantee a long term stability, especially under varying environmental conditions, a comparator system (Heidenhain VM 182) is used. The comparator consists of a scale embedded in a U-shape steel profile and a scanning head that moves over the grating without mechanical contact. The two phase grating allows to measure not only along the axis of travel but also to detect movements perpendicular to the direction of motion, see Figure 1.

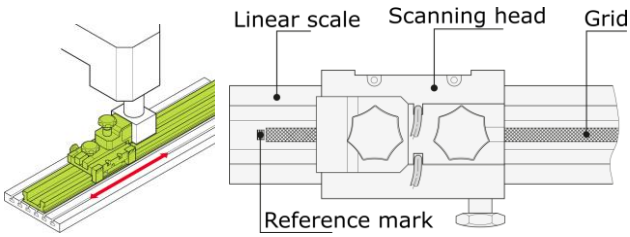

Figure 1. Illustration of components and installation of the comparator system (Heidenhain VM 182) [8]

The gantry type machine tool linear axis under investigation is a servo motor driven horizontal ball screw Y-axis with a stroke length of 510 mm. The thermal characterization measurement is conducted as an alternating sequence of standard positioning measurements as defined in ISO 230-2:2014 [9]. Along the axis of interest 10 measurement points are evaluated, while moving the axis up- and downwards, see Figure 2. According to the standard this measurement is performed five times to evaluate the positioning and straightness error of the corresponding axis. To measure the thermal behaviour, each up and down cycle is repeated a single time in fixed time intervals. The positioning error is computed by subtracting the nominal position value from the measured one, while the up and down errors are averaged. In the case of a Y-axis abbreviated with E_{YY}, according to ISO 230-2:2014 [9].

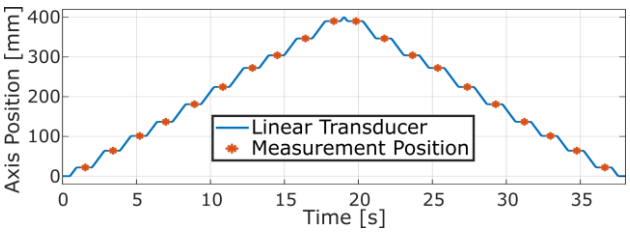

Figure 2. Positioning measurement according to ISO 230-2 [9] with 10 measurement positions along the axis under investigation

The linear comparator works with a relative measurement scheme, where only movements relative to its initial position are recorded. Thus the measurement system is continuously recording even during the fast axis movements, where the displacements are not evaluated. To automatize the measurement point extraction, an algorithm is developed, which identifies a stand still position of the comparator system and averages the measured position over 70 % of the samples of the stand still position. This position is then compared to the programmed axis position of the MT.

For the machine tool under investigation the thermal behaviour of the straightness error is of marginal importance and therefore not further considered in the course of this paper.

3. Thermal characterization of a linear axis

In order to characterize the thermal behaviour of a gantry type linear axis, the thermal response of the TCP under different load cases needs to be evaluated. It is chosen to use four different load scenarios to represent different extreme use cases of the MT. Figure 3 depicts the four different load cases. The objective is to have different time intervals and locations of thermal loads introduced in the linear axis, by oscillating the axis under investigation over its full stroke or at parts of it. The “Cold” test is measuring the impact of the changing environmental conditions on the linear axis. The “WarmCold” test characterizes the step response and the steady-state behaviour. In the third test, “MultiRange”, the impact of different oscillation locations is investigated and in the last test, the “Stairs” test, the variability of the duration of the thermal load is analysed. On top of the different load scenarios four different feed rates for the oscillations are chosen, namely 3’000 mm/min, 5’000 mm/min, 6’000 mm/min and 12’500 mm/min. Positioning measurements are carried out every 10 minutes respectively every 20 minutes for the load case “Cold”. The duration of each test is around 144 hours for the “Cold” load case, 12 hours for “WarmCold”, 36 hours for “MultiRange” and 24 hours for “Stairs”.

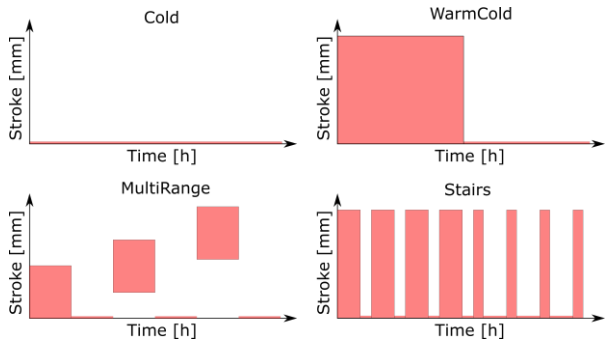

Figure 3. Schematics of different used load cases for the characterization of a linear axis. The area in red depicts the oscillation length/duration of the ball screw drive.

Additionally to positioning measurements various temperatures are recorded to characterize and model the thermal behaviour. Several MT structure temperatures as well as motor and linear comparator temperatures are recorded. Additionally the environmental and the coolant temperature are saved. In total 12 temperature values are collected with a sample time of 1 minute.

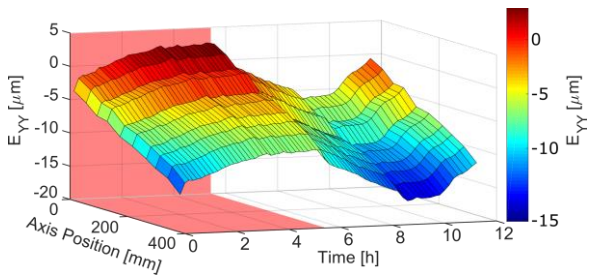

Figure 4. Positioning error of the Y-axis (E_{YY}) measured over a stroke length of 400 mm during a “WarmCold” heat load of around 12 hours. The Y-axis was oscillating with a feed rate of 12500 mm/min for approximately 5.5 hours, illustrated with red area, followed by a cool down phase. Measurement time interval: 10 min

In Figure 4 the positioning error of a Y-axis (E_{YY}) as function of axis position and time is shown. Measurements as described in Section 2 are done every 10 minutes. The load case “WarmCold” is performed for a total of 12 hours, where the Y-axis is oscillating over the full axis stroke with a feed rate of 12500 mm/min. After 5.5 hours the oscillation is stopped and

only measurements every 10 minutes are performed. One can see that the thermal load is influencing the positioning error of this gantry type axis. Three characteristic effects can be observed: The heating up phase followed by the cooling down phase is apparent. In the later stage of the cooling down phase an increase in the positioning error can be observed. Figure 5 shows five characteristic temperatures recorded during this experiment. One can see that the environmental temperature stays very stable throughout the heating up, while at the end of the cooling down phase the temperature is increasing by around 2 °C. This effect is even intensified, due to the fact that the MT is actively cooled to the environmental temperature. This implies that environmental temperature fluctuations play an important role for the thermally induced positioning error.

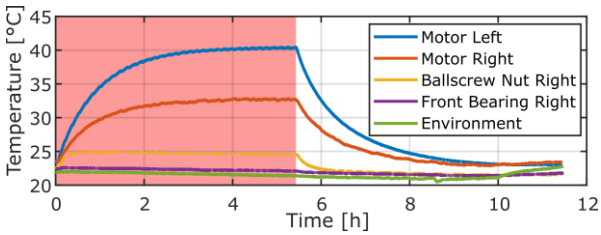

Figure 5. Temperatures during a "WarmCold" heat load of around 12 hours. The Y-axis is oscillating with a feed rate of 12500 mm/min for approximately 5.5 hours, red area, followed by a cool down phase.

To investigate the local thermal heating effects on the positioning error of a gantry axis, the load case "MultiRange" is performed for 36 hours. As schematically illustrated in Figure 3, the axis is oscillating only on a segment of its full stroke followed by a stand still period. This is repeated twice on different sections while the positioning error is measured every 10 minutes. The sections of oscillation are as follows: 0 – 200 mm, 100 – 300 mm and 200 – 400 mm.

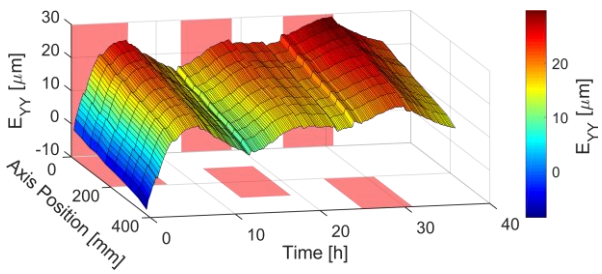

Figure 6. Positioning error of the Y-axis (E_{YY}) during a "MultiRange" heat load of around 36 hours. Oscillation feed-rate 12'500 mm/min, for three intervals, indicated by red areas, followed by intermediate intervals at standstill. Measurement time interval: 10 min.

The positioning error measurement results can be seen in Figure 6. The graph shows that also under this load case the thermal behaviour of the linear axis is similar as in the previous experiment.

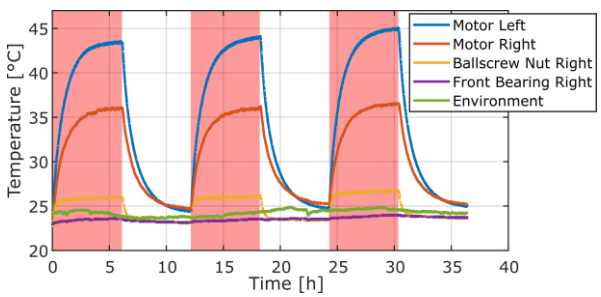

Figure 7. Temperatures during a "MultiRange" heat load case of around 36 hours. The Y-axis is oscillating with a feed rate of 12500 mm/min for approximately 5.5 hours, illustrated with a red area, followed by a cool down phase, repeated 3 times.

When considering the environmental temperatures, shown in Figure 7, one can see, that there may again be some disturbances caused by environmental effects on the positioning accuracy. Nevertheless, the most important result of this experiment is that there is no significant local positioning error change due to the bound oscillation ranges. This leads to the conclusion, that the location of the axis movement in this case is of minor importance for the thermal dependencies of the positioning error E_{YY}.

4. Modelling of positioning error

The positioning error E_{YY}, under the load case "Cold", is depicted in Figure 8 as a function of position. The different colours represent different points in time. The errors are approximated by the following linear function with least squares fitting:

$$E_{YY}(y,t) = A(t) \cdot y + E_0(t) \qquad (1)$$

In Equation (1), A represents the slope and E_0 the intersection point with the ordinate, these two values are functions of time t. It is in particular noticeable that the slope A does not vary much over time during an experiment, the most significant variation occurs at the intersection point E_0. This can also be seen in the standard deviations of the slopes. In

Table **1** the average slope $\tilde{A}$ and the corresponding standard deviation σ over the whole duration of the experiment are listed. It can be seen, that the slope only marginally changes throughout these 14 experiments and that the standard deviation is never bigger than 12 % of the average slope over the whole duration.

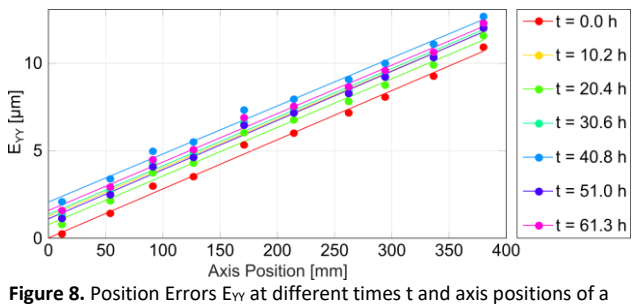

Figure 8. Position Errors E_{YY} at different times t and axis positions of a "Cold" experiment. The lines are linear regression lines . Each colour represents a different point in time.

The largest variation in slope shows experiment 10 with a variation of 11.7 %, this corresponds to an estimation uncertainty of ± 1.16 µm for a stroke of 400 mm compared to a linear regression fitted line. For comparison reasons, the measuring uncertainty of the linear comparator is ± 1 µm. Thus, for this MT type the spatial description of the positioning error can be assumed to be linear.

To model the temperature dependency of the positioning error, a set of equations of polynomial structure is chosen. Five commonly used combinations, Finite Impulse Response (FIR), Autoregression with Exogenous Input (ARX), Autoregression–Moving-Average with Exogenous Input (ARMAX), Box-Jenkins (BJ) and Output Error (OE), are evaluated to find the optimal model structure, as explained by Mayr et al [10]. It is found that the ARX model structure is the most robust and shows the best fitting quality, according to the normalized root mean square error (NRMSE) criterion. The set of polynomials can therefore be described by the following equation:

$$A(q) \cdot y(k) = B(q) \cdot u(k) + e(k) \qquad (2)$$

Table 1. Mean values and standard deviations of the least squares fitted linear slopes of E_{YY} for different experiments.

ID	Load Case	Feed rate [mm/min]	Average Slope $\widetilde{A}$ [µm/m]	Standard Deviation σ [µm/m]	$\sigma/\widetilde{A}$ [%]
1	Cold	0	27.7	0.3	1.1
2	Cold	0	29.6	0.2	0.8
3	WarmCold	3’000	25.6	0.7	2.6
4	WarmCold	3’000	25.9	1.2	4.7
5	WarmCold	5’000	26.3	0.5	2.0
6	WarmCold	5’000	26.2	0.3	1.2
7	WarmCold	6’000	27.7	0.8	2.7
8	WarmCold	12’500	27.0	2.0	7.3
9	WarmCold	12’500	24.8	2.8	11.3
10	WarmCold	12’500	25.0	2.9	11.7
11	MultiRange	12’500	19.9	0.7	3.5
12	MultiRange	12’500	31.5	0.6	2.0
13	Stairs	5’000	25.9	0.2	0.8
14	Stairs	12’500	24.8	2.8	11.1

According to Ljung [11], in Equation (2) q stands for the time shift operator in discrete time representation. $A(q)$ and $B(q)$ denote the different polynomials influencing the input $u(k)$ and the output $y(k)$ and $e(k)$ represents the noise term. To increase the robustness of the parameter estimation a least squares regulator is used in order to reduce the effects of input collinearity. As a regulator term a multiple of the identity matrix is chosen, which corresponds to the concept of ridge regression. This showed that the model quality drastically increases.

Nevertheless a suitable set of input temperatures has to be additionally chosen with this method. Preliminary results show that for each experiment different inputs perform better. Therefore to elaborate this effect for all 14 experiments all combinations for a set of 5 inputs are computed. This results in 61’152 different sets of inputs whereas the NRMSE of each model varied drastically. As optimal inputs for all experiments the following temperatures are chosen: Coolant inlet rotary axes, coolant inlet Y-axis, Y-axis motor right, ball screw nut right, environment and comparator temperature. The chosen temperatures are a compromise for all the different load cases. By considering each experiment on its own, different inputs will lead to a better model quality. Figure 9 shows a comparison between a measurement of the positioning error E_{YY} and the modelled error with these optimal inputs. The data set is split in a training and a validation set, in a 50/50 manner. The resulting NRMSE for the training data set is 80.9 % and for the validation data set an NRMSE of 40.7 % can be achieved. This corresponds to an average prediction error of 0.11 µm and a maximum deviation of 0.5 µm from the measurements.

5. Conclusion

A measurement setup and procedure for thermal error characterization of gantry type linear axis is introduced. Four different load cases are presented to capture different thermal characteristics at the MT TCP. The results on a real MT shows that not only the heat introduced by the axis movement but also by the cooling system and the environmental temperature changes have a significant impact on the linear TCP positioning error. It is shown that with an ARX modelling approach the time and position dependent thermal errors can be modelled accurately. An analysis on optimal input selection is performed and an optimal set of inputs for all four different load cases is selected.

In future work an algorithm for the time efficient evaluation of optimal input selection will be developed and an adaptive input selection depending on the load cases will be implemented.

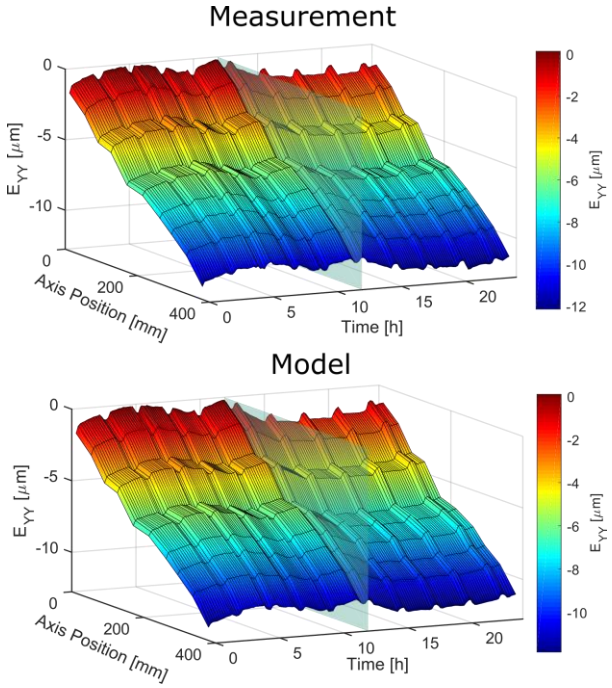

Figure 9. Results of E_{YY} measurement (top) and model (bottom) of experiment 14. Illustrated with a green plane is the separation between training and validation data. The resulting average prediction error is 0.11 µm.

Acknowledgement

The authors would like to thank the Machine Tool Technologies Research Foundation (MTTRF), the Swiss Innovation Agency (Innosuisse) and the Swiss National Science Foundation (SNSF) for their support.

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