REPRODUCIBILITY OF THERMAL ERROR BEHAVIOUR IN MACHINE TOOLS FROM THE SAME MODEL TYPE

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The present paper deals with predictive modelling of thermal deviation of the machine tool due to thermal deformations. Thermal deformation of the machine tool structure is one of the basic problems that need to be addressed when increasing the accuracy of machine tools. For each particular machine tool, it is necessary to measure its behaviour, evaluate it, and, based on the acquired knowledge, create compensation functions, which is time consuming. This study is concerned with whether it is possible to reproduce a compensation model created for one particular machine tool on the machine tools of the same production series. A reproducibility of the model was examined on two machine tools. Temperature measurements were performed at different machine tool locations along with the positioning of the tool centre point (TCP). A regression analysis was used to find the relationship between the temperature on the components and the observed change of TCP position. A method of calculating linear regression coefficients of a regression model has been defined. Furthermore, a predictive capability of the regression model among the manufactured machine tools was compared based on the size of the data set and whether the model can also be reproduced under different ambient conditions.

KEYWORDS

machine tool, ambient environment, thermal behaviour, error prediction, linear regression model, compensation

1 INTRODUCTION

In the machine tool components, changes in the ambient temperature, along with the surface temperature of the surrounding bodies and the hall structure, generate the changes in length and geometry that will be reflected by the TCP deviation from the original position. Linear and angular deviations occur in the structure of the machine tool [Zuo et al., 2013]. These are also greatly affected by the heat generated inside the machine tool. The effects of internal and external heat sources are described in [Weck et al., 1995]. These effects are observing for more than 30 years. There are multiple approaches to elimination of the error on the workpiece resulting from this process. The basic methods are the machine tool start-up prior to the machining process itself and additional compensations based on the component re-measurement. However, these methods are time and energy inefficient. The general measure recommended by machine tool makers is to place the machine tool in a thermally-stable environment; however, this leads to the construction of air-conditioned premises and higher operating costs, including a reduction in the ecological production. In addition, to particularly compensate for the Z-axis, compensating tables with a pre-measured temperature dependence of a selected component or a combination of multiple components and variations on the TCP are used. Advanced techniques for predicting the TCP deviation based on temperature information such as deployment of neural networks, transmission functions, fuzzy logic, and others are presented in publications [Turek et al., 2010][Chen 1996][Lee et al. Al., 2001]. Based on these articles, it is possible to compare the effectiveness of predictive models over a short time interval of several hours. In the article [Tan et al., 2014], the method of predicting the change of ambient temperature and its effect on the TCP deviation is analysed in detail. This relationship is also evaluated in between the seasons.

2 TASK FORMULATION

It is well known that a degree of influence on the machine tool in respect of the ambient environment and internal heat sources is high. At the same time, the approaches to how to solve the predictive model were in past compared. The trend in this field is to propose a methodology that is as simple as possible in terms of reproducibility to another machine tool. One option is to create a parameterized predictive model based on a kinematic structure of the machine tool that can adjust its parameters based on the measured data and adapt it to another machine tool with another kinematic structure. This, however, requires a relatively large amount of data measured on the machine tool to which the model is to be reproduced. This procedure is undoubtedly beneficial when reproducing a model between the machine tools that are significantly different in terms of their structure. However, if machine tools are similar, this procedure seems unnecessarily lengthy. Therefore, the question arises, if it is not possible to directly apply the predictive algorithm to another machine tool without the need for further modelling? Major tasks of this study are to address this issue and to compare the behaviour of two same machine tools of the same type series. A reproducibility of the predictive algorithm created by linear regression will be examined. In order to create a model, it is necessary to measure the temperature courses characterizing the behaviour of the machine tool and TCP deviations. A degree of compliance of the thermal deformation behaviour between the two machine tools will be compared, and since one series of measurements is performed in the summer while the other in the winter, the behaviour of the machine tool at different seasons will also be compared. The predictive algorithm created from the data measured on the 1st machine tool will be applied to the 2nd machine tool, the prediction quality will be evaluated, and the reproducibility of the model will be evaluated. Also, the predictive capability of the model will be compared between the production pieces of the machine tool, depending on the size of the learning data set.

3 THERMAL ERROR MODEL

The compensation function was created using the linear regression method. Therefore, the shape of the function is a polynomial that is linear in its parameters. Specifically, the first-degree polynomial was used. The function represents the dependence of the TCP deviation on the temperature change of a machine tool structure.It can be used for all observed axes. The TCP was considered as only one constant coordinate. The desired function y is a dependent variable of the measured temperatures$T_{1..n}$ and has the following shape. The linear regression coefficients are labelled as $b_{0..n}$.

$$y(T_1, T_2 \dots T_n) = b_0 + b_1T_1 + b_2T_2 \dots b_nT_n \quad (1)$$

The regression function is provided with the measured temperature courses and the corresponding TCP displacementcourses for the given axis. The task of the regression function is to find the coefficients$b_{0..n}$, this is done by minimizing the MSE (mean square error) between the desired function and the measured course of displacement.

$$MSE = \frac{1}{n}\sum_{i=0}^{n}(y_i^P - y_i^M)^2 \quad (2)$$

Where y^P is the vector of n values of the predicted displacement, $y^M$is the vector of n values of measured displacement. The mean square deviation was also used as a benchmark in predicting the model; it was used in the form of "root MSE (rMSE)". This will be obtained bysquare root of MSE; the advantage of this variable is that it acquires its values in the same units as the original variable under examination.

The created compensation algorithm consists of two compensation functions. One of them describes the effect of changing the ambient temperature on the TCP displacement. The other function describes the structural behaviour of the machine tool depending on the heat generated by the machine tool itself. In the case of the executed tests, this is in particular the heat generated by the rotation of the spindle, i.e. losses in spindle windings, the heat generated in the spindle bearings, etc.

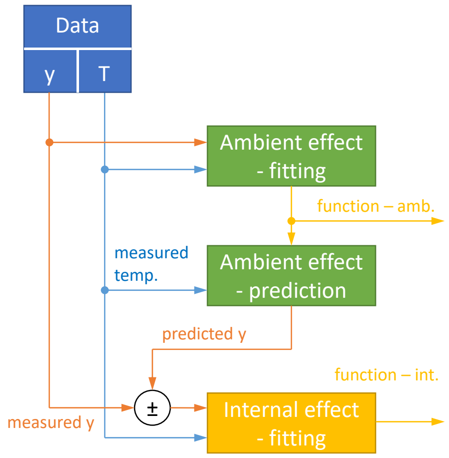

Figure 1.Block diagram of fitting

First, the function representing the ambient effects is created; it is further used to predict a deviation that is subtracted from the measured deviation. The obtained vector is then used as a model when fitting the function that represents the internal effects. When fitting, each regression function uses another set of the measured data and also uses different points of placement of temperature sensors. The function representing the ambient effects uses temperature sensors that are only slightly affected by the heat generated in the machine tool structure. At the same time, to create this function, the used data were measured during the tests when the machine tool drives were not active or the machine tool was completely switched off. On the contrary, the part of the model, which represents the internal effects, uses the sensors that are positioned close to heat sources; it is fitted to the data from the tests when the drives were active. Functions created in this way are more likely to be able to accurately describe the respective effect.

Thus, by performing the fitting process, we obtain two partial compensation functions. The resulting functions can then be used to predict the deviation as indicated in the following diagram in Fig. 2.

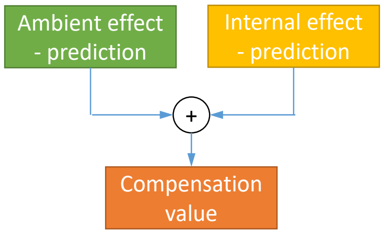

Figure 2. Prediction diagram

In the prediction, enter each function the same temperature sensors as in fitting. The resulting predicted value of TCP deviation is obtained for each time point as the sum of partial predicted values. This approach, when the individual effects are separated, is particularly beneficial because, when fitting the compensation functions, two simpler functions are more lucid than one more complex, and we can affect the quality of compensation for each effect separately.

4 EXPERIMENTAL VERIFICATION

The study was carried out on a 3-axis machining centre of the upper gantry type with a work table of 1 200 mm x 1000 mm and the ram feed of 600 mm.

The machine tool was equipped with 41 temperature sensors, of which 10 were selected using statistical methods of a regression and cluster analysis; these measuring points represent the temperature field of the machine tool for all 3 axes, see Fig. 3.

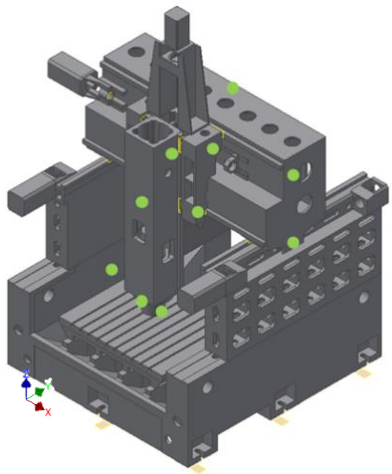

Figure 3. Positioning of sensors for the compensation algorithm

A measurement method of TCP deviation was in compliance with ISO 230-3, see Fig. 4. Five position probes and a precise measuring arbour were used. The orientation of position probes corresponds to machine tool coordination system in Fig. 3. Further, the study focuses only on the behaviour in the Y-axis, since in this axis, in terms of manufacturing accuracy of the machine tool, TCP deviations in relation to temperature are relatively significant.

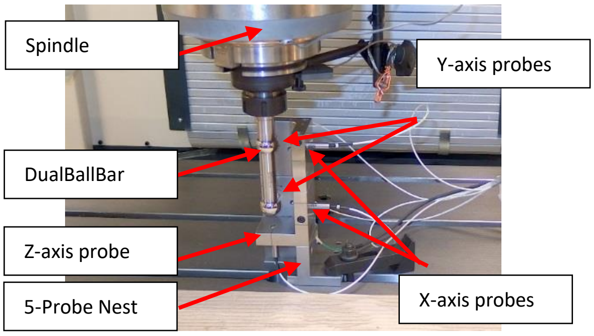

Figure 4. Arrangement of measurement

Throughout the tests, the values of temperatures and deviations were recorded at intervals of 60s continuously. The test cycle always included the test of ambient effect on the off-state machine tool, a start-up test of the machine tool up to a standby mode androtation cycles of spindle idle run. In order for the measured data from both experiments to be comparable, the temperature sensors and the TCP deviation measurement device for both machine tools were positioned at the same locations.

5 RESULTS AND DISCUSSION

In the next sections, the circumstances of experiments, fitting process, results of prediction and the impact of the size of learning data set on the prediction quality are presented.

5.1 Ambient conditions

Dominant circumstances affecting a thermal deformation behaviour of the machine tool are its ambient temperature. Fig. 5 - 8, and the Tab. 1 and Tab. 2 show a comparison of the ambient temperature in different height above the ground level. The machine tool was tested in a standard production hall with windows and skylights in the roof. The hall has a hot-air heating (in the case of machine tool 2, winter season), in the case of machine tool 1, heating was not activated (summer season).The average and the standard temperature deviation in the Tab. 1 and 2 are derived from periodic peaks of observed temperature, see Fig. 5 and 6.

Average height difference of temperatures [K/m]				
	Summer – M1. evening		Winter – M2. evening	
Height [m]	Average	Stand. deviation	Average	Stand. deviation
0.5–1.4	0.74	0.12	0.52	0.19
1.4–2.3	0.11	0.14	0.58	0.21

Table 1. Height difference of temperatures

The temperature in the hall is, in long-term, more reproducible in the winter (heating) period than in the summer when the indoor environment of the hall is sensitive to changing weather conditions. The temperature sensors are positioned in a vertical line on different high levels above the floor level (Tair down = 0.5 m, Tair mid = 1.4 m,Tair up = 2.3 m). In Fig. 5-8 mentioned Tair Machine volume represents the temperature inside a cutting area. The scale of the time axis on all next figures is in days (d).

Change in temperature during the day (height 2.3 m)		
	Summer – M1	Winter – M2
Average [K]	3.14	3.20
Stand. Deviation [K]	0.61	1.28

Table 2. Change in ambient temperature

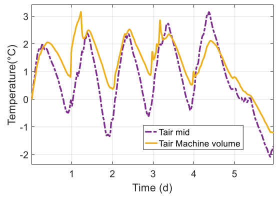

Figure 5. Air temperature – machine tool 1

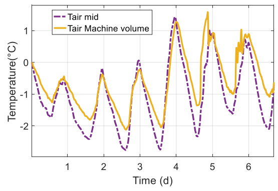

Figure 6. Air temperature – machine tool 2

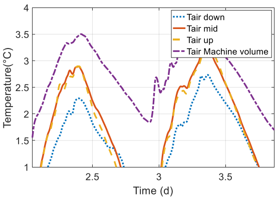

Figure 7. Air temperature – machine tool 1 detail

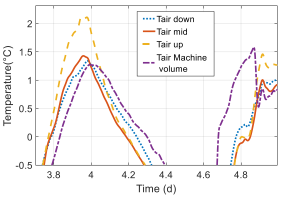

Figure 8. Air temperature – machine tool 2 detail

5.2 Thermal behaviour of machine tools

In the further subsections, the fitting process and the results of prediction for both machine tools are presented.

5.2.1 Machine tool 1

To create the compensation model, measured TCP deviations and temperatures from the measurements on the 1stmachine tool were used. Based on these data, partial compensation functions were created using the methodology described above.

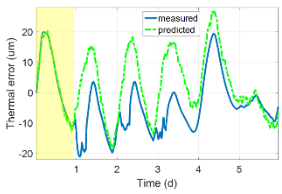

Figure 9. M1 – Predicted deviation caused by ambient effects

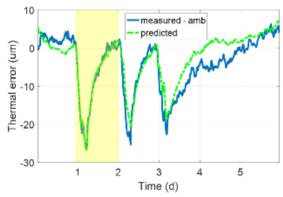

Figure 10.M1 – Predicted deviation caused by internal effects

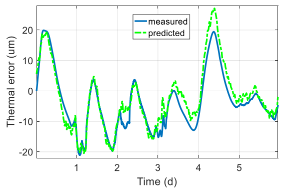

Figure 11. S1 - Total predicted deviation (compensation value)

Fig. 9 shows the course of measured displacement and the displacement predicted by the function that describes the ambient effects. There is a difference between the prediction and measurement, because another tests were focused on internal heat sources. The influence of internal heat sources causes the difference. To learn this compensation function, the first part of the measureddata (machine tool stand-by mode) was used; this is highlighted in the graph and forms 16% of the length of the course measured on the 1stmachine tool. The second part of the plotted courses never entered the fitting process and the predicted displacement is therefore obtained only on the basis of measured temperatures as a result of ambient conditions. While fitting, rMSE was 2.8 % and the following function was used:

$$y_a = -0.148 - 9.18T_1 + 16T_2 - 6.28T_3 \tag{3}$$

The graph in Fig. 10 shows the result of prediction of internal effects. The highlighted part of the plotted course was used in fitting and forms 18 %. The rMSE in fitting was 2.8 % and the rMSE prediction was 6.8 %.

$$y_b = -2.83 + 7.48T_1 - 4.46T_2 - 5.01T_3 - 0.60T_4 \quad (4)$$

Fig. 11 shows a graph with the measured displacement in the Y axis and the total compensation value (after summation). A total rMSE between the measured and predicted displacements is 6.0 %, and the improvement in accuracy is 91 %.

5.2.2 Machine tool 2

After reproducing the compensation algorithm created for the first machine tool to the second machine tool, the TCP deviation was again predicted. The courses obtained are plotted in the following graphs.

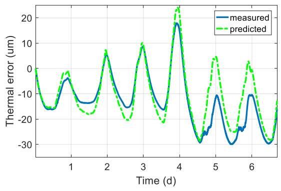

Figure 12. M2 – Predicted deviation caused by ambient effects

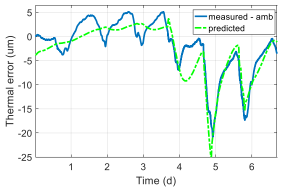

Figure 13. M2 – Predicted deviation caused by internal effects

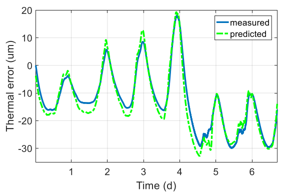

Figure 14. M2 - Total predicted deviation (compensation value)

Fig. 12 shows the measured deviation and the predicted deviation caused by the ambient effects. The predicted deviation caused by internal effects is shown in Fig. 13. The total compensation value is then plotted in Fig. 14. Its rMSE relative to the measured course is 6.8 %. When using this compensation function, the accuracy of the machine tool increased by 88% in the monitored section (2nd series of measurements).

The predicted TCP deviations caused by ambient effects (Fig. 9 and Fig. 12) show a periodic course which, according to our assumptions, corresponds to the course of ambient temperature (Fig. 5 and Fig. 6), with a course period of one day. The machine tool load on individual tests started at approximately the same hour, i.e. at the same phase of daily cycle. Therefore, the internal effects always act against the ambient effects and are clearly distinguishable in the measured courses. Therefore, during the machine tool loading, the measured TCP deviation differs from the predicted ambient conditions and returns to them once the load has been released. Based on this, it can be assumed that the created model describes, quite credibly, the ambient effects for both sets of data.

From the graphs in Fig. 10 and Fig. 13 and the above rMSE values, it is clear that the model describes the internal effects slightly better for the 1st set of data, but in both cases, the compliance with the measured courses is satisfactory.

The quality of the overall model prediction is satisfactory for both sets of data. For the first set, rMSE = 6 % and for the second one, rMSE = 6.8 %. Therefore, in the case of the second set, the prediction is worse by 0.8 %. However, both values meet the preselected criterion and are less than 10 %. This criterion was selected based on experience.

From the above findings, it can be concluded that the prediction model is reproducible between the individual machine tools and periods. Therefore, in the further research and creation of compensation functions, the data measured on various production pieces of one type of machine tool can be used. Also, the compensation function may be reproduced within different seasons, and whether the hall is running in heating mode or not, it also does not have a significant influence on the quality of prediction.

5.3 Impact of the size of learning set on the prediction quality

It has also been compared how the increase in the size of the learning data measured on the 1stmachine toolaffects the success rate of the prediction for the data measured on the 2ndmachine tool.

Size of learning set	rMSEfitting [µm]	rMSE prediction [µm]
34 %	1.3	3.4
49 %	2.0	3.9
54 %	2.1	3.6
100 %	2.2	3.7

Table 3. Impact of the size of learning set on the prediction quality

Although it may seem that the more data is used to learn the model, the better its predictive capability, in this case it is not true. By increasing the size of the learning set, rMSE for the fitting part stays on similar level, which can lead to the resultant function with the same predictive capability.Due to less claim on the length of measuring, the smallest size of the learning data is useful and fully sufficient.

6 CONCLUSIONS

The present study deals with the reproducibility of the predictive model between the machine tools from one type series. Therefore, a predictive model was proposed and learned on the set of the data obtained from the experiment performed on the first test machine tool. Furthermore, the TCP deviation was predicted using this model. For the prediction evaluation, the remaining part of the data from the 1st set of measurements and the data measured on the 2ndmachine tool were used. For both data sets, the predicted deviation was compared with the measured one. For each machine tool, the predictive quality was evaluated and quantified. The predictive quality between both machine tools was also compared. For the first machine tool, on which the model was learned, the predictive capability was only slightly better than that for the second machine tool. Therefore, it was assessed that the predictive model is reproducible between the individual machine tools. The main benefit of the study is that it is possible to reproduce a model created for one machine tool to another machine tool from the same production series without any significant deterioration in its predictive capabilities. It has also been assessed that the model is reproducible within the respective seasons; therefore, it is not necessary to implement any adaptive model modifications depending on the changes in the season or heating conditions in the production hall where the respective machine tool is operated.

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