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Thermal Model of a Swiss-type Lathe

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Abstract
An ARX model is applied offline to a Swiss-type lathe under a complex thermal load case. The lathe is subjected to thermal influences from running driven tools, the main spindle and changing cutting oil temperature. A cycle corresponding to the machining of a thermal test piece is run on the machine without material for 120 hours. The model is trained on a cycle of randomly varying spindle, driven tools and axis speeds, as well as varying cutting oil temperatures. Errors are measured with pneumatic probes in X- and Y-directions and corresponding root mean square errors are reduced by 90%. The paper preliminarily demonstrates the suitability of a short training cycle with randomly varying thermal influences to compensate a longer machining process of a real part.

Thermal errors, thermal compensation, Swiss-type lathe, machine tool

1. Introduction

Machine tools are susceptible to a range of error sources including kinematic errors, dynamic excitations, geometrical inaccuracies, gravitational forces etc., and most importantly, thermal influences. Research of Mayr et al. [1] on thermal issues in machine tools highlighted that thermal errors are one of the most dominant sources of geometric errors of manufactured parts. Influences contributing to the overall thermal error, summarized in the thermal chain of causes diagram from Wegener et al. [2], include internal influences such as friction in bearings, ball screws, gear boxes, heat generated in electrical components such as motors etc., and external influences that are the cutting process and the environment. To counteract thermal influences and reduce thermal errors, options are to thermally stabilize the machine (e.g. via cooling) or to thermally compensate it. Thermal compensation is a knowledge-based approach that predicts the thermal errors at the tool centre point. Due to demand from industry and society to push for higher machine tool efficiency, thermal compensation is an increasingly popular solution, as stated by Wegener et al. [3].

In recent years, a lot of progress has been made in the field of thermal compensation. A particularly successful compensation model has been the autoregressive model with exogenous inputs (ARX). Blaser et al. [4] used ARX to develop a thermal adaptive learning control approach for the compensation of rotary axes of a 5-axis machine tool, and further demonstrated the suitability of the model for long-term compensation [5]. This approach was extended by Zimmermann et al. [6], who adapted the compensation model to optimally select and reselect model inputs for each thermal error. Mareš et al. [7] applied ARX to compensate thermal errors in X-, Y- and Z-directions in a 5-axis machine tool under various internal and external heat sources. Mareš et al. [8] also proposed an approach to modelling the thermal errors of a turning-milling centre based on ARX, tested three typical experimental setups (drilling, milling, and turning) under load free conditions and applied compensation offline. Fundamental to the success of a compensation model is also the choice of model inputs, and to this end, various approaches have been investigated, such as correlation theory, neural networks, fuzzy clustering, partial correlation analysis, all summarized in the work of Liu et al. [9].

The bulk of thermal error measurement and compensation methodology in literature has been developed for 5-axis machine tools, from which the kinematic chain and working space composition of a Swiss-type lathe differs markedly. In this paper, modelling via ARX and input selection via k-means clustering are applied to a Swiss-type lathe. Focus is placed on error measurement and compensation of linear errors between the spindle and the lathe tool holder, which is a significant heat source during the operation of driven tools.

2. Experimental Setup

2.1. Investigated Lathe

The kinematic chain of the used Swiss-type lathe is denoted as H[w-[S1'-Z1' S2'-Y2'-Z2'-X2']-b-[t X1-Y1-[t (S11)-t]]], derived from the notation outlined in ISO 10791-1:2015 [10] for machining centres. A tool holder, as shown in Fig. 1, contains non-driven and driven tools, and moves in the X-Y-plane. Cutting oil is used as a workspace coolant and is sprayed at the location of the work piece and driven tools.

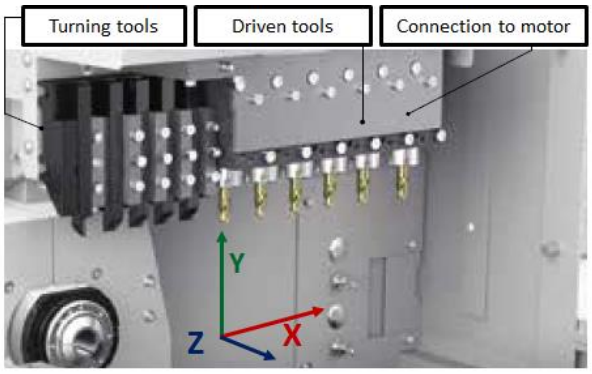

Figure 1. Working space of the Swiss-type lathe. Turning (non-driven) and driven tools are shown. The axis configuration is also shown.

2.2. Measurement Equipment

Pneumatic displacement probes are mounted at the positions of tools to measure thermal errors in the X- and Y-directions, as shown in Fig. 2.

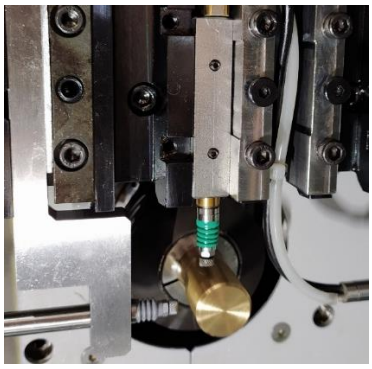

Figure 2. Pneumatic probes are clamped in the location of the tools and measure thermal errors in the X- and Y-direction relative to an artefact clamped in the spindle.

Temperatures are measured in the working space, around the machine structure, and directly on the tool holder with Pt100 sensors. Furthermore, the cutting oil (used as a workspace coolant) and spindle internal cooling temperature as well as all axis, spindle and driven tools motor temperatures are also recorded. Twelve temperature inputs in total are monitored. Additionally, the spindle and driven tool speeds taken directly from the NC are also recorded.

2.3 Thermal Test Piece

A machining cycle for a thermal test-piece, shown in Fig. 3, runs on the machine tool without material cutting. The cycle lasts approximately 60 seconds: this corresponds to a typical industrial production on a Swiss-type lathe, in which a manufacturing cycle for a single part can last around a minute.

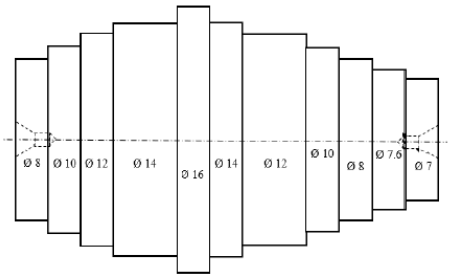

Figure 3. Thermal test-piece. A cycle corresponding to the thermal test-piece runs on the machine but without any machining because tools are replaced by pneumatic probes.

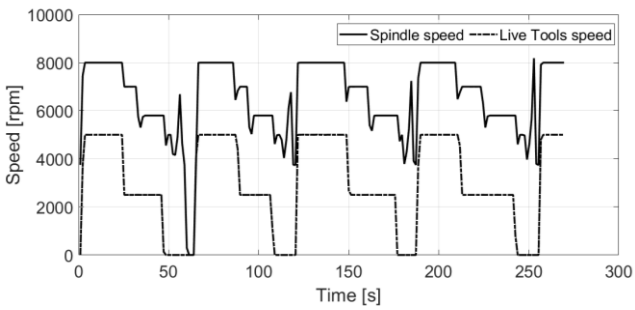

Figure 4. Speed profiles of the spindle and driven tools. Four speed cycles are repeated before a short measurement cycle takes places around 250 seconds. The speed cycles are repeated for 120 hours corresponding to a working week mass production run on a Swiss-type lathe.

The cycle is a combination of X- and Y-axis movements as well as spindle and driven tool speeds up to 8000 and 5000 rpm respectively. The machining cycle is repeated four times, before a thermal error measurement cycle lasting 15 seconds is triggered, as shown in Fig. 4. The entire experiment lasts approximately 120 hours.

2.4 Model Calibration

The compensation model is calibrated on cycle different from the thermal test piece cycle described in the preceding section. This corresponds to an industrial scenario in which a calibration procedure may not be possible just before or during production (for example due to time constraints related to mounting measurement equipment). A separate training cycle is therefore executed a priori at a different time. This training cycle is shorter, lasts approximately 48 hours, and consists of randomly varying spindle and driven tools speeds as well as varying cutting oil temperatures. The proposed training cycle is devised such that it could function as a universal training cycle for similarly sized parts without exact knowledge of the part. To capture the transient thermal behaviour of the machine, spindle and driven tools speeds are kept constant for hours rather than minutes, as show in Fig. 5.

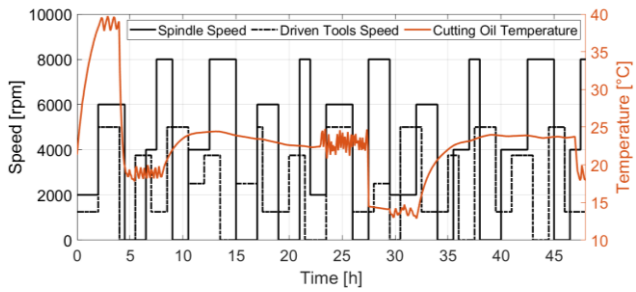

Figure 5. Speed profiles of the spindle and driven tools and the varying cutting oil temperature of the model training cycle are shown. The x-axis has now the units of hours, not seconds as in Fig. 4.

3. Methodology

3.1. Autoregressive Model with Exogenous Inputs (ARX)

The ARX model is a linear representation of a dynamic system in discrete time steps. ARX considers past and present system inputs as well as past system outputs to compute the prediction for the current system output. The model structure is expressed by the following linear difference equation, adapted from the work of Ljung [11]:

$$y(t) + a_1 y(t-1) + \cdots + a_{n_a} y(t-n_a) = b_1 u(t-1) + \cdots + b_{n_b} u(t-n_b) \quad (1)$$

y represents the model output (thermal error) and u the model input (e.g. temperature). The model coefficients can be collected in the $\underline{\theta}$ matrix and the time series of past outputs and inputs in the matrix $\underline{\varphi}(t)$.

$$\underline{\theta} = [a_1 \ a_2 \ \dots \ a_{n_a} \ b_1 \ b_2 \dots \ b_{n_b}] \quad (2)$$

$$\underline{\varphi}(t) = [-y(t-1) \ \dots \ -y(t-n_a) \ u(t-1) \ \dots \ \dots \ u(t-n_b)] \quad (3)$$

n_a and n_b are user inputs to the model that express how far the model looks into the past. To start a compensation process, initialisation values for y are required. However, in a practical manufacturing scenario, an initial calibration run may not always

be feasible, and initialisation values must be taken from elsewhere, e.g. an a priori executed training cycle. It is therefore desirable to keep n_a as low as possible. To retain the functionalities of a dynamic system n_a is set to 2 for all compensation models. The coefficient matrix θ can be minimized via least squares and the thermal error $\hat{y}$ predicted:

$$\underline{\hat{\theta}} = \left[\sum_{i=1}^{N} \underline{\varphi}(t)\underline{\varphi}^T(t)\right]^{-1} \sum_{i=1}^{N} \underline{\varphi}(t)y(t) \tag{4}$$

$$\hat{y} = \underline{\varphi}^T(t)\underline{\hat{\theta}} \tag{5}$$

3.2. k-means Clustering

The challenge in compensation is to select appropriate inputs for the compensation model, as choosing all measured variables as inputs may not necessarily lead to the best performing model. k-means clustering groups similar variable time series together into clusters, from each of which one input is selected for the model. The number of clusters is determined via the Elbow method and cluster centres are initialised via the k-means++ algorithm. The input choice from each cluster is selected by training the ARX model on possible combinations and evaluating performance against training data. The k-means algorithm is as follows: cluster centres $\mu^{(0)}$ are initialised, each point x_i is assigned to the nearest cluster centre z_i, and finally the cluster centre is iteratively updated as a mean of assigned data points until there are no further cluster assignment changes.

$$\underline{\mu}^{(0)} = \left[\mu_1^{(0)}, \dots, \mu_k^{(0)}\right] \tag{6}$$

$$z_i \leftarrow arg\,\min_j \left\|\underline{x_i} - \underline{\mu}_j^{(t-1)}\right\|_2 \tag{7}$$

$$\underline{\mu}_j^{(t)} \leftarrow \frac{1}{n_j} \sum_{i:z_i=j} \underline{x_i} \tag{8}$$

4. Results

The timeline of the experiment with significant thermal events is shown in Fig. 6. The machine tool is subjected to a variety of temperature changes, most notable of which are also visualised in Fig. 6. Ambient conditions changed due to day/night variation and alternately running machine hall air conditioning during the day. In the first 24 hours, the cycle runs without cutting oil; after the cutting oil spray onto the tool holder and the machining area is started. Cutting oil temperature is varied by the operator after 72 hours of the experiment. Driven tools motor temperature is affected by the presence of the cutting oil spray. Temperatures are plotted as ΔT from the initial ambient temperature.

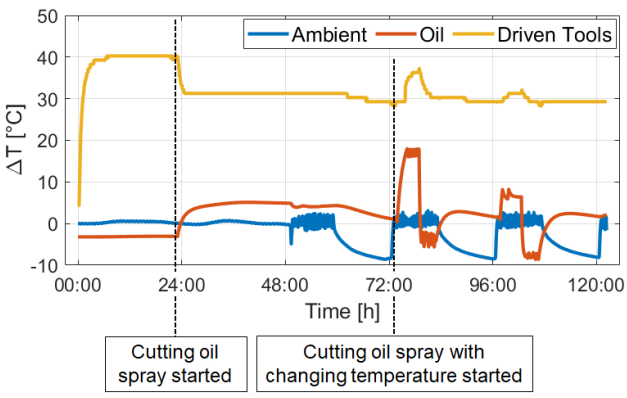

Figure 6. Timeline of the experiment and temperature variation of the ambient, cutting oil and driven tools motor temperature.

Thermal compensation is applied to model E_{X0S} and E_{Y0S} direction errors between the spindle and the tool holder. Modelling results in the X- and Y-direction are shown in Fig. 7 and Fig. 8 respectively. Root-mean-square and peak-to-peak error reduction are summarized in Table 1. As the thermal error in the Z-direction E_{Z0S} progresses much more slowly than the cycle time of 60 seconds, this error is neglected in the investigation.

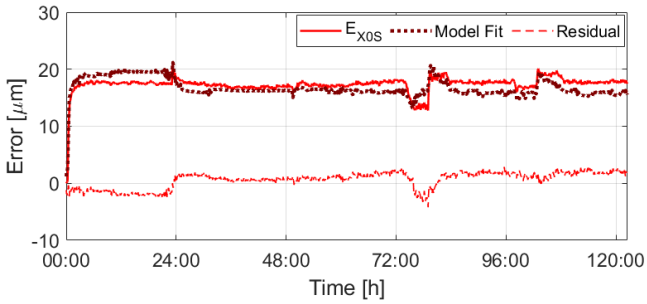

Figure 7. Model fit to the E_{X0S} error and residual.

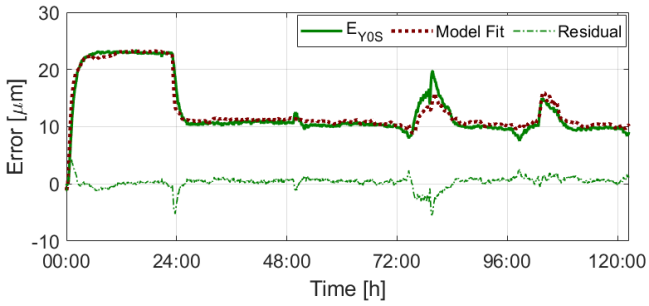

Figure 8. Model fit to the E_{Y0S} error and residual.

Results show that the cutting oil spray affects the Y-direction thermal error more than the X-direction. The model has some deficiencies in that it struggles to predict accurately the thermal error where the temperature steeply changes. Nevertheless, it is able to attenuate peaks during sudden cutting oil temperature change by 60%, as seen in Table 1, and reduces thermal errors during stable operation to zero.

Table 1: Summary of uncompensated and modelled error values.

	E_{X0S}	E_{Y0S}
Uncompensated peak-to-peak error	20.6 µm	23.5 µm
Modelled peak-to-peak error	7.1 µm	9.9 µm
Peak-to-peak error reduction	66%	58%
Uncompensated RMS error	17.4 µm	13.7 µm
Modelled RMS error	1.5 µm	1.1 µm
RMS error reduction	91%	92%

5. Conclusion and outlook

This publication presents the offline application of a thermal compensation model to a Swiss-type lathe. Displacement probes are mounted in positions of tools in the tool holder and temperature sensors are mounted in the working space, around the machine structure, and on the tool holder. The model is applied to a virtual thermal test piece cycle with a machining time of 60 seconds over a period of 120 hours. The thermal load case consists of changing driven tool and spindle speeds, changing ambient conditions and changing cutting oil temperature. The model is trained on a shorter training cycle lasting 48 hours. Results show that the application of the ARX model reduces steady state errors to zero and attenuates peaks in thermal errors caused by sudden boundary condition changes. Results also preliminarily demonstrate the suitability of the training cycle to compensate a virtual machining process of a real part. This work will be followed by several additional steps: the training cycle will be validated on a different thermal test piece cycle, and the model will be implemented online into the machine to translate compensation values into axis movements.

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