

Investigating the Energy Efficiency of Thermal Error Compensation in Machine Tools

Lenny Rhiner^{1,2}, Sebastian Lang^{1,2}, Josef Mayr¹, Markus Bambach²

¹inspire AG, Technoparkstrasse 1, 8005 Zurich, Switzerland

²Advanced Manufacturing Lab ETH Zurich, Technoparkstrasse 1, 8005 Zurich, Switzerland

Lenny.rhiner@inspire.ch

Abstract

Sustainability in manufacturing is increasingly essential for improving energy efficiency and reducing waste. This study explores the benefits of thermal error compensation as an alternative to conventional machine tool warm-up cycles. During controlled experiments, temperature data around the machine tool is combined with measurement data from a discrete R-test, to form training data for an ARX-based compensation model. During the same experiments the energy consumption of the machine tool and its components is measured. The compensation model using 150 hours of training data, achieves an up to 83% reduction in thermal error. Compared to standard warm-up routines, thermal compensation can be more efficient in terms of energy consumption and productivity after as little as 8 weeks. These results highlight the potential for thermal error compensation to enhance precision manufacturing processes while reducing environmental impact.

Thermal Error Compensation, Energy Efficiency, Machine Tools, Precision, Warm-up Cycles

1. Introduction

Thermal errors are one of the largest challenges for sustainable and high precision production using machine tools [1]. To ensure thermal stability during the production of high-precision parts, according to Putz [2], 85 % of manufacturers rely on warm-up cycles, 97 % implement cooling measures that exceed overheating prevention requirements and 55 % use air-conditioned production halls. While these methods are effective, they are also energy- and cost-intensive. In contrast, thermal error compensation utilizes predictive models to estimate and correct thermal errors through the machine's control system. This approach is resource-efficient, and improves accuracy, which enables the production of parts with tighter tolerances.

Blaser [3] and Mayr et al. [4] developed the thermal adaptive learning control (TALC), a closed loop thermal error compensation using an autoregressive model with exogenous input (ARX) capable of predicting thermal error from temperature measurements. Zimmermann et al [5, 6] expanded this work with adaptive input selection methods.

While the increase in machining accuracy is well documented, few resources highlight the potential for sustainability considerations such as energy efficiency as well as production efficiency. This study contributes to closing that gap by measuring and analyzing the energy intake with and without thermal error compensation on a high-precision 5 axis machine tool.

2. Methods

For this investigation, the 5-axis Mori Seiki NMV 5000 DCG machine tool is used. A touch trigger probe clamped in the spindle and a measurement artefact are used to measure the thermally induced error as described by [3]. This enables the determination of the error of the C-axis in X, Y and Z-axis

direction (X0C, Y0C and Z0T) as well as the rotational errors ROT, A0C, B0C and C0C with high repeatability [2].

The machine tool is thermally excited using randomized axis movements of all linear and rotary axis as well as the turning and milling spindles at varying speeds. Temperatures are measured at strategic locations around the machine tool.

2.1. Compensation model

To predict thermal errors from temperature measurements an ARX derived from the work of [3, 5] is used. Furthermore, it employs adaptive input selection [6] and the TALC structure [9], which automatically triggers the gathering of new measurements to update the model to novel thermal behaviour.

2.2. Energy measurement

The machine is cooled with 2 independently controlled cooling cycles. One of which is utilized solely for the cooling of the C-axis as it can be used as a turning table with up to 1200 rpm, while the other cools the remaining axes and the spindle.

The setup as visualized in Figure 1 measures the power consumption of the rotational and linear axes, the spindle and the two cooling aggregates as well as the hydraulic pump. The total power consumption is also measured to estimate the effects of other components such as lubricant pumps, tool changer and chip conveyor.

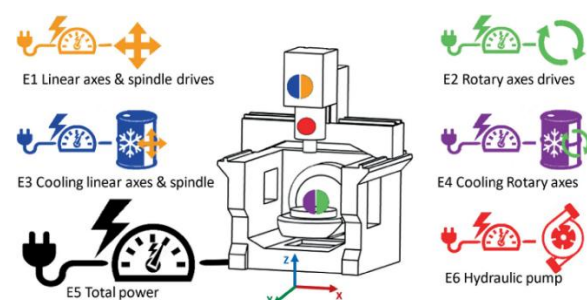


Figure 1 Energy measurement setup from [10]

3. Results

In a controlled set of experiments totalling around 300 hours of measurements, the accuracy of the thermal compensation model (see Figure 2) is evaluated using Peak to Peak (P2P) and root mean square errors (RMSE). After a training period of 156 hours, it manages a P2P error reduction of 77.15 % - from 32.75 μm to 7.43 μm - on the most significant axis-specific error (E_{YOC}) during the validation period. The averaged RMSEs are listed in Table 1.

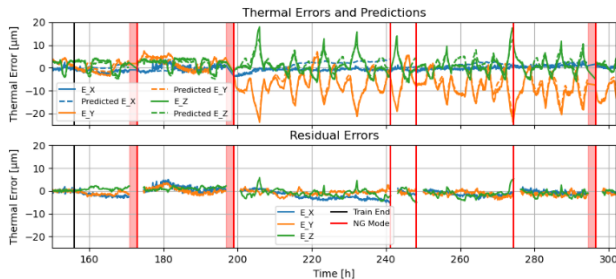


Figure 2 Thermal errors and predictions above and residual errors below. Red bars mark an interruption in the experiment and red lines an interruption due to updating of the compensation model.

RMSE	E_{XOC}	E_{YOC}	E_{ZOT}
Uncompensated [μm]	2.39	8.64	4.04
Compensated [μm]	1.44	1.43	1.81
Reduction [-]	39.6%	83.3%	55.2%

Table 1 Averaged thermal errors with and without compensation

3.1 Sustainability and machine uptime considerations

Figure 3 shows the measured energy consumption dissected into the different components. The machine consumed a total of 1.12 MWh, which averages to 3.56 kW. During this period 2768 measurement cycles consumed 222.3 kWh for an average of 0.08 kWh per measurement. Noteworthy, 27.7 % of the energy consumed is due to the two cooling aggregates.

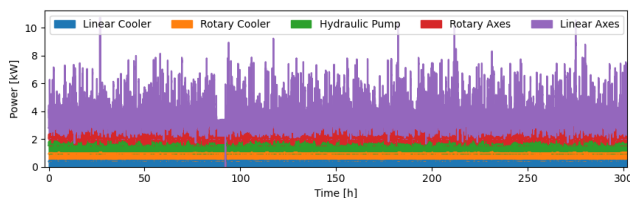


Figure 3 Component-specific energy consumption of an NMV 5000 DCG

During the experiment, the compensation model needed to update 3 times, leading to an average productivity loss of around 2.4h per week. This model is optimized for accuracy, similar models have been trained on 24 or even fewer hours of initial training data [3].

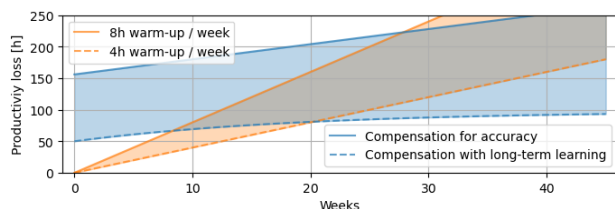


Figure 4 Productivity comparison between warm-up cycles and thermal compensation for a range of scenarios

The weekly updating/retraining time of the compensation model is expected to decrease over time, as novel thermal states become scarcer. Therefore, it can be assumed that the thermal error compensation model not only requires less retraining over time, but the accuracy of the thermal compensation also increases. Figure 4 compares scenarios and indicates that

thermal compensation might be more time efficient from around 8 weeks. In this optimistic scenario, a total of 1.1 GWh can be saved during the first year by employing thermal error compensation instead of warm-up cycles.

4. Conclusions and outlook

This study investigates the use of thermal error compensation to improve the sustainability and efficiency of machine tools. By using an ARX-based thermal error compensation model, it is possible to reduce the P2P error by up to 77 % and RMSE by up to 83 %. At the same time, long term use of thermal compensation can also increase the production efficiency of machine tools relying on warm-up cycles to achieve thermal stability.

A key limitation of this study is the use of air cuts during the load cycle, which do not fully represent the energy consumption and thermal error patterns during actual machining operations.

27.7 % of the investigated machine tool's energy consumption is attributed to the cooling aggregates, a significant portion of which is used to maintain thermal stability rather than solely keeping the motors within their operational temperature range. This highlights vast potential for further reductions in energy consumption by optimizing the cooling system, in conjunction with thermal error compensation. Similarly, reducing the energy required for air-conditioned production halls is another area that warrants further investigation.

Acknowledgements

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