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Characterization and compensation of volumetric error variations over time in medium size machine tools

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Abstract

An artifact-based fast and automated volumetric error mapping solution for medium size 3-axis machine tools that enables the calibration of a 1m3 workspace in less than one hour is proposed for characterizing how temperature variations affect the volumetric accuracy of the machine without a priori knowledge of the temperature variations. A continuous measurement during seven days is performed on a medium sized milling machine affected by different heat sources and a volumetric error variation model is identified. Residual errors remaining from the identification process are used to estimate the uncertainties of individual parameters and motion errors, and Monte Carlo simulations are used to propagate them to the TCP. This model is used to understand how the volumetric positioning error of the machine changes over time and how it is generated within the kinematic chain of the machine.
Finally, a second experimental test is carried-out, this time equipping the machine with several temperature sensors. A compensation model based in multiple linear regression is implemented to predict the different component errors affecting the volumetric accuracy of the machine tool.

Machine tool, volumetric error, thermal error, uncertainty

1. Introduction

In modern manufacturing industries, precision in machine tools is crucial for ensuring the dimensional accuracy of manufactured parts. Geometric and thermal errors represent significant sources of deviation in the volumetric accuracy of machine tools and have been studied independently for decades [1]. Traditional approaches, exemplified by [2] and [3], have treated geometric and thermal errors separately, employing distinct methodologies for their characterization [4].

Geometric error characterization and compensation have been extensively explored, particularly in medium and large-sized machine tools, using advanced technologies such as Laser Trackers (LT) and multilateration-based solutions [5]. An alternative, cost-effective method involves artefact-based solutions, despite limitations in range and measurable positions [6]. These solutions primarily focus on the characterization of the geometric errors due to manufacturing and assembly imperfections [7]. However, thermal errors can influence the characterization of geometric errors, leading to two main approaches: assuming stable thermal conditions for geometric error characterization [8] or incorporating thermal effects as uncertainties in calibration [9]. The latter approach, while more reliable, often relies on oversimplified models that may lead to inaccurate assessments of thermal effects.

On the other hand, approaches to characterize thermal effects usually focus on very localized effects, ignoring the variation of the error along the whole working volume. Digital Twin-based approaches, utilizing Finite Element models, offer a potential solution to volumetric limitations. However, challenges arise in accurately modelling complex thermomechanical systems, making these approaches difficult to implement in industrial environments with diverse machines and strict production deadlines. While experimental training for phenomenological models appears promising, comprehensive error characterization across the entire volume requires addressing constraints.

Preceding works have explored artifact-based volumetric calibration methods [10], with an optimized implementation for an automatic and repeatable procedure [11]. This work introduces a compensation model for thermal errors within the machine tool's volume, treating geometric and thermal errors as a unified source of error. The study focuses on a moving column milling machine, conducting two distinct thermal tests to establish and validate the compensation model. A network of up to 52 temperature sensors was employed to comprehensively capture the machine's thermal state over time.

The structure of this paper is as follows: Section 2 provides a comprehensive account of the methodology employed, showing both the experimental setup and the theoretical basis of the volumetric calibration and thermal compensation model. Section 3 presents a summary of the experimental results, with some in-depth analysis. Section 4 closes with conclusions and outlook.

2. Methodology

2.1. Experimental setup

Following the methodology developed in previous works, an artifact-based calibration procedure is carried out in a medium-sized milling machine. It is a moving column type milling machine, with fixed table in the workpiece side. The actual setup is shown in Figure 1.

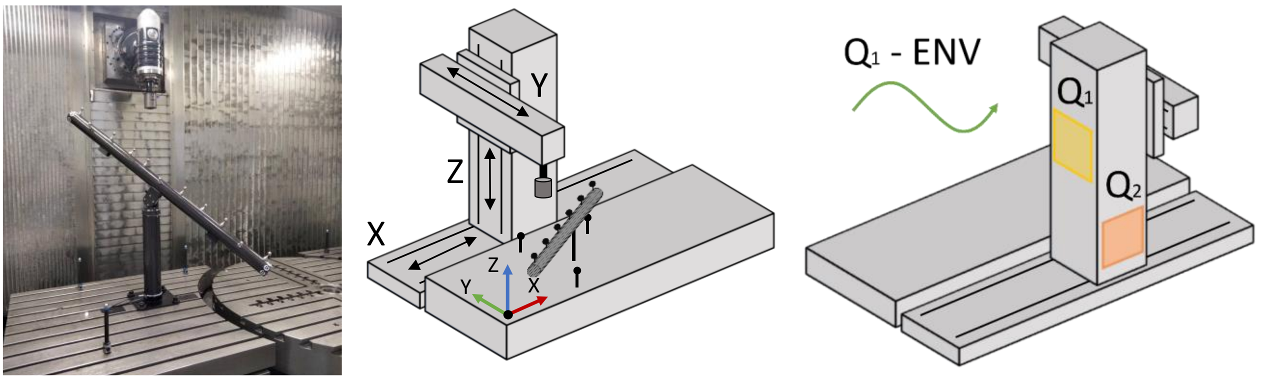

Figure 1. (left) Calibration setup with the ball array and 3 individual spheres on the machine table and the measuring probe mounted in the machine head. (middle) Schematic depiction of the machine kinematics. (right) Schematic depiction of the heat sources

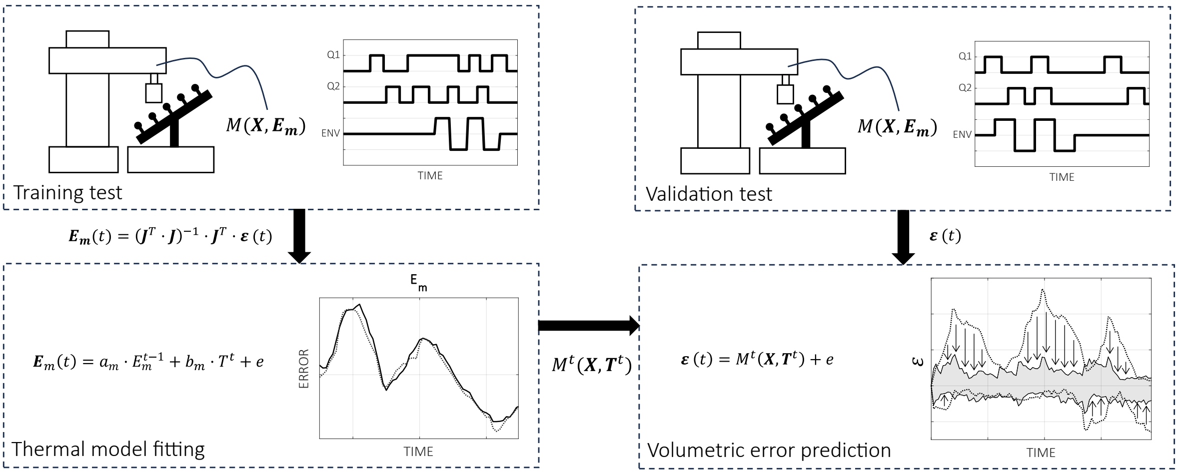

Figure 2. Summary of process for the obtention of a thermal volumetric error prediction model. (Top-left) Training test with the consequent obtention of the volumetric errors changing over time; (Bottom-left) ARX regression with temperatures as inputs obtaining a compensation model; (Top-right) Validation test measuring distance errors; (Bottom right) Volumetric error prediction and compensation using model M over errors measured in validation test.

The calibration process consists of measuring a ball array with high precision spheres over several orientations inside the machine working volume. These measurements are repeated over several days in order to capture the thermal variation of the machine errors. To make this process automatic, the artefact is mounted in a cylindrical base with an embedded rotary motor. The inclination around horizontal (elevation) angle is set manually and locked through all the test as the rotation around the vertical (azimuth) angle is provided by the rotary motor. To map the thermal state of the machine, up to 50 temperature sensors have been installed in different parts of the structure: 10 in the workpiece side table, 10 in the X axis bed, 16 in the column, 12 in the ram and 4 ambient sensors. Three controlled heat sources (two local hot air ventilators and room climate) can be activated or deactivated during the thermal test.

2.2. Volumetric thermal error model

In order to calculate TCP errors at any axis position a kinematic model of the machine is developed using Homogeneous Transformation Matrices (HTM), which is a widespread technique for machine tool modelling [12]. The result is a model capable of predicting the volumetric error at any point in the calibrated space, which will be referred generically as M(X,E_X), denoting its dependence on axes positions (X) and component errors motions (E_X). The position dependent error motions for each axis are modelled by linear combinations of Legendre polynomials of order n.

In [10] the shape of the artefact and the measurement positions were optimized, resulting in a pseudo-1D ball array with a primary longitudinal direction and small transversal offsets between 11 spheres. It is necessary to measure the ball array at 8 different orientations in order to get a proper compensation model. The geometric errors contained in E_X are estimated by minimizing the error between the calibrated and measured distances between the spheres in the ball array using least square regression.

The procedure is repeated periodically every hour, and a volumetric error model is obtained for each measurement cycle while thermal conditions are varied. Thus, the parameters obtained for the volumetric error model will experience a variation over time that is then fitted to a multiple linear regression model relating temperatures and parameter variations. A training test and a validation test are carried out separately varying the three thermal sources with different intensities and frequencies. Figure 2 summarizes the procedure.

3. Experimental results

As mentioned in the previous section, training and validation tests are carried out in a medium sized milling machine. The thermal model obtained from the training test is applied in the validation test and the improvement in distance errors is observed. Figure 3 shows distance errors between spheres before and after applying the compensation model for both tests.

Alternatively, error prediction capabilities can be evaluated by observing individual parameter predictions made by the thermal

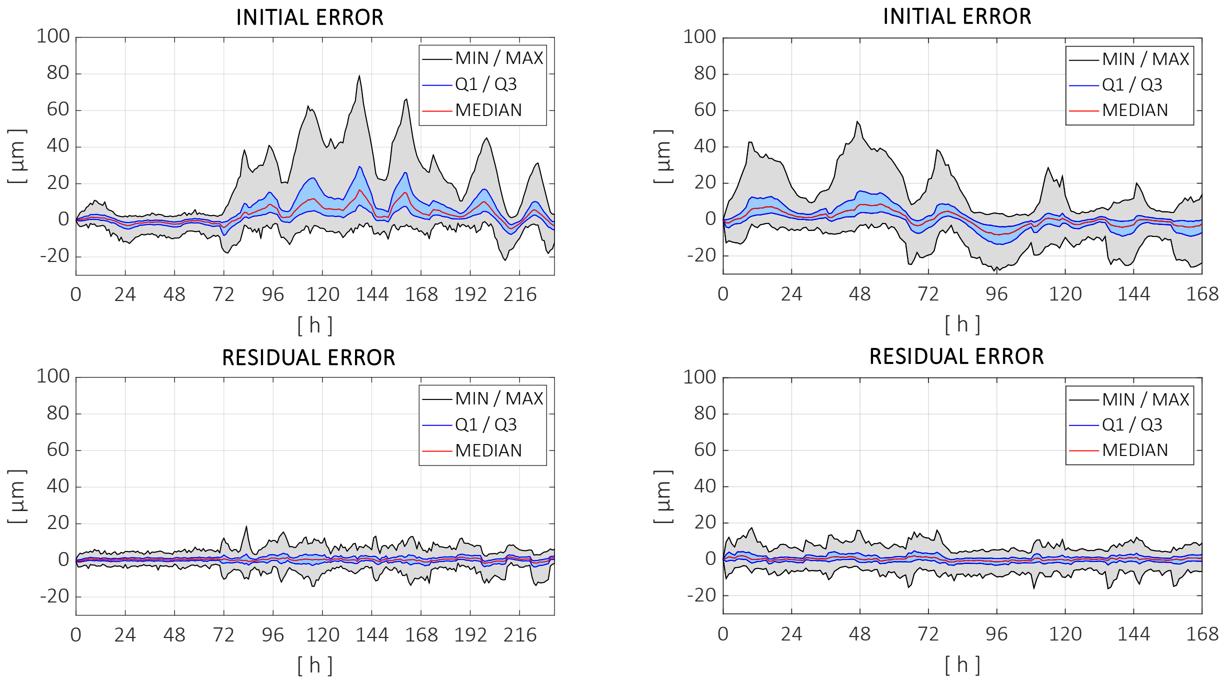

Figure 3. Distance error between spheres relative to the first measurement for the training test (left) and validations test (right). Errors are shown before (top) and after (bottom) the compensation model has been applied.

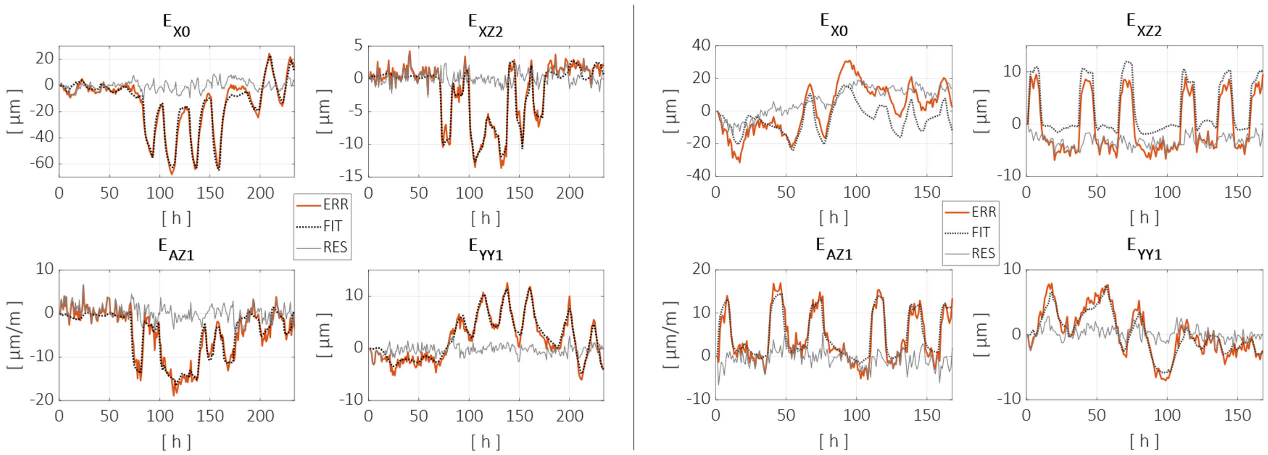

Figure 4. Evolution of specific error parameters during the training (left) and validation (right) tests. Model fit and prediction are shown respectively with a black dotted line. Residual error is shown in grey.

model for the validation test. Figure 4 shows the evolution of some parameters for the training test and the validation test along with the model prediction made based on temperature inputs.

To fully evaluate the error improvement in the working volume X, Y and Z straight trajectories are simulated using the kinematic model of the machine before and after compensation. These straight lines are evaluated for each time step so that the evolution of the error and the improvement can be observed. Figure 5 shows the evolution of the error along a straight line in X direction, centred in the working volume in Y and Z positions. Error reduction of 50% (RMS) is achieved in X direction error and improvements up to 65% in Y and Z directions.

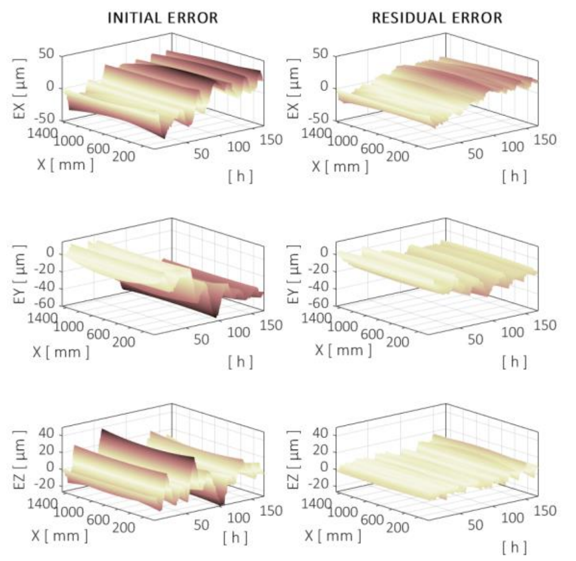

Figure 5. Evolution of the directional errors at TCP over a centered trajectory along the X axis during the validation test. Initial (left) and compensated (right) errors are shown.

4. Conclusions

This work introduces a novel methodology for measuring and compensating thermal variations of volumetric errors in machine tools. Unlike traditional approaches that separate geometric and thermal errors, this work acknowledges that all geometric errors in a machine tool can change over time due to temperature influence. The proposed unified methodology combines spatial and temporal dimensions, utilizing a fully automated measuring process to calibrate geometric errors, repeated over time. The compensation model relies on the assumptions that geometric errors can be approximated by lower-order polynomials and that the parameters of these polynomials experience temporal variations predictable by temperature changes. While the first assumption is widely accepted, the second assumption, though less common, is validated through the paper's results, demonstrating a correlation between temperatures and most parameters.

The key enabler for understanding and validating measurements is a kinematic model of the machine that incorporates position-dependent behavior of geometric errors and temperature-dependent effects. The model predicts errors at the tool center point (TCP) based on machine position and temperatures, serving as a powerful tool for validation using various trajectories and workpiece machining tests. Despite the promising results, compensation outcomes are not perfect, revealing uncertainties related to the measurement system, calibration procedure, and the extent to which the assumptions hold. Long-term drifts and dissimilar results in compensating errors of different time intervals are attributed to uncertainties, incomplete temperature field information, and the inherent approximations in the methodology.

References

[1] Bryan J 1967 *CIRP Annals* **16** 203

[2] Mayr J, Jedrzejewski J, Uhlmann E, Alkan Donmez M, Knapp W, Härtig F, Wendt K, Moriwaki T, Shore P, Schmitt R, Brecher C, Würz T and Wegener K 2012 *CIRP Annals* **61** 771–791

[3] Schwenke H, Knapp W, Haitjema H, Weckenmann A, Schmitt R and Delbressine F 2008 *CIRP Annals* **57** 660–675

[4] Weck M, McKeown P, Bonse R and Herbst U 1995 *CIRP Annals* **44** 589–598

[5] Schwenke H, Franke M, Hannaford J and Kunzmann H 2005 *CIRP Annals* **54** 475–478

[6] Belforte G, Bona B, Canuto E, Donati F, Ferraris F, Gorini I, Morei S, Peisino M, Sartori S and Levi R 1987 *CIRP Annals* **36** 359–364

[7] Szipka K, Laspas T and Archenti A 2018 *Precision Engineering* **51** 59–67

[8] Maeng S and Min S 2020 *Precision Engineering* **63** 94–104

[9] Liebrich T, Bringmann B and Knapp W 2009 *Precision Engineering* **33** 1–6

[10] Iñigo B, Colinas-Armijo N, López de Lacalle LN and Aguirre G 2021 *Precision Engineering* **72** 823–836

[11] Iñigo B, Ibabe A, López de Lacalle LN and Aguirre G 2021 *Precision Engineering* **81** 167–182

[12] Srivastava A K, Veldhuis S C and Elbestawit M A 1995 *International Journal of Machine Tools and Manufacture* **35** 1321–1337