Towards Early and Reliable Detection of Thermal Degradation in High-Precision Machine Tools via Hybrid Condition Monitoring

Darío Fernández [1], Lars Penter[1], and Steffen Ihlenfeldt[1, 2]

[1] *Chair of Machine Tools Development and Adaptive Controls, Dresden University of Technology, 01069 Dresden, Germany*
dario_sebastian.fernandez_riquelme@tu-dresden.de
lars.penter@tu-dresden.de

[2] *Fraunhofer Institute for Machine Tools and Forming Technology, 09216 Chemnitz, Germany*
steffen.ihlenfeldt@tu-dresden.de

Abstract

Thermal Condition Monitoring (TCM) provides a means to monitor the operation of precision machine tools on a continuous basis to maintain micron level accuracy and allow for the identification of the early stages of component degradation. Gradual changes in the mechanical aspects of friction, lubrication, pre-load and wear all contribute to variations in both heat generated and transferred which directly affect the location of the tool center point (TCP). While conventional TCP correction models are highly effective at compensating for instantaneous positioning errors in real time, their residuals are heavily influenced by reversible operational and environmental factors. Consequently, these residuals alone do not allow reliable differentiation between reversible variations and irreversible, slow-evolving degradation processes. This research will propose an innovative hybrid model combining physical based thermal modeling for increased interpretability, with data driven methods to improve the sensitivity of progressive changes. Data-driven components will analyze the machine's full operational history to identify how the system evolves over time and the normal patterns and relationships between variables. Key innovations include (i) the systematic determination of residuals, and (ii) a dual-time scale methodology that isolates fast transient thermal responses from slower degradation processes. In this manner, the framework utilizes TCP correction models as baseline diagnostics to extract physically meaningful degradation parameters that can be monitored along with residuals. Preliminary modeling results demonstrate the effectiveness of the hybrid model separating the reversible and irreversible effects.

1. Introduction

1.1. Background and problem statement

Industry 4.0 has transformed manufacturing by enabling greater connectivity between machines, systems, and operators, along with more extensive use of data analytics and automation. These developments have improved real-time monitoring, process control, and overall productivity (Azari, Flammini, Santini, & Caporuscio, 2023), specifically, enhancing the ability to monitor and analyze equipment operation. In addition, it enables improved process control, greater flexibility, and increased productivity (Azari et al., 2023). The need to ensure continuous and reliable operation of manufacturing equipment is still paramount. Equipment downtime whether planned or unplanned results in lost production, reduced capacity, and ultimately costs to manufacture products at lower levels of quality. Proactive or Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM) have become increasingly important as manufacturers seek to reduce unplanned downtime, maintain higher levels of equipment availability, and improve the overall efficiency of the manufacturing process (Gupta, Kumar, & Maiti, 2024; Veldman, Wortmann, & Klingenberg, 2011). PdM/CBM represents a fundamental shift away from time-based and/or reactive maintenance to proactive and predictive maintenance practices. High-precision machine tools are particularly susceptible to the negative impacts of thermal effects due to the nature of the equipment and the high precision required to perform operations within the tool boundary conditions. Heat generated from motors, bearings, ball screws, spindle, feed drives, transmission, and cutting processes activities travels through the structure of the equipment resulting in thermal expansion, geometric drift, stiffness variations, and increased wear rates. These thermal effects negatively impact the TCP location accuracy and also shorten the life of the various machine tool components (Clough, Fletcher, Longstaff,

& Willoughby, 2012; Brecher, Ihlenfeldt, Neus, Steinert, & Galant, 2019).

Traditional thermal error compensation models provide an excellent means to correct for instantaneous TCP location inaccuracies caused by thermal effects experienced during machining operations. These models focus primarily on correcting the current or instantaneous TCP inaccuracies and do not assess the fundamental health of the machine components. Critically, the residuals of conventional TCP correction models, defined as the difference between the measured and predicted Tool Center Point (TCP) positions, are influenced by multiple factors (Thiem, Kauschinger, & Ihlenfeldt, 2019). These include operational variability (such as changes in load or friction), environmental conditions, and uncertainties inherent to the modeling process. As a result, these residuals alone cannot reliably distinguish between reversible operational effects and irreversible, slow-evolving degradation.The inability of traditional thermal error compensation models to directly detect degradation prior to functional failure highlights a fundamental limitation in current approaches. While these models are highly effective for real-time error compensation, they were not designed for health monitoring. This creates a clear opportunity for new methods that go beyond pure compensation. Although thermal correction maintains momentary precision, effective PdM requires early identification of degradation mechanisms prior to functional failure of the machine components. Thus, interpreting residuals in conjunction with low dimensional, physically interpretable degradation parameters offers a possible solution to distinguishing between reversible and irreversible thermal effects and thus enable early anomaly detection, degradation tracking, and robust condition based maintenance in high precision manufacturing.

1.2. Research Questions

The primary objective of this study is to answer the following three key research questions:

1. How can thermal behavior in high-precision machine tools be leveraged for early degradation detection and prognostics, going beyond the capabilities of traditional instantaneous TCP error correction?

2. How can residuals from thermal TCP correction models be re-interpreted together with physically meaningful degradation parameters to reliably distinguish reversible operational and environmental effects from irreversible, slow-evolving degradation?

3. How can a unified, physically interpretable framework effectively separate fast thermal dynamics from slow degradation processes to enable sensitive anomaly detection and robust condition monitoring

1.3. Motivation and expected contributions

This paper provides a solid base for condition monitoring of high-accuracy machines, since the thermal behavior of structural and drive elements is highly dependent upon the mechanical state. Any variations in friction, wear, pre-load or lubrication will cause changes in the amount of heat generated and dissipated, which can be measured as changes in the temperature pattern. For example experimental studies performed on hexapods under nearly constant load conditions have shown characteristic temperature developments based on the type of friction occurring (e.g. sliding, rolling), which clearly show when maintenance actions (such as relubricating or adjusting the preload) should take place(Thiem et al., 2019). Early indication of thermally induced degradation is important, because most times the process has gone unnoticed until the positioning accuracy or dynamic performance has been severely affected. Nevertheless, using traditional TCP correction models and analyzing residuals does not give enough reliability in detecting degradation due to the variety of sources of error in operation, environment, etc. Therefore, this work uses an integrated method where the low dimensional, physically meaningful degradation parameters, which evolve over longer time periods, are used to improve residual analysis. The integration allows the distinction between reversible fast transient states and irreversible long term degradation states while increasing the diagnostic confidence for proactively making decisions. Therefore, this research delivers the following expected contributions to the field of predictive maintenance:

- Novel hybrid framework for early thermal anomaly detection: structured residual isolation and dual time-scale modeling
- Repurposing of thermal TCP correction models as diagnostic baselines for predictive maintenance
- Robust method to separate reversible from irreversible thermal effects via integrated residual and parameter evaluation, enhancing anomaly detection and prognosis
- Preliminary demonstration of framework Applicability with potential transferability to other systems with similar thermal architectures

2. PROPOSED RESEARCH FRAMEWORK AND METHODOLOGY

2.1. Conceptual Framework

The proposed conceptual framework repurposes thermal TCP correction models as diagnostic baselines for early anomaly detection and prognostics. Residuals between measured and predicted TCP positions serve as sensitive indicators of changes in heat generation and transfer. A structured isolation scheme attributes residuals to degradation only after ruling out operating condition variations, environmental effects, and modeling uncertainties, thereby reducing false alarms

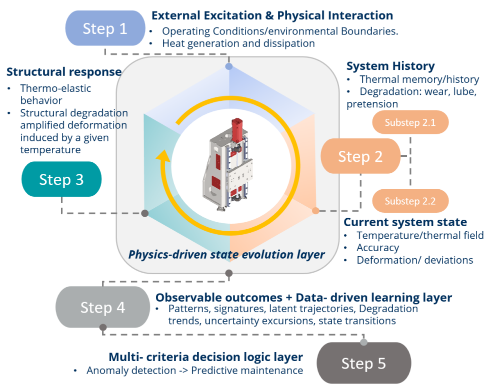

Figure 1. Closed-loop hybrid prognostic framework for machine tool thermal behavior

while preserving physical interpretability.As shown in Figure 1, the framework conceptualizes thermal degradation as a closed-loop, multi-layered diagnostic system. In the Physics-Driven State Evolution Layer, operational and environmental inputs drive heat generation and dissipation through friction, conduction, and thermo-elastic coupling, building the system's thermal memory while interacting with slowly evolving degradation mechanisms (e.g., lubrication loss, preload relaxation, and wear). This leads to measurable outputs including temperature profiles, TCP deviations, residuals, and physically meaningful degradation parameters. These outputs feed into the Physics-Informed Representation Learning Layer, which extracts temporal patterns, degradation trends, and latent state trajectories to separate reversible transient effects from irreversible degradation. Finally, the Multi-Criteria Decision Logic Layer evaluates statistical consistency, temporal persistence, and degradation evolution to detect anomalies and support predictive maintenance decisions. By transforming conventional TCP correction models into diagnostic and prognostic digital twins, the framework enables reliable distinction between temporary thermal fluctuations and progressive degradation.

2.2. Method

The proposed hybrid uncertainty-aware anomaly detection framework will combine physics-based thermo-elastic modelling with data-driven machine learning in a closed-loop workflow, as shown in Fig. 2. Operational context X_t (commands to motion, state of actuators, environmental factors and control variables) to represent physical stimuli $Q(t)$ (heat generated and lost at an instant in time). Then we apply these inputs to a physics-based thermo-elastic model (MORFE or LPTN) to calculate the expected healthy thermal field $T(x,t)$ and the corresponding Tool Center Point (TCP) response $y_{\text{sim}}(t)$. The model accounts for thermal memory and path dependency by incorporating historical operational environment. This allows us to represent slow changes due to mechanical wear, such as lubricant loss and pre-load re-

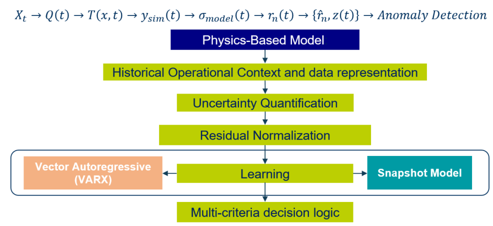

Figure 2. Hybrid uncertainty-aware anomaly detection workflow for thermo-mechanical condition monitoring in machine tools

laxation. A time-varying uncertainty envelope, $\sigma_{\text{model}}(t)$, to reflect model confidence in variable operating conditions is generated by an uncertainty quantification layer. A normalized residual can be calculated using the equation below:

$$r_n(t) = \frac{y_{\text{meas}}(t) - y_{\text{sim}}(t)}{\sigma_{\text{model}}(t)} \tag{1}$$

Normalization of the residual allows for the creation of deviation signal which does not depend on operating regimes (or physical characteristics) and therefore is statistically significant. Both temporal models f_θ that capture how the system evolves over time and persists and latent representation models $z(t)$ that identify compact structural representations of normal system behavior and its hidden signatures are created from the processed normalized residual trajectories. The final step involves feeding the output of both types of models along with the uncertainty-aware residual values into a multi-criteria decision logic. This allows for reliable differentiation of reversible operational/environmental changes from persistent degradation related faults.

2.2.1. Modeling and Analysis Methods

The modeling approach follows a structured hybrid workflow adapted from the Data Mining Methodology for Engineering Applications (DMME) (Wiemer, Drowatzky, & Ihlenfeldt, 2019) and digitalization frameworks in production technology (Drowatzky, Mälzer, Wejlupek, Wiemer, & Ihlenfeldt, 2024). It combines internal control signals of the machine (axis position, axis velocity, axis acceleration, spindle speed, motor current) with external temperature measurements to create a digital representation of the thermal behavior. Physics-based models create structured residuals and parameter trajectories as low-dimensional, interpretable features for subsequent data-driven analysis.

2.2.2. Physics-based Thermo-Elastic Modeling

Thermal TCP correction models are repurposed as diagnostic baselines. In healthy states, residuals represent fast intra-cycle dynamics plus small amounts of noise/environmental influence; a statistical envelope developed from repeated nominal experiments represents the healthy reference. Two complementary physics-based approaches trade-off between fidelity and efficiency: reduced-order finite element (MOR-FE) models simulate localized heat generation and thermal gradient spatial distributions. Lumped parametric thermal networks (LPTN) provide rapid, structurally simple representations for initial validation. Both MOR-FE and LPTN are calibrated to healthy behavior across multiple conditions and validated for diagnostic sensitivity, robustness and computational efficiency. The LPTN will support early framework deployment, with progressive augmentation by MOR-FE as required.

2.2.3. Data-Driven Interpretation, Degradation Parameters, and Health Monitoring

The normalized residuals $r_n(t)$, together with multivariate machine data (axis speed, acceleration, jerk, motor current, PT100 temperatures, and ambient air temperature), are analyzed through two complementary data-driven components. The **temporal model** employs a Vector Autoregressive (VAR) approach with exogenous inputs to capture the dynamic evolution and persistence of system behavior over time. It is governed by the equation:

$$X_t = c + \sum_{i=1}^{p} A_i X_{t-i} + Bu_t + \epsilon_t \tag{2}$$

where X_t is the vector of variables (including the normalized residual and sensor readings), A_i are the coefficient matrices for each lagged term, and u_t denotes exogenous operating conditions. The model predicts future residuals based on recent history, and persistent prediction errors are used as indicators of potential degradation. The **snapshot model** captures static and contextual information from the current machine state (such as sensor correlations, short-term trends, and operating regime statistics) to learn a representation of normal behavior. Deviations from this learned representation are detected using distance-based or one-class classification methods. These two perspectives, temporal dynamics and structural/contextual patterns, are jointly evaluated with degradation parameter trajectories in a multi-criteria decision logic. This enables reliable discrimination between reversible transient effects and persistent degradation processes.

3. RESEARCH PROGRESS AND PRELIMINARY RESULTS

Substantial progress has been achieved in the modeling foundation. CAD defeaturing of a representative vertical column with elemental components (bearings, synchronous motor, ball screw and guideways) has been completed to preserve essential thermal and structural features. A modular ANSYS FE model has been built with subsystems based on their dynamic behavior, an APDL scripts automate the export of nodes, elements, component properties, and interfaces for post-processing (See first block from Fig.2).

4. DISCUSSION AND FUTURE WORK

The proposed hybrid approach overcomes a major limitation of thermal condition monitoring approaches by converting TCP correction model diagnostics into baseline diagnostics, and combines physics-based models (e.g. LPTN and MOR-FE) with data driven interpretation models. CAD defeaturing and preliminary ANSYS modeling has established a good basis for this methodology. Future work will be focused on development of LPTN and MOR-FE modules; development of the physics informed temporal and latent models; integration of uncertainty quantification; validation of the framework using experimental test cases; long term implementation including online predictive maintenance and potential application to other fields. Ultimately, this research is seeking to provide a method that can effectively and interpretably detect early stages of thermal degradation in precision manufacturing applications.

REFERENCES

Azari, M. S., Flammini, F., Santini, S., & Caporuscio, M. (2023). A systematic literature review on transfer learning for predictive maintenance in industry 4.0. *IEEE access*, *11*, 12887–12910.

Brecher, C., Ihlenfeldt, S., Neus, S., Steinert, A., & Galant, A. (2019). Thermal condition monitoring of a motorized milling spindle. *Production Engineering*, *13*(5), 539–546.

Clough, D., Fletcher, S., Longstaff, A. P., & Willoughby, P. (2012). Thermal analysis for condition monitoring of machine tool spindles. In *Journal of physics: Conference series* (Vol. 364, p. 012088).

Drowatzky, L., Mälzer, M., Wejlupek, K. A., Wiemer, H., & Ihlenfeldt, S. (2024). Digitization workflow for data mining in production technology applied to a feed axis of a cnc milling machine. *Procedia Computer Science*, *232*, 169–182.

Gupta, S., Kumar, A., & Maiti, J. (2024). A critical review on system architecture, techniques, trends and challenges in intelligent predictive maintenance. *Safety Science*, *177*, 106590.

Thiem, X., Kauschinger, B., & Ihlenfeldt, S. (2019). Online correction of thermal errors based on a structure model. *International Journal of Mechatronics and Manufacturing Systems*, *12*(1), 49–62.

Veldman, J., Wortmann, H., & Klingenberg, W. (2011). Typology of condition based maintenance. *Journal Article*.

Wiemer, H., Drowatzky, L., & Ihlenfeldt, S. (2019). Data mining methodology for engineering applications (dmme)—a holistic extension to the crisp-dm model. *Applied Sciences*, *9*(12), 2407.