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Temperature Compensation in Ball Screws of CNC Machines. Review

Volodymyr Korenkov[1] • **Taras Skrypnyk**[1]

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Abstract: *This article presents a comprehensive review of temperature compensation techniques for ball screw feed drives in CNC machine tools, where thermally induced errors account for up to 70 % of total positioning errors. Ball screws are particularly susceptible to thermal expansion as frictional heat generated in the screw, nut, and bearings causes axial elongation, directly compromising machining accuracy. The problem intensifies in high-speed machining conditions, where increased feed rates and duty cycles produce greater frictional heating. We analyze three key aspects of thermal compensation: modeling approaches, temperature measurement techniques, and accuracy validation methods. Modeling approaches range from physics-based analytical methods using finite element and heat transfer principles to empirical techniques employing multiple linear regression, principal component analysis, and machine learning algorithms including artificial neural networks. Temperature monitoring strategies span from traditional contact sensors at strategic points to advanced wireless sensor arrays with embedded temperature sensors along the screw length, as well as non-contact infrared thermography for capturing detailed thermal profiles. Accuracy validation methodologies primarily utilize laser interferometry with sub-micrometer accuracy, eddy-current displacement sensors and coordinate measuring machines for part verification. The reviewed studies demonstrate significant improvement in positioning accuracy, with thermal errors reduced by up to 85 % in some implementations, achieving positioning accuracy below 10 micrometers. Empirical modeling enhanced by comprehensive non-contact thermal sensing and calibration through laser interferometry emerges as a particularly promising approach for robust compensation. Future research directions should focus on adaptive models that maintain effectiveness under varying operating conditions, as compensation strategies continue to evolve toward improving the precision and reliability of next-generation CNC systems.*

Keywords: *CNC machine tools; ball screw; thermal error compensation; temperature sensing; accuracy measurement*.

Introduction

Thermally induced errors have a dominant influence on machine tool accuracy, accounting for up to 70 % of the total positioning errors [1]–[11]. In CNC machines, ball screw feed drives are especially susceptible to thermal expansion, as heat generated from friction in the screw, nut, and bearings causes the screw to elongate. This thermal elongation directly translates into positioning error along the axis [1], [12]. The problem is acute in semi-closed-loop systems, in which only the rotary encoder on the motor is used for positioning feedback, meaning any change in screw length remains undetected by the control and leads to lost accuracy. [12]. Thermal expansion intensifies with faster feed rates. In particular, high-speed machining (HSM) conditions exacerbate this issue: faster axis feed rates and longer duty cycles produce more frictional heating in the screw assembly, leading to larger temperature rises and expansions [1], [13]. As shown in Fig. 1, faster rotational speeds produce more rapid temperature changes and a higher equilibrium temperature. Such speed-dependent thermal errors are crucial in modern high-speed machining, as expansions on the order of a few micrometers can force a precision component beyond its specified tolerance.

Machine builders have pursued two general strategies to tackle thermal errors: error avoidance and error compensation [2]. Error avoidance aims to minimize thermal disturbances through design or environmental control – examples include symmetric machine designs, pre-tensioned ball screws, cooling systems, or maintaining constant ambient conditions. One approach is passive or active cooling of the ball screw, for example by internal cooling channels [1].

✉ *T. Skrypnyk*
sumpfheer@yahoo.com

[1] *Igor Sikorsky Kyiv Polytechnic Institute, Kyiv, Ukraine*

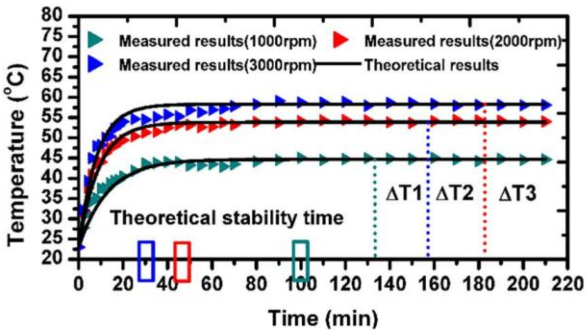


Fig. 1. Temperature dependence from rotational speed [14]

In contrast, when error compensation is used, the machine is permitted to heat and deform, while a corrective offset is applied in the CNC controller to counteract the thermal expansion. Compensation techniques sense or predict the thermal-induced displacement and adjust the tool position command in real time to maintain accuracy. This approach is generally more convenient and cost-effective in practice than rigid avoidance of thermal effects [2].

Ball screw thermal error compensation requires understanding the relationship between temperature changes in the feed drive and the resulting axial growth. Researchers have developed a variety of modeling methods to capture this relationship, as well as sensor systems to monitor temperature and calibration techniques to measure the actual elongation for validation. High-speed ball screws pose particular challenges, as they heat rapidly and unevenly along their length, necessitating dynamic compensation models. Moreover, sensors or estimation approaches must account for a moving heat source, namely the translating nut.

This article reviews the state of the art in temperature compensation for ball screw feed drives, based exclusively on recent scientific studies. We organize the review into three thematic areas: Compensation methods – the modeling and control algorithms used to predict and offset thermal errors; Temperature measurement methods – the techniques and sensor arrangements for monitoring the thermal state of ball screws; and Accuracy measurement methods – how the resulting positioning errors are measured and quantified for model development and validation. Within each theme, we highlight key developments and compare the merits of different approaches. Finally, we discuss the trends and identify the most promising techniques. In particular, based on the literature surveyed, empirical modeling methods combined with advanced non-contact temperature sensing and laser interferometer calibration emerge as highly effective solutions for ball screw thermal error compensation.

Compensation Methods for Ball Screw Thermal Errors

Physics-Based and Analytical Models. These methods derive the thermal behavior from physical principles to predict screw expansion. FEM simulations and analytical heat transfer models have been used to describe temperature distribution and expansion of ball screws. For example, finite element thermal models can calculate the temperature profile along a screw under given operating conditions, which is then translated into axial growth. Xu et al. [1] present a classic example by developing thermal models based on the finite element method and a modified lumped-capacitance approach for a ball screw with and without an internal cooling system. In this work, the heat generated by the nut in the ball screw and the heat transfer coefficient are represented by the following formulas [1]:

$$H_n = 0.12\pi f_0 v_0 n M \, ; \tag{1}$$

$$h = N_u k_{fluid} \, / \, d \, ; \tag{2}$$

$$N_u = 0.133\,\mathrm{Re}^{2/3}\,\mathrm{Pr}^{1/3} \, . \tag{3}$$

In (1), H_n denotes the thermal power generated by the nut; f_0 is a coefficient dependent on nut type and lubrication method; v_0 represents the kinematic viscosity of the lubricant; n corresponds to the rotational speed of the screw; and M signifies the total frictional torque in the nut, including both preload and dynamic load. The convective heat transfer coefficient (2) h is defined via the Nusselt number N_u, which is calculated from the Reynolds number Re and the Prandtl number Pr as shown in (3), k_{fluid} denotes the thermal conductivity of the ambient air and d represents the diameter of the screw where convection occurs. Such principle-based models can capture detailed effects such as heat generation at contacts and heat diffusion, but they often require extensive calibration of material properties, convective coefficients, and contact friction parameters to accurately reflect real conditions.

An accurate physics model may also be computationally heavy for real-time use. To address the challenge of a moving heat source, represented by the nut traversing the screw, researchers have introduced techniques such as moving node renumbering in FEM [15] or finite difference formulations that shift the heat input along the screw over time [3]. Jedrzejewski et al. [15] developed a precise FEM model including moving heat sources and time-varying loads, enabling estimation of the nut's thermal expansion contribution as it travels. Liu et al. [3] similarly treated the ball nut as a moving heat source in a finite difference thermal simulation, which improved modeling accuracy under actual reciprocating motion conditions. As illustrated in Fig. 2, heat generated by the nut is unevenly distributed along the screw, resulting in a non-linear elongation profile. Qiu et al. [17] further advanced theoretical modeling by incorporating the dependence of frictional heat generation on both speed and temperature. They derived a friction heat equation that includes screw raceway geometry and accounts for the drop in viscous friction torque as the grease warms. This yielded an analytical model where the steady-state temperature rise at different rotational speeds follows an exponential relationship with speed. These approaches yield a detailed understanding of screw thermal behavior; however, implementing them for real-time compensation is difficult due to computation complexity and the need to measure or estimate many physical parameters in operation.

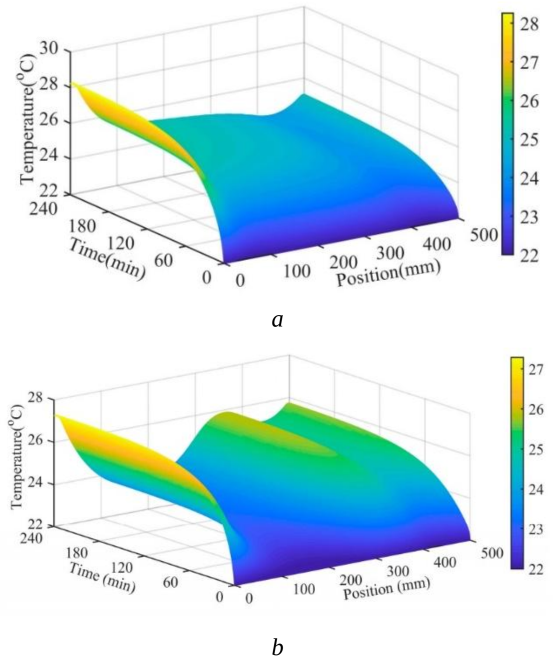


Fig. 2. Distribution of heat along the ball screw under different operating conditions [3]: axis movement along full stroke (*a*); movement in short range along the axis (*b*)

Instead of purely relying on forward physical simulation during machining, some strategies use physics-based hybrid models in a precomputed or auxiliary manner. In a recent hybrid compensation scheme, Geist et al. [16] employ pre-calculated thermo-elastic characteristic diagrams derived from FEM. These characteristic diagrams map thermal states to error values. During machining, a simplified structure model monitors thermal state of the machine and selects the appropriate precomputed map; if an unmodeled state is encountered, a new FEM simulation can be initiated in a semi-automatic manner to update the compensation. This method effectively outsources heavy computation to an offline process, allowing complex physics to inform real-time compensation with manageable computational load. Rong et al. [4] propose an iterative finite-difference thermal error model that is computationally efficient for CNC implementation. By assuming an approximately linear relationship between heat generation, convective cooling, and feed speed, they reduce the number of parameters that must be identified experimentally. The model updates the temperature and expansion state of the ball screw iteratively during operation. After compensation, the maximum thermal error decreased by 88.7 % in the *X* direction, 87.1 % in the *Y* direction, and 56.7 % in the *Z* direction. Such hybrid approaches highlight the ongoing integration of theoretical modeling with practical control.

Empirical Modeling and Data-Driven Methods. Given the difficulties in obtaining a perfect physics model for complex CNC machines, empirical modeling has become the backbone of most thermal error compensation systems. Empirical models utilize measured data, such as temperature and deformation, to determine how temperature at specific points relates to the resulting thermal expansion. A straightforward example is the multiple linear regression model used by Zhang et al. [12]. They separated the total screw positioning error into a geometric component, caused by screw pitch errors and mounting alignment, and a thermal expansion component. By collecting data of screw expansion at various temperatures and positions, they fit a multiple linear regression model for the thermal error as a function of screw temperature and position along the axis. Their model, fitted for a specific mounting configuration of the screw, could predict thermal drift at any position given the screw's temperature, and compensation based on this model improved positioning accuracy significantly. In a similar way, Chebyshev polynomial-based orthogonal least-squares method has been employed to develop thermal error models that closely align with measured thermal drift curves. [2]. The general form of least-squares method is shown in (4). These linear models are straightforward, require modest computation, and have been successfully implemented in CNC controllers for real-time error correction.

$$y = a_1 f_1(x) + \cdots + a_k f_k(x) . \tag{4}$$

Empirical modeling often involves choosing a few key temperature-sensitive points on the machine structure to serve as inputs. The temperatures at these points are used as proxies for the overall thermal state. Determining the optimal sensor locations is non-trivial – the best locations are those whose temperature strongly correlates with the screw expansion. Miao et al. [5] demonstrated that temperature-sensitive sensor locations can drift under varying operating conditions, such as changes in ambient environment or spindle speed, thereby undermining a fixed model. They proposed using Principal component regression (PCR) to handle multi-collinearity among sensor readings. By effectively combining temperature inputs, the PCR-based model achieved more stable accuracy even when the thermal pattern shifted, and their traverse optimization method helped choose an optimal subset of sensors automatically. Another study by Liu et al. [6] introduced ridge regression for thermal error modeling, similarly aimed at improving robustness against collinear temperature inputs. By employing a ridge regression model, this approach mitigated overfitting to noise or specific thermal scenarios and maintained superior predictive stability. Using this method, the thermal error along the *Z* axis was reduced from over 40 micrometers to below 10 micrometers.

These studies highlight that, even within empirical linear models, careful algorithm choices can markedly improve performance in real machining environments where thermal conditions are not identical to the training data.

Beyond linear models, a variety of machine learning techniques have been explored for thermal compensation. **Artificial neural networks** (ANNs) have long been used due to their ability to approximate nonlinear relationships between temperatures and error. Zhang et al. [7] combined grey system theory with neural networks, creating hybrid grey-neural models that outperformed stand-alone neural nets in both accuracy and robustness on a five-axis machine tool. Their serial and parallel grey neural network models could better generalize from limited training data (a frequent scenario in thermal testing) compared to basic back-propagation networks. Support Vector Regression (SVR) is another machine learning approach applied to thermal error modeling. Miao et al. [18] compared SVR against linear models on a CNC spindle and found that SVR maintained strong prediction accuracy even when trained on a small data set, whereas linear models' accuracy degraded with sparse data. However, with more abundant data, all models improved and advantage of SVR became less pronounced or even unstable, indicating that model selection may depend on practical data availability and required robustness.

More recently, deep learning models have gained attention for thermal compensation. Zhou et al. [19] proposed a comprehensive error compensation method for a CNC ball screw drive, employing a deep learning model based on a Long short-term memory (LSTM) neural network optimized by a whale optimization algorithm. Their deep model could capture complex thermal error patterns and was implemented in the machine's numerical control system in real time. During the experiments, applying this compensation reduced Z-axis error from ±14.5 micrometers to ±6 micrometers. This marked improvement demonstrates the potential of modern neural network models in handling the nonlinear, time-dependent nature of thermal errors. The downside is that neural networks require more extensive training data and careful validation to ensure they do not overfit to specific thermal cycles. Nonetheless, as CNC controllers and industrial PCs become more powerful, deploying such models is increasingly feasible.

Real-Time Implementation Considerations: Regardless of modeling approach, implementing thermal error compensation on an actual CNC machine involves practical considerations. The model must run fast enough not to impede the control cycle. Empirical models are typically algebraic and execute quickly, an advantage over iterative physics simulations. For example, a simple regression or even a multi-layer neural network can be computed in a fraction of a millisecond on modern hardware. Many researchers have successfully embedded their compensation algorithms into CNC controllers or external modules. Pajor et al. [8] developed an on-line neural network compensation system for a conventional CNC axis: they instrumented a ball screw with sensors and implemented an ANN model in the controller that adjusted position commands in real time. This exemplifies that even relatively advanced models can be deployed on industrial equipment effectively.

Another implementation challenge is **maintaining model accuracy** over long-term machine operation. Machine characteristics can evolve over time due to factors such as wear and lubrication changes, which may alter thermal behavior. Zimmermann et al. [20] addressed this with an adaptive compensation approach: their Thermal adaptive learning control (TALC) framework periodically updates the model using new data and employs Group – least absolute shrinkage and selection operator (Group-LASSO) auto-regressive with exogenous (ARX) models to automatically re-select the most relevant temperature inputs as conditions evolve. This underscores the benefit of adaptive and self-learning models in compensation of ball screw errors, especially for long-running precision machines where initial models might drift over months of use.

Finally, a few methods dispense with physical temperature sensors entirely and infer thermal error from other signals. One innovative approach uses the CNC's internal servo data. Zhou et al. [9] proposed modeling thermal deformation of a ball screw using real-time motor current, motor speed, and axis position information from the CNC system, instead of direct temperature measurements. Used by authors formula (5) expresses Q_p as the heat generated in the ball screw, where I denote the current in the drive motor, S the distance covered by the nut, and k the coefficient of heat generated by the work of motor.

$$Q_p = k \cdot I \cdot S \ . \tag{5}$$

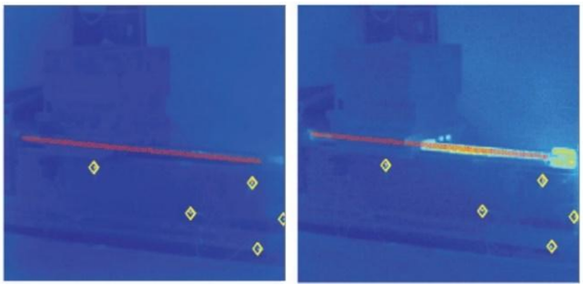
They reasoned that motor load and motion data indirectly reflect heat generation through friction work and could be employed to predict expansion. They built a model via multiple linear regression relating these internal signals to the thermal drift of the screw. Experiments on a small machine tool showed this sensor-less method could estimate the screw expansion in both warm-up and cool-down phases with high accuracy. Similarly, Xu et al. [15] developed a compensation system that required no temperature or position feedback during operation – all inputs to the model were given by command signals and a pre-characterized thermal model of the screw. These open-loop predictive approaches remove the cost and lag associated with sensors, though they typically require extensive off-line identification of model parameters and may be sensitive to unmodeled disturbances such as unexpected friction changes. In practice, **purely sensor-less methods** are still less common than sensor-based empirical models, but they demonstrate the range of strategies being explored.

Temperature Measurement Methods for Ball Screws

Effective thermal compensation hinges on accurately capturing the thermal state of the ball screw in real time. Traditionally, this is accomplished using **contact temperature sensors** such as thermocouples, attached to strategic points on the screw or related structures. A common approach is to mount temperature sensors near the ends of the screw, nut, and bearing housings, where much of the heat is generated or conducted. For example, in a study on an *X*-axis of a drilling machine, three key temperatures were monitored: the ambient end of the screw, the nut end, and the motor-side bearing [21]. These were found to correlate with the thermal expansion the screw, and provided inputs to a compensation model. Many researchers use between 2 to 10 sensors distributed along the screw. Pajor et al. [8] implemented a diagnostic system featuring nine thermistor sensors evenly distributed along a pre-tensioned ball screw, along with an additional sensor on the machine frame. By measuring a temperature profile along the screw, their system could better capture the non-uniform heating pattern and thus improve the effectiveness of the compensation. The sensors were inserted into transverse holes in the screw and wired out through an axial bore via a slip ring collector, allowing continuous readings from the rotating screw. Similarly, Tanaka et al. [10] developed a ball screw with a built-in wireless temperature sensor array. They embedded 25 miniature temperature sensors along length of a ball screw, with wireless transmission of the data from the rotating screw to a base station. This overcame the longstanding issue of how to instrument a fast-moving, rotating component without tangled wires or slip rings. Although contact sensors typically offer high reliability and accuracy, integrating them within a ball screw and performing subsequent maintenance can be both costly and technically challenging.

Important question is where to place these sensors for the best predictive power. The optimal sensor locations may not be obvious, as different regions of the screw and machine heat up at different rates depending on duty cycle and environment. Researchers have applied statistical analyses to select temperature-sensitive points. One technique is fuzzy clustering and correlation analysis to identify which sensor positions have the strongest relationship to the thermal error. Miao et al. [18] used such methods on a spindle system to choose sensor locations, and then built models relating those temperatures to axial drift. More directly, some studies simply trial multiple sensor placements and evaluate model accuracy. An important finding by Miao et al. [5] was that the contribution of certain sensors can change with different operating conditions. This variability means a fixed set of sensor inputs could yield high accuracy in the scenario it was trained on but lose effectiveness elsewhere – a lack of robustness. To address this, they proposed employing principal component regression to ensure that the temperature inputs to the model remain orthogonal and thus independent. They also introduced a “traverse optimization” method to systematically search for the best combination of sensor points for the PCR model. The result was a compensation model less sensitive to which specific sensors were included, thus more resilient to changes.

While most implementations use wired contact sensors, there is growing interest in **non-contact and advanced sensing** for ball screws. Infrared (IR) thermography is a powerful non-contact method to obtain the temperature distribution over a surface. Modern infrared cameras can capture the entire thermal field of a machine component in real time. Mayr et al. [22] noted that IR cameras are commonly used in research to measure temperature on machine tool structures. The temperature difference between cold and warm condition of the ball screw is shown on Fig. 3.



a *b*

Fig. 3. Ball screw in cold condition (*a*) and after 4000 cycles (*b*) [22]

As demonstrated by Zapłata [23], this method can capture detailed thermal profiles that reveal critical hotspots and gradients necessary for effective thermal error compensation. However, its accuracy is strongly dependent on the precise calibration of the surface emissivity and careful management of ambient reflections, which can otherwise lead to discrepancies compared to contact-based sensors. The thermogram on Fig. 4. reveals non-uniform emissivity across the screw.

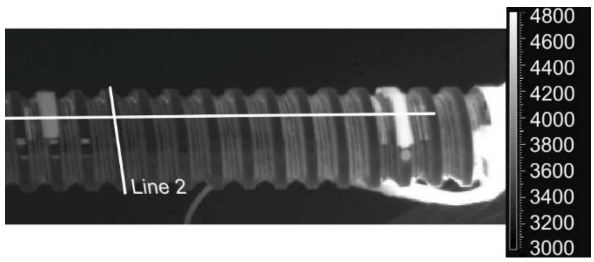


Fig. 4. Thermogram of the heated ball screw [23]

To mitigate such issues, methods including the application of high-emissivity coatings or using reference contact measurements have been proposed [23]. Overall, IR thermography offers a rapid and effective means to monitor transient thermal states in high-speed machining applications.

Another non-contact approach is to measure proxies of temperature. We saw earlier that Zhou et al. [9] avoided temperature sensors by relying on motor current and other CNC internal signals. In essence, they treat the servo drive as a thermo-sensor: when the axis is under load, the current goes up, indicating friction work and thus heat generation. Over time, this method infers the temperature rise indirectly. Although it does not directly measure temperature, it eliminates the need for additional sensors and wiring on the machine.

In addition to the screw itself, some approaches monitor temperature of the surrounding machine structure. Since the relative expansion between the screw and the machine frame matters, sensing both can improve compensation. For example, a sensor on the machine's base or column can capture ambient drift. The system proposed by Pajor at. al. [8] included a single sensor on the machine body to serve as a reference. In the research conducted by Tanaka et. al. [10], in addition to the 25 screw sensors, temperatures were measured at 277 points on the machine structure using an array called LATSIS (Large-scale Array of Temperature Sensors in Series). The combination allowed them to distinguish errors due to screw expansion versus those from the machine frame deformation, leading to more accurate overall compensation.

Lastly, it is worth noting the importance of response time and noise in temperature measurements. Typical sensors employed, such as small thermocouples or thermistors, have response times on the order of seconds or faster, which is usually sufficient for the application. Non-contact IR can be near-instantaneous, but might be affected by surface reflections or dirt. In either case, filtering techniques are often applied to temperature readings in compensation systems to smooth out noise. The ridge regression method by Liu et al. [6] inherently helps in noise reduction by regularization. Another approach is sensor fusion, which combines or averages readings from multiple sensors to minimize the impact of any single noisy measurement.

Accuracy Measurement and Validation Methods

Developing and tuning a thermal error compensation system requires accurate measurement of the actual positional errors caused by thermal expansion. These accuracy measurements serve two main purposes: first, they supply ground truth data for modeling during the calibration or training phase, and second, they verify the effectiveness of the compensation by measuring residual errors once it is applied. Because these thermal expansions are relatively minor, often in the range of tens of micrometers across several hundred millimeters of travel, high-precision measurement instruments are required.

The most prevalent tool for this task is the **laser interferometer**. A laser interferometer can directly measure the linear displacement of an axis with sub-micrometer accuracy over the full travel. According to ISO 230-2:2014 [24], calibrated laser interferometers are the preferred instruments for determining the accuracy and repeatability of numerically controlled axes, especially for linear axes up to 2,000 mm. In thermal error studies, a common approach is to drive the machine axis through a series of positions or cycles and then use a laser interferometer system to record the positioning error over time as the screw heats up. Pajor et al. explicitly report that they measured the axis positioning accuracy using a Renishaw XL-80 laser system shown on Fig. 5.

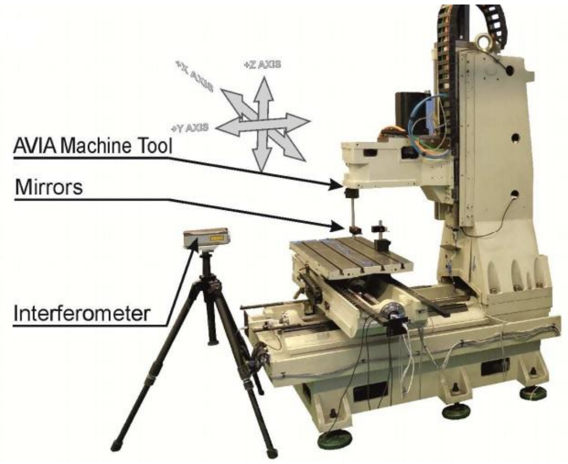


Fig. 5. Measurement arrangement using a laser interferometer [8]

They performed a sequence of movements and captured both the temperature readings and the corresponding expansion of the axis measured by the interferometer, with own encoder-based feedback of the machine considered as reference.

One important detail is that many modern interferometers incorporate automatic environmental compensation for air temperature, pressure, and humidity that affect the laser wavelength. Pajor et al. [8] note that they enabled environmental compensation of the laser during tests to ensure that the measured errors were exclusively attributable to the thermal deformation under investigation.

Typically, the thermal error manifests as a slowly changing bias in the axis length. Therefore, frequent measurements are taken, for example every few minutes or after a predetermined number of cycles. Yu et al. [21] provide a good example of using a laser setup for thermal compensation development. In their work, they specifically measured the deformation of the screw for every 1 °C change in temperature, controlling ambient conditions to isolate the effect.

Another method for measuring thermal expansion is using displacement sensors such as **eddy-current or capacitive sensors**. Instead of measuring the entire axis travel, these sensors can directly measure the relative displacement between two components. Tanaka et al. [10] used an eddy-current displacement sensor to measure the *Z*-axis thermal drift at the tool center point (TCP) while their machine ran through thermal cycles. The sensor was positioned to continuously monitor how much the spindle head moved relative to the machine base due to thermal growth of the structure and screw. Capacitive sensors similarly can detect small changes in distance. However, these are typically used in research or calibration rather than installed permanently on industrial machines, except in some ultra-precision systems, because they require stable targets and are sensitive to environmental noise such as vibrations.

Some studies also use reference parts and measuring machines. For instance, to validate multi-axis compensation, researchers might machine a test piece and measure it on a coordinate measuring machine (CMM). In Rong et al., after applying their real-time compensation on a three-axis machine, they performed a test by machining a precision test piece (Fig. 6) and measuring its dimensions. This kind of validation is more indirect but very practical – ultimately, the goal of compensation is to improve part accuracy, so checking a machined part under thermal load is a strong proof of effectiveness. However, when this measurement method is used, additional factors such as tool deformation must be taken into account, as they can influence the final result.

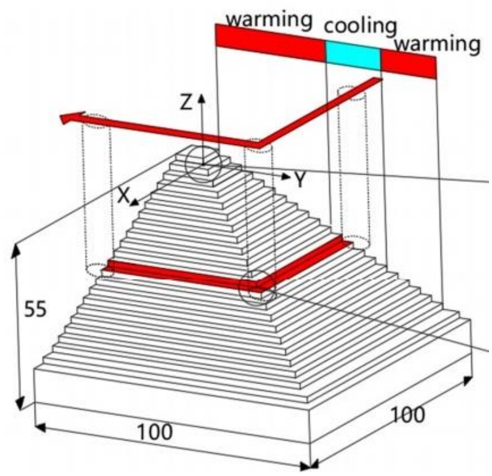


Fig. 6. Test piece for measurement on coordinate measuring machine [4]

Conclusion

This review highlights that robust thermal error compensation in CNC ball screw feed drives requires a holistic integration of advanced modeling, sensing, and calibration techniques to maintain precision in machining operations. State-of-the-art compensation modeling approaches span physics-based analytical models, empirical regression models, and machine learning algorithms, each offering distinct advantages in predicting thermally induced displacements. Likewise, thermal monitoring methods range from traditional contact sensors to non-contact infrared thermography and even sensor-less inference strategies, providing the data necessary to drive these models. Coupled with rigorous accuracy validation of models – employing laser interferometry, high-resolution displacement sensors, and coordinate measuring machine verification – these techniques ensure that compensation strategies can significantly mitigate positional errors caused by temperature variations. The practical importance of accurate thermal compensation is evident in improved part quality and dimensional accuracy, as well as reduced downtime, while its theoretical importance lies in advancing the understanding of machine tool thermo-mechanical behavior. The reviewed studies indicate that in some instances thermal errors were reduced by as much as 85 %, achieving positioning accuracy of under 10 micrometers. Looking ahead, the authors plan to focus future research on empirical compensation models enhanced by comprehensive non-contact thermal sensing data and calibration through laser interferometry, as this approach promises to yield more robust, adaptive compensation strategies and further elevate the precision and reliability of next-generation CNC systems.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, including financial, personal, authorship, or any other nature that could affect the research and its results presented in this article.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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Компенсація температурних деформацій в кульково-гвинтових парах верстатів з ЧПК. Огляд

В. М. Кореньков[1] • Т. М. Скрипник[1]

[1] *КПІ ім. Ігоря Сікорського, Київ, Україна*

Анотація: *У даній статті представлено комплексний огляд методів температурної компенсації для кульково-гвинтових пар у верстатах з ЧПК, де похибки спричинені нагрівом складають до 70 % загальних похибок позиціонування. Кульково-гвинтові пари особливо схильні до теплового розширення, оскільки фрикційне тепло, що генерується в гвинті, гайці та підшипниках, спричиняє осьове видовження, безпосередньо погіршуючи точність обробки. Проблема посилюється в умовах високошвидкісної обробки, де підвищені швидкості подачі та цикли роботи створюють більше фрикційне нагрівання. Ми аналізуємо три ключові аспекти термічної компенсації: підходи до моделювання, методи вимірювання температури та методи перевірки точності. Підходи до моделювання варіюються від фізичних аналітичних методів з використанням скінченних елементів та принципів теплопередачі до емпіричних методів, що використовують множинну лінійну регресію, аналіз головних компонент та алгоритми машинного навчання, включаючи штучні нейронні мережі. Стратегії моніторингу температури охоплюють від традиційних контактних датчиків у стратегічних точках до передових бездротових масивів датчиків з вбудованими температурними датчиками вздовж довжини гвинта, а також безконтактну інфрачервону термографію для отримання детальних теплових профілів. Методології перевірки точності переважно використовують лазерну інтерферометрію з субмікрометричною точністю, датчиками переміщення на основі вихрових струмів та координатно-вимірювальні машини для верифікації оброблених деталей. Розглянуті дослідження демонструють значне покращення точності позиціонування, зі зменшенням термічних похибок до 85 % у деяких випадках, досягаючи точності позиціонування нижче 10 мікрометрів. Емпіричне моделювання, посилене комплексним безконтактним термічним вимірюванням та калібруванням за допомогою лазерної інтерферометрії, є особливо перспективним підходом для надійної компенсації. Майбутні напрямки досліджень мають зосередитися на адаптивних моделях, які зберігають ефективність за різних умов експлуатації, оскільки стратегії компенсації продовжують розвиватися в напрямку підвищення точності та надійності систем ЧПК наступного покоління.*

Ключові слова: *верстати з ЧПК; кульково-гвинтова пара; компенсація температурних деформацій; вимірювання температури; вимірювання точності.*