Special Interest Group meeting
Thermal Issues
Eindhoven, The Netherlands, March 2024
www.euspen.eu

Data and mechanism fusion modeling approach for real-time prediction of spindle transient temperature field

Yun Yang [1], Zhilin Zeng [1], Zhengchun Du [1]

[1] *State Key Laboratory of Mechanical System and Vibration, School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China*

zcdu@sjtu.edu.cn

Abstract

The trend toward intelligence in the spindle of high-end CNC machining centers has put forward new requirements for the real-time sensing capability of the spindle's various states. However, the characteristics of compact structure, large heat generation, and complex thermal mechanisms, making it difficult to directly measure and estimate the temperature of internal regions of a spindle. To address this issue, a real-time temperature estimation method is proposed based on the fusion of mechanism and data. Firstly, a real-time thermal characteristic modeling method is presented based on thermal network. Then, a two-step model parameter optimization approach is proposed by combining the temperature field simulation data and the measured temperature from multiple operating conditions. Finally, the proposed data and mechanism fusion modeling approach is applied to two different kind of spindles. The root mean square errors (RMSE) of the predicted temperature after implementation for the two different spindles, a motorized spindle and an external-driven spindle, are 0.6443°C and 0.5457°C, respectively. For the unmeasurable rotating shaft area, the average prediction error is 2.96°C. Involving the model predicted temperature in the establishment of a thermal error model can improve the prediction accuracy, with the maximum residual decreasing from 9.30 µm to 6.87 µm. All the results demonstrate the accuracy, universality and practicality of the proposed approach.

Machine tool spindle; Transient temperature field; Real-time prediction; Thermal network model; Genetic algorithm

1. Introduction

Spindle is a key component of high-end CNC machining centers, but the characteristics of compact structure, large heat generation, and complex thermal mechanisms cause serious thermal issues [1-3]. Research on the thermal characteristics of motorized spindles is extremely important for the optimization of the thermal structure [4], the compensation of thermal errors [5], the development of the temperature control scheme [6], and the improvement of the thermal stiffness [7], etc. After the concept of intelligent spindles [8] was proposed, intelligent diagnosis [9] and digital twins [10] for spindles have become popular research topics in recent years. The development of spindle intelligence has placed new demands on real-time temperature monitoring of the entire spindle [11]. Especially in intelligent unmanned production lines, the ability to accurately predict the entire temperature field of a motorized spindle in real time is essential to monitor the running state of the spindle. The predicted real-time temperature distributions also have great potential in areas such as thermal error compensation and intelligent cooling strategy.

In the field of spindle temperature field modeling, most of the modeling methods are based on the heat transfer mechanism, including the most popular FE method [12], the finite difference method [13], the thermal network model [14], the bond graph method [15], etc. However, the instantaneous temperature distribution inside the spindle, especially on that of the rotating components, is still difficult to obtain rapidly. To meet the new challenges in terms of thermal issues of intelligent spindles, it is necessary to establish a thermal characteristic model that can predict the complete temperature field of a spindle in real time.

The rest of the manuscript are organized as follow: Section 2 describes the proposed data and mechanism fusion modeling approach. In section 3, the approach is applied to a motorized spindle and the accuracy of the undetectable region is indirectly verified. In section 4, the approach is conducted to an external-driven spindle and applied to improve the accuracy of thermal error modeling. Section 5 concludes the achievements.

2. Data and mechanism fusion modeling approach

To achieve a real-time estimation of the temperature field in the undetectable region of motorized spindles, a data and mechanism fusion modeling approach is adopted. The thermal network with real-time temperature simulation capability is selected as the basis for the mechanistic model. A novel dual source data parameter optimization method is also proposed by combining the temperature field simulation data and the measured temperature from different working conditions.

2.1. Real-time thermal characteristic modeling method based on thermal network

The thermal network method divides a heat transfer system into multiple thermal capacitances, which are connected via thermal resistance, and ultimately transforms the entire heat transfer system into a network of thermal capacitances and thermal resistances. The external input sources of the heat transfer system are divided into temperature sources and power sources. Figure 1 shows a demonstration of a single thermal capacitance in the thermal resistance network.

A time-varying state-space expression describing the thermal network of the spindle can be obtained by combining the temperature differential equations of all thermal capacitances.

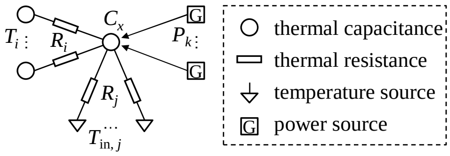

Figure 1. Demonstration of a single thermal capacitance in the thermal resistance network

2.2. Data-driven approach for parameter estimation of the thermal characteristic model

In order to determine the parameters of the thermal characteristic model, a novel data-driven approach is proposed, and the process is shown in Figure 2.

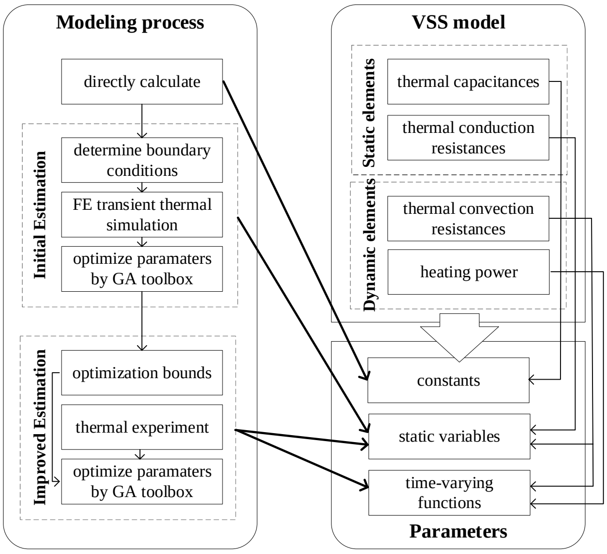

Figure 2. Flow chart of the data-driven approach for estimation of model parameters

First of all, the parameters are divided into three groups. The thermal capacitances can be determined directly and precisely based on the structure of the spindle and the specific heat capacities of the materials. Thus, the thermal capacitances are grouped as constants.

Other parameters are divided into static variables and time-varying functions according to whether they vary with the working conditions. The static variables include conduction resistances, convective interface areas, and static convective heat transfer coefficients. The time-varying functions reflect the transient heat-generating power and the forced thermal convection of air.

A two-step parameter optimization based on genetic algorithm is proposed. During the first step, static parameters are estimated by analyzing transient temperature data from finite element simulations that accounts for the internal heat transfer relationships of the motorized spindle. The second step involves determining the time-varying functions and further optimization of static parameters to improve the model prediction accuracy under actual working conditions.

3. Case 1: application to a motorized spindle

Based on the data and mechanism fusion modeling approach, the transient temperature field model of machine tool spindles can be established. The first application object is a C01 series motorized spindle manufactured by Ningbo SKYNC Five Axis Numerical Control Technology Co. The diameter is 155 mm, and the maximum speed is 20,000 RPM.

3.1. Thermal network modeling of the motorized spindle

According to the heat transfer characteristics of the motorized spindle, the spindle thermal network is obtained by analyzing and simplifying the heat generation and transfer path inside the spindle, as shown in Figure 3.

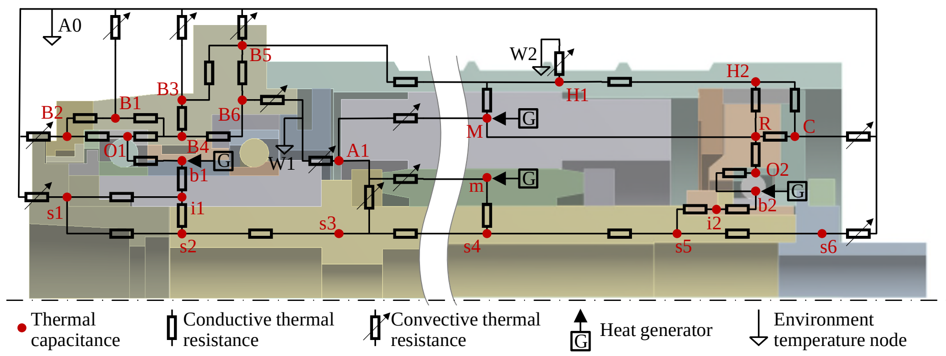

Figure 3. Thermal network of the motorized spindle

The thermal network consists of 28 temperature nodes including 25 thermal capacitances inside the spindle and three environment temperature sources. The 29 conductive thermal resistances seem as static values and the 13 convective thermal resistances influenced by the working conditions are considered dynamic values. The heat generation powers of the front/rear bearings, stator, and rotor of the spindle motor are also regarded as dynamic values. The three environmental temperatures, including the ambient air, the coolant of front bearings, and the coolant of the stator, are measured directly by the RTDs. The average of the inlet and outlet temperatures are approximated as the coolant temperature in both pipelines.

3.2. Model parameter determination of the motorized spindle

The constant values of 25 thermal capacitances are estimated based on the volume and material of the actual components. The thermal resistances and the heat generation functions ought to be determined according to the two-step parameter optimization.

In the first step, all static unknown parameters are identified by GA optimization using the transient temperature field result of the finite element simulation under the specific boundary conditions.

In the second step, the static parameters are improved and the time-varying parameters are determined by GA optimization using 3 of the measured temperature sets under 18 different working conditions from the thermal behavior test shown in Figure 4.

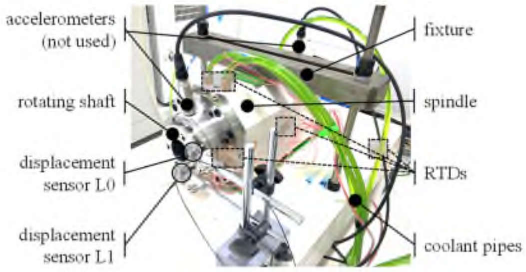

Figure 4. Thermal behavior test of the motorized spindle

3.3. Predicting accuracy verification

The accuracy of the model's temperature prediction for the detectable region is verified using the rest 15 thermal behavior test set under working conditions that were not involved in parameter optimization. Three examples of the transient RMSE of the deviations of predicted and measured temperatures for are shown in Figure 5. The average RMSE of the 15 verification sets is 0.6443°C.

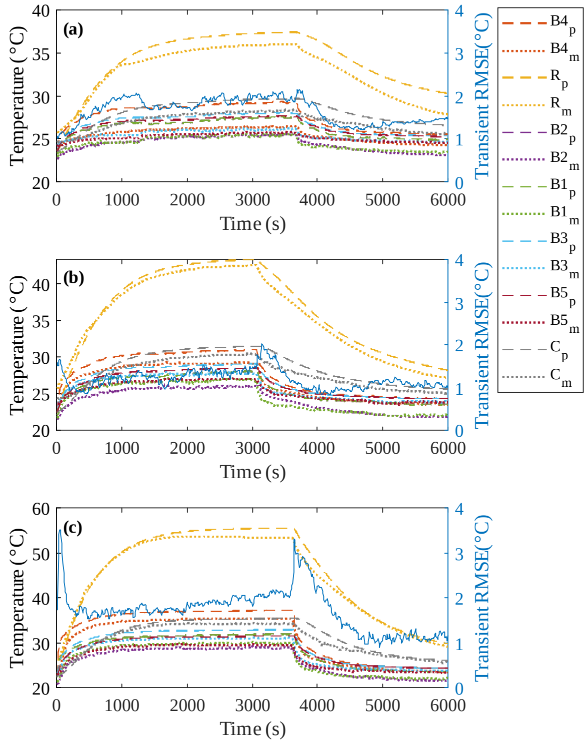

Figure 5. Comparison of predicted and measured temperatures after the second step of model parameter optimization: (a) maximum speed 6000 RPM; (b) maximum speed 12000 RPM; (c) maximum speed 18000 RPM; subscript "p" and subscript "m" correspond to the model prediction and sensor measurement results, respectively

The internal steady-state temperature distribution of the rotating shaft is captured using a thermal infrared imager, as shown in Figure 6, to indirectly verify the accuracy of the estimated undetectable region temperature. The average error of the estimated steady-state temperature for the undetectable region is 2.96°C and the maximum error is 8.65°C.

The results show that the real-time temperature field distribution of motorized spindles can be rapidly, accurately, and completely inferred based on the proposed method using the rotational speed and a few temperature sensors.

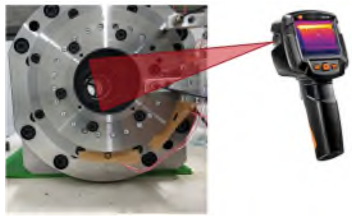

Figure 6. Temperature distribution measurement of the rotating shaft

4. Case 2: application to an external-driven spindle

Case 2 takes the external-driven spindle of VMC850E vertical machining center as the object of study. The thermal effects of the spindle headstock and the external drive motor are also considered in the modeling process.

4.1. Thermal network modeling of the external-driven spindle

Based on the simplified structure of the spindle, the mechanism of heat transfer and production is analyzed. The heat generated from bearing friction is the main heat source of the spindle. The spindle motor is located at the top of the spindle headstock. In addition, there is convective heat transfer in the area where the spindle comes in contact with the air, where forced convection occurs in the rotating parts and natural convection occurs in the stationary parts.

The main components of the spindle are further simplified into a thermal network consisting of 20 heat capacities, 21 internal static thermal resistances, 6 internal dynamic thermal resistances, 8 natural convection resistances, 4 forced convection resistances, three power heat sources including the front bearings, the rear bearings, the spindle motor, and an ambient temperature source, which is shown in Figure 7.

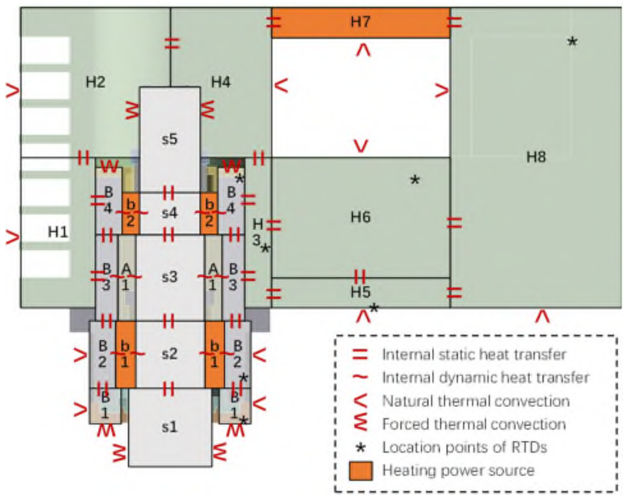

Figure 7. Thermal network of the external-driven spindle

4.2. Model parameter determination of the motorized spindle

The parameters in the thermal network model are optimized through dual-source data-driven parameter optimization.

In the first step, finite element transient temperature simulation is performed on the spindle, and the temperature changes of the finite element simulation results corresponding to the nodes of the thermal network model are exported. Genetic algorithm is used for initial optimization of the static parameters of the thermal network model.

In the second step, a thermal characteristic testing experiment on the spindle is carried out as shown in Figure 8. A set of working conditions measured in the thermal characteristic testing experiment is selected as the modeling data in the second step optimization. Based on the genetic algorithm toolbox, the time-varying functions of the thermal network model are determined and the static parameters are further optimized.

Another set of working conditions measured in the thermal characteristic testing experiment is taken as the validation data. The RMSE between the predicted temperature results of the thermal network model after two-step optimization and the measured temperature is 0.5457°C.

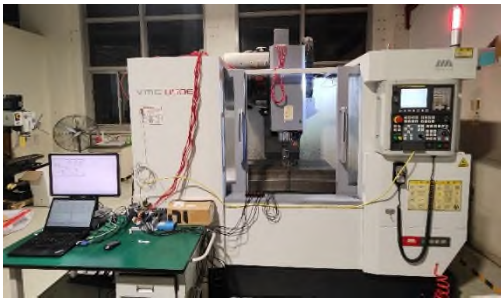

Figure 8. Thermal behavior testing of the external-driven spindle

4.3. Thermal error model based on the predicted temperatures

Based on the predicted temperature results of the thermal network, a main spindle thermal error prediction model is established through LSTM neural network machine learning. The predicted results are compared with the traditional method of directly modeling using temperature sensors as shown in Figure 9.

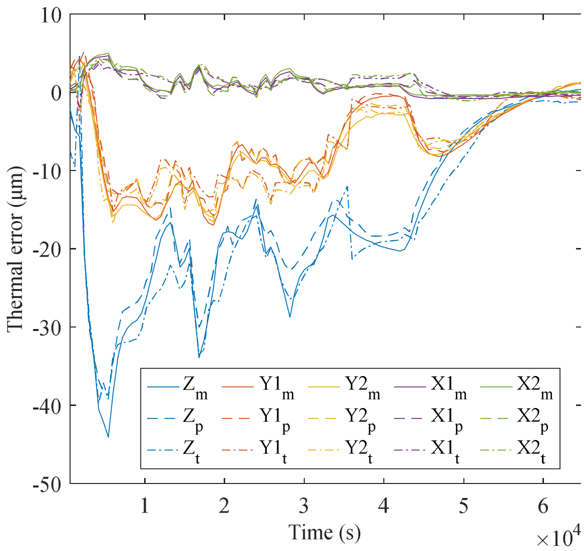

Figure 9. Comparison between predicted thermal error and the traditional method: subscript "p" means model prediction results, subscript "m" is measurement results, and subscript "t" correspond to traditional methods

The thermal error model established based on the predicted temperature results of the thermal network has higher prediction accuracy compared to traditional methods. The maximum residual in the Z direction decreased from 9.30 μm to 6.87 μm, the maximum residual in the Y direction decreased from 9.03 μm to 5.67 μm, and the maximum residual in the X direction decreased from 3.16 μm to 2.28 μm.

5. Conclusion

In order to establish a thermal characteristic model that can predict the complete temperature field of a spindle in real time, a data and mechanism fusion modeling approach is adopted by combining the mechanistic thermal network modeling with a novel dual source data parameter optimization method. The approach is applied to the modelling of a motorized spindle and an external-driven spindle, and the conclusions are drawn:

1) This approach makes up for the existence of undetectable regions in temperature sensors.

2) The models are of high prediction accuracy, with the RMSE of 0.6443°C and 0.5457°C for the motorized spindle and the external-driven spindle, respectively.

3) The models can predicted the transient whole temperature distribution in real time and meets the new requirement of intelligent spindles.

4) The accuracy of thermal error model based on involving the model predicted temperature is better than traditional sensor-based methods, with the maximum residual decreasing from 9.30 μm to 6.87 μm.

References

[1] B Denkena, B Bergmann and H Klemme 2020 Cooling of motor spindles-a review *Int. J. Adv. Manuf. Tech.* **110** 3273-3294

[2] M Alfares, O Saleem and M Majeed 2019 Analytical study of thermal variation impact on dynamics of a spindle bearing system *P. I. Mech. Eng. K-J. Mul.* **233** 871-898

[3] Yi, W Zhao, S Ni, W Wu and B Lu 2015 A review on spindle thermal error compensation in machine tools *Int. J. Mach. Tool. Manu.* **95** 20-38

[4] Z Lin, J Zhang, P Feng, D Yu and Z Wu 2018 Modeling and optimization of thermal characteristics for roll grinders *Int. J. Adv. Manuf. Tech.* **97** 993-1004

[5] Y Li, M Yu, Y Bai, Z Hou and W Wu 2021 A review of thermal error modeling methods for machine tools *Appl. Sci-Basel.* **11** 16

[6] W Chiang, F Wang and Kusnandar 2021 An experiment investigation of temperature control performance for machine tool oil coolers with hot-gas bypass temperature control scheme and inverter temperature control scheme *J. Mech. Sci. Technol.* **35** 771-778

[7] Y Dong, F Chen, T Lu and M Qiu 2022 Research on thermal stiffness of machine tool spindle bearing under different initial preload and speed based on FBG sensors *Int. J. Adv. Manuf. Tech.* **119** 941-951

[8] H Cao, X. Zhang and X Chen 2017 The concept and progress of intelligent spindles: A review *Int. J. Mach. Tool. Manu.* **112** 21-52

[9] T Chan, Z Jian and Y Wang 2021 Study on the Digital Intelligent Diagnosis of Miniature Machine Tools *Appl. Sci-Basel.* **11**

[10] R Xue, X Zhou, Z Huang, F Zhang, F Tao and J Wang 2022 Digital twin-driven CNC spindle performance assessment *Int. J. Adv. Manuf. Tech.* **119** 1821-1833

[11] J Xiao and K Fan 2022 Research on the digital twin for thermal characteristics of motorized spindle *Int. J. Adv. Manuf. Tech.* **119** 5107-5118

[12] V Than, C Wang, T Ngo and J Huang 2017 Estimating time-varying heat sources in a high speed spindle based on two measurement temperatures *Int. J. Therm. Sci.* **111** 50–65.

[13] J Jedrzejewski, Z Kowal, W Kwasny and W Modrzycki 2004 Hybrid model of high speed machining centre headstock *CIRP Ann-Manuf. Technol.* **53** 285–288

[14] Y Liu, Y Ma, Q Meng, X Xin and S Ming 2018 Improved thermal resistance network model of motorized spindle system considering temperature variation of cooling system *Adv. Manuf.* **6** 384–400

[15] Y Yang, Y Xiao, Z Du and X Feng 2023 Data-driven varying state-space model based on thermal network for transient temperature field prediction of motorized spindles Appl. Therm. Eng. **219** 119456