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Servo Sensor Signal Utilization in Machine Tool Condition Monitoring and Fault Diagnosis

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Because of changing consumer habits, manufacturing processes are shifting from mass production to small-batch production, which is making machining more complex and increasing demands for precision and stability. Machine tools, and thus machining accuracy, are affected by factors such as temperature and cutting load. Existing online estimation techniques often require the installation of additional sensors at specific locations, an approach that has cost and reliability issues, thus limiting industry's acceptance of these techniques. In practice, most manufacturers rely on offline detection methods, meaning that machining accuracy deviations can take some time to detect. In this study, we developed a technology for monitoring the status of machine tools; this technology, rather than requiring the installation of sensors, uses servo sensor signals to estimate accuracy, diagnose faults, and make recommendations regarding cutting depth parameters. The proposed method leverages a small number of experiments combined with extensive finite element analysis to construct a big data database, followed by the sensitivity and regression analyses of the generated database to produce an estimation model that evaluates machine tool conditions through servo feedback. The results showed that using linear regression to estimate the machine tool's status achieves good accuracy and that linear regression is easier to implement for real-time compensation. Ultimately, these results can enhance production efficiency and machining accuracy, as well as prevent unforeseen breakdowns.

1. Introduction

The machining industry is moving toward a digital smart production and manufacturing model. Machine manufacturers provide value-added services in their products, which are achieved through a wide range of software features such as conversational operation interfaces for shortening process preparation times, optimizing processes, or the utilization of Internet of

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Things technologies to monitor equipment for pre-emptive maintenance. These features facilitate the realization of smart plants. Such value-adding software typically replaces human operations with sensors and communication technologies and thus enhances performance and lowers costs by reducing labor requirements. To enter or remain in high-end machine tool markets, machine tool manufacturers have changed their industry development strategies by shifting from the research and development mindset of the past, which focused on improving the specifications and performance of single machines, toward providing application-end solutions and after-sales service systems that meet customer needs and address actual problems in production.

For terminal processing plants, changes in consumer habits have led to a transition from mass production to small-batch production. Consequently, machining behaviors have grown increasingly complex. To respond to shortening product lifespans, the adaptability and stability demands in machining have become greater. The most competitive vendors are those who respond fastest to market demands. The selection of machining parameters through outdated practices such as the onsite staff's trial and error results in large numbers of rejects, and the material and time costs do not support small-batch production. Machining businesses must find a way to automate their analysis of the machine state and adjust depth-of-cut parameters to ensure high product efficiency. Precision is a key indicator of the performance of machine tools, which can be compromised by factors such as temperature changes, the cutting load, and wear. Approximately 20% of the yearly operating costs of machining businesses go toward machine maintenance and repairs, and 50% of those expenses are spent on precision machine calibration. Therefore, given the current requirements for high precision and efficiency, the accuracy of machining equipment must be estimated and its faults diagnosed; the advance detection of abnormalities and the elimination of problems result in less machine downtime while improving machine utilization, efficiency, and production value.

Two major components of a machine tool are its transmission shaft and rotating axis; their performance and precision determine the production efficiency and machining precision. As the total machining time performed by a machine increases, changes occur in the precision and health (backlash, precompression, and abnormalities) of the transmission shaft (straightness variation) and rotating axis (axial thermal elongation), compromising the precision of the machine. Moreover, an abnormality in one of these shafts that is not detected in time may lead to a considerable drop in machining quality, resulting in a massive number of defective products and even a shutdown. Some technologies that can detect the machine status in real time have been employed for precision compensation, fault diagnosis, and parameter recommendations, but these technologies require the installation of additional sensors in specific locations; in practice, mechanical designs or machining constraints often prevent the installation of such sensors, meaning that the desired physical measurements must instead be calculated indirectly. The cost and lifespan of sensors may also lower system reliability to such a degree that a machining business may be unable to tolerate; at this stage, most businesses rely on offline detection, preventing punctual adjustment when changes in precision are detected. Furthermore, even with regular shutdowns (e.g., once per month) for maintenance and repairs, a sudden malfunction that cannot be prevented or resolved in a timely fashion may occur.

The objective of the present study was to develop a technology for monitoring the condition of machine tools. This technology, rather than requiring the installation of additional sensors, uses servo sensor signals to estimate accuracy, diagnose faults, and make recommendations for cutting depth parameters. The proposed method involves the extensive finite element analysis of basic parameters obtained through experiments or mechanical designs, with this analysis being achieved through the simulation of the relationship between the inputs (such as the servo feedback signal) and outputs (temperature, abnormality, and torque) under various conditions (including environmental and movement conditions). A small number of sampling experiments were performed to evaluate the accuracy of the simulations and correct the simulation conditions to improve the fit of the simulation results to actual machine statuses. This facilitated the establishment of a big data database and estimation model. This estimation model evaluates the condition of machine tools by analyzing servo feedback signals—such as stator temperature, motor speed, motor current, and motor torque signals—to estimate the thermal displacement and component stress and thus diagnose faults. The proposed system can enhance production efficiency and machining accuracy and prevent unforeseen breakdowns and subsequent impacts on manufacturers' production capacity and delivery time. Digital predictions based on servo feedback may be less accurate than sensor detections, and machines may deviate from the digital model over time, resulting in a decrease in prediction accuracy; however, the proposed approach overcomes the issues of an inability to install sensors owing to the spatial and design restrictions of machines and the possibility that sensor installation will compromise system reliability (sensors may fail) and increase costs. The digital model can be updated by comparing its results with actual machining results and then calibrating it to maintain high prediction accuracy.

In the relevant literature, researchers have proposed various approaches to the autonomous care of machining equipment through accuracy estimation and fault diagnosis. Research on accuracy estimation has included the study of Kong,[1] who performed simulation experiments and optimized the thermal characteristics of a machine tool by establishing a heat transfer model that could be used as a foundation for enhancing machining precision. Ma *et al.*[2] measured the thermal errors of vertical machining centers by collecting experimental data and analyzing the impact of these errors on the machining output; their study offers a practical reference for optimizing the performance of vertical machining centers. Tangjitsitcharoen[3] compared the abilities of neural network and regression analysis models to predict the variation in the straightness of a transmission shaft during computer numeric control (CNC) turning and presented the advantages and limitations of applying machine learning techniques in manufacturing processes. Czerwinski *et al.*[4] utilized machine learning to monitor the current in a brushless DC motor and calculate its temperature changes, thereby achieving sensor-less temperature estimation. In research on fault diagnosis, Douglas *et al.*[5] proposed an algorithm that uses wavelets to analyze transient motor current characteristics and, for the transient operations of induction machines, applied the algorithm to detect and analyze abnormalities on the basis of waveform features. Kar and Mohanty[6] monitored gear vibrations by performing current signature analysis and wavelet transform; in addition to the monitoring of gear condition, their detailed waveform-transform-based analysis provided a reference for evaluating equipment health. Dambrauskas *et al.*[7] reported an approach for monitoring and diagnosing the condition of bearings in induction motors; their approach, based on cloud services and artificial neural networks, integrates cloud computing with deep learning. Proposing an approach for speed and failure detection in brushless DC motors, Medeiros *et al.*[8] presented a novel approach for detecting speed and failures in brushless DC motors using chaos theory. Their proposed method leverages chaotic behavior to enhance the detection accuracy of both speed variations and motor failures. By employing a chaotic oscillator, the technique effectively identifies irregularities in the motor's operation, which are indicative of potential failures. They demonstrated the method's efficacy through extensive experimentation, showing significant improvements in detection precision. The results highlight the potential of chaos-based systems in industrial applications for the real-time monitoring and maintenance of brushless DC motors, ensuring greater reliability and operational efficiency. Medeiros *et al.*[8] employed the chaotic behaviors exhibited by a motor to monitor the motor's reliability. Azeem *et al.*[9] have introduced an advanced AI feature called the AI Servo Monitor. This tool collects high-speed data related to machine tool feed and spindle control. It employs deep learning techniques on this data to display anomaly scores reflecting the current condition of machine components. During normal machine operation, the AI Servo Monitor uses motor torque data to train the model, identifying characteristics that indicate normal torque conditions. In real-time operation, the AI Servo Monitor compares incoming torque data with the normal state, calculating and displaying anomaly scores. This functionality enables machine tool operators to detect early signs of feed or spindle failures. By alerting operators to perform maintenance before any failures occur, the AI Servo Monitor helps enhance machine availability. Totu *et al.*[10] created the Intelligent Thermal Shield (ITS) system to tackle thermal displacement problems. This system utilizes sensors strategically placed in areas prone to thermal displacement to gather data. ITS compensates the rapid and dynamic thermal displacement occurring during axis rotation by analyzing surface displacement data in relation to the thermal response of the rotational speed. In contrast, for slower, more uniform thermal displacement due to environmental temperature changes, ITS uses temperature application formulas for compensation. By conducting experiments and observations, Totu *et al.* refined thermal displacement compensation using the collected sensor data, ensuring consistent and precise machining performance across different environmental conditions. Liang *et al.*[11] introduced a novel system for predicting thermal errors in heavy-duty CNC machines. This system employs long short-term memory (LSTM) networks and a fog–cloud architecture. The findings demonstrated that, compared with traditional methods, this new system reduces data transfer by 52.63% and enhances machining precision by 46.53%. Gui *et al.*[12] explored the prediction and control of spindle system thermal errors, proposing a new mist–edge fog–cloud system (MEFCS). This system utilizes Bi-LSTM networks and cosine and sine gray wolf optimization (CSGWO) algorithms. The results indicated that the accuracy of tooth profile deviation improved from ISO level 5 to ISO level 3 with the implementation of the MEFCS. Guo *et al.*[13] investigated the spatiotemporal correlation of data in the static thermal deformation modeling of CNC machine tools using a hybrid CNN-LSTM model with spatiotemporal correlation (ST-CLSTM). The ST-CLSTM model demonstrates excellent prediction performance, robustness, and generalization ability. It surpasses other comparison models in terms of prediction accuracy, generalization, and robustness in three different directions, as evidenced by thermal error studies conducted under various conditions, including varying spindle speeds and ambient temperatures. Kuo *et al.*[14] presented a method of autonomous optimization using a bidirectional gated recurrent unit (GRU) to accurately predict manufacturing errors. Their approach utilizes an optimized automatic logistic random generator time-varying acceleration coefficient particle swarm optimization (LRGTVAC-PSO) method to enhance a branch-structured bidirectional GRU neural network. The results indicated that the bidirectional GRU outperforms other optimized algorithms in terms of prediction accuracy, achieving a three-axis average accuracy of 0.945. This demonstrated the superior performance of their proposed method in time-related prediction tasks. Kuo *et al.*[15] employed advanced algorithms to predict the thermal displacement of machine tools. Their method utilizes an ensemble model that combines LSTM with a support vector machine (SVM). The experimental results indicate that the LSTM–SVM hybrid model outperforms other machine learning methods in prediction accuracy. Specifically, the prediction RMSEs were reduced to 2.13, 3.91, and 2.04, with an overall mean RMSE of 2.69. This performance surpasses those of the standalone LSTM and SVM models, which had mean RMSEs of 3.28 and 2.97, respectively. Liu *et al.*[16] investigated the relationship between spindle thermal errors and temperature fluctuations, aiming to develop a reliable and efficient spindle thermal displacement modeling method. They compared three modeling approaches: LSTM, multiple linear regression (MLR), and backpropagation neural network (BPNN). The results indicated that, particularly at high spindle rotation speeds, the ANN-based models (LSTM and BPNN) significantly outperformed the MLR method. Additionally, across all spindle operating conditions, the LSTM model showed a lower root mean square error (RMSE) than the BPNN model. The proposed spindle thermal error prediction technique was validated at spindle rotation speeds of 3000, 6000, and 9000 rpm. Liu *et al.*[17] conducted a study on spindle systems, focusing on thermal error modeling and compensation based on the error mechanisms of these systems. They employed the VMD-GW-LSTM network, the VMD-LSTM network, and RNN for their methods. The results showed that the compensation rates for the VMD-GW-LSTM network model were 77.78% for two of the experimental setups and 75.00% for the third setup. Additionally, the VMD-GW-LSTM network model outperformed the VMD-LSTM network and RNN models in both prediction and compensation analyses. Nguyen *et al.*[18] focused on reducing thermal errors in workpieces by developing a thermal deformation prediction model using an artificial neural network specifically applied to a three-axis vertical CNC milling machine during cutting processes. Their method employs LSTM with Pearson's correlation coefficients for feature selection. Their study results illustrated the effectiveness of a real-time error correction system when an LSTM neural network is used as the temperature error prediction model. During an 8 h cutting experiment, real-time error compensation significantly reduced thermal errors—from 7 to 3 μm on the X-axis, from 74 to 21 μm on the Y-axis, and from 64 to 20 μm on the Z-axis—thereby enhancing the precision of the workpiece dimensions. Zeng *et al.*[19] developed a method of predicting thermal error in machining using a sequence-to-sequence LSTM network with an attention mechanism (SQ-LSTMA) integrated into an edge cloud system. Their results indicated that the SQ-LSTMA model surpasses other networks such as BP, RNN, and standard LSTM in prediction accuracy and convergence rate, achieving an accuracy of 99.02%. Additionally, the attention mechanism significantly reduces computation time, making SQ-LSTMA faster and more efficient than traditional methods. Ji *et al.*[20] presented a proactive anomaly detection framework for robot navigation using multisensor fusion. Their approach integrates data from various sensors to enhance the reliability and accuracy of anomaly detection during navigation tasks. Their results demonstrated that the proposed method effectively identifies potential anomalies before they impact the robot's performance, thereby improving the safety and robustness of autonomous navigation systems.

These papers offer various approaches and techniques for estimating the accuracy of and diagnosing faults in machine tools and their components. The techniques can be divided into two principal categories: those involving the direct acquisition of necessary physical quantities through the installation of additional sensors and those involving the use of sensorless technology based on current signals to determine heat generation and thus estimate temperature and motor efficiency. The strengths of both these categories were combined in our study. Our proposed approach is to employ existing sensors in a servo motor (including sensors for stator temperature, rotation speed, current, and torque) to estimate temperature, thermal deformation, and component stress conditions and to perform fault diagnoses; these actions will ultimately improve machining precision and prevent unforeseen failures. The proposed approach can enhance system reliability without requiring the installation of additional sensors and thus will reduce costs while providing a higher estimation accuracy than that offered by other sensorless prediction technologies. Our system meets the machining demands of the machine tools industry and can help manufacturers improve machining efficiency and accuracy while avoiding losses in production value owing to sudden failures.

2. Experimental Equipment and Methods

2.1 Equipment for analysis and experiment

The thermal deformation of machine tools is mainly caused by environmental changes and the thermal expansion of structural materials owing to thermal energy. In this study, we conducted experiments combined with extensive finite element analysis to build a database and a model for estimating thermal deformation. Figure 1(a) is the schematic diagram of the experimental machine tool. The model of the machine tool is IT-25, which is a lathe structure and was developed and designed by the Industrial Technology Research Institute in Taiwan. Figure 1(b) shows a specifications table of the lathe machine.

The PT100 resistance temperature detector was used to measure the temperature changes, and the eddy current sensor AEC S-06 was used to measure the thermal deformations. The temperature changes and the thermal deformations of the lathe were recorded by GRAPHTEC's GL820 data logger for subsequent analysis. Figure 2 shows the measurement equipment.

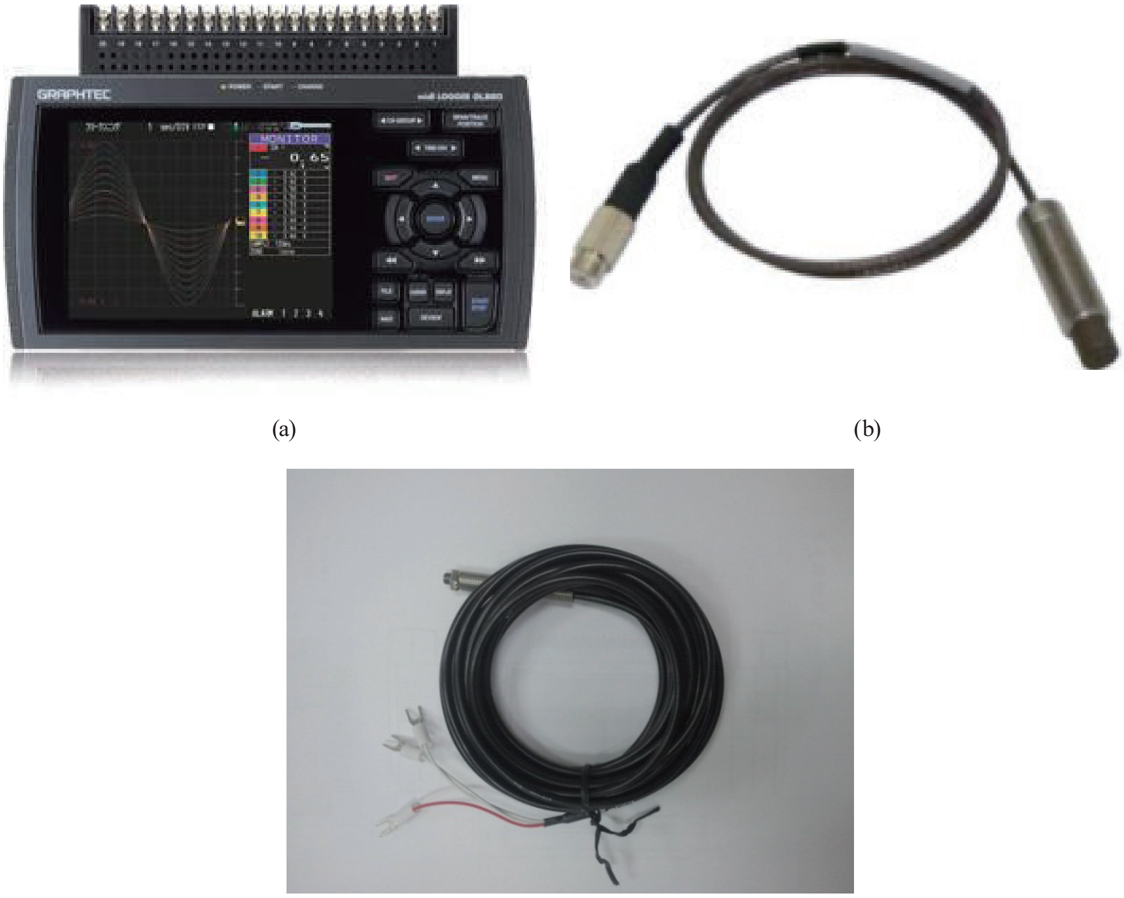
2.2 Prediction methodology

Regression analysis is mainly used to analyze the relationship between one or more independent and dependent variables. The regression analysis can be divided into simple

Spindle motor(kW)	15/18.5
Spindle nose	A2-8
Chuck size (inch)	10"
Rod processing diameter (mm)	81
Spindle speed(rpm)	3500(Max.)
Number of spindles	1
Turret type	T12

(a) (b)

Fig. 1. (Color online) The experimental machine tool: (a) IT-25 lathe and (b) specifications table of the lathe.



(a) (b)

(c)

Fig. 2. (Color online) Measurement equipment: (a) signal recorder (GL820); (b) eddy current sensor; and (c) PT100.

regression and multiple (or complex) regression. Simple regression is an analytical method with only one independent variable and one dependent variable in the regression equation to represent the relationship between the independent variable and the dependent variable. However, multiple regression is an analytical method that includes two or more independent variables in the regression equation, allowing for the understanding of the response levels or quantities of the dependent variables on the basis of the levels or quantities of the independent variables.

In this study, the room temperature was controlled in accordance with the spindle load and experimental conditions. Consequently, multiple regression was employed to determine the appropriate supply oil flow rate for the spindle under varying cooling demands. Multiple regression can be expressed as

$$y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \ldots + \beta_n x_{nt} + \varepsilon_t, \tag{1}$$

where y_t is a dependent variable, x_{it} are independent variables, β_0 is a constant, β_1 to β_n are regression coefficients, and ε_t is the error.

After performing the regression analysis, a regression equation was obtained, allowing the relationship between the dependent and independent variables to be determined. In this study, an F-test was then used to evaluate the prediction accuracy and significance of the developed regression equation. The following assumptions apply to the F-test:

$$\mathrm{H}_0\text{:}\ \beta_1 = \beta_2 = \ldots = \beta_n = 0$$

$$\mathrm{H}_1\text{:}\ \beta_k \neq 0\ (\text{where } 0 < k < p), \tag{2}$$

where p represents the number of independent variables. The following statistical test quantity is adopted to evaluate the prediction and significance of the regression equation.

$$F^* = \frac{MSR}{MSE} \tag{3}$$

Here, MSR and MSE represent mean square regression and mean square error, respectively. If the significance level is set as α, the determination rule of significance is as shown below.

- If $F^* \leq F\,(1 - \alpha; p - 1, n - p)$, the significance does not exist. The assumption H_0 is valid.
- If $F^* > F\,(1 - \alpha; p - 1, n - p)$, the significance exists. The reliability of the regression equation can be accepted. The assumption H_1 is valid.

F represents the critical value obtained from the F distribution table at a specific significance level α. The coefficient of multiple determination is used to represent the goodness of fit of the regression model and is defined as

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}, \tag{4}$$

where *SSR*, *SSE*, and *SST* represent the sum of squares for regression, the sum of squares for error, and the total tum of squares in statistics, respectively. The range of R^2 is $0 \leq R^2 \leq 1$. The value of R^2 indicates the strength of the relationship between the dependent and independent variables. A high R^2 value suggests that the dependent variables can be accurately predicted from the independent variables in the regression equation. R^2 is defined as the ratio of the variance explained by the regression model to the total variance of the dependent variable y_i. A large R^2 means that the regression model explains a greater proportion of the total variation.

2.3 Simulation analysis and experiment

The commercial software ANSYS Fluent was employed to simulate the flow field, temperature distribution, and corresponding thermal deformations within the computational domain. In this study, the finite volume method and fluid–solid coupling calculations were utilized to model the flow field within the lathe structure, as well as the temperature distribution and associated thermal deformations. To ensure the uniformity of the flow field within the lathe structure, a low flow velocity was maintained, and the fluid in the flow field was assumed to be incompressible. For model simplification, the Navier–Stokes equations and the energy equation for a three-dimensional incompressible fluid are presented as follows:

$$\frac{\partial U_j}{\partial x_j} = 0\,,\quad j = 1, 2, 3$$

$$\frac{\partial (U_i U_j)}{\partial x_j} = -\frac{1}{\rho}\frac{\partial P}{\partial x_j} - g_i \beta (T - T_\infty) + \frac{\partial}{\partial x_j}\left(\nu \frac{\partial U_i}{\partial x_j} - \overline{u_i u_j} \right),$$

and

$$\frac{\partial \left(T U_j \right)}{\partial x_j} = \frac{\partial}{\partial x_j}\left(\frac{\nu}{Pr}\frac{\partial T}{\partial x_j} - \overline{T u_j} \right), \tag{5}$$

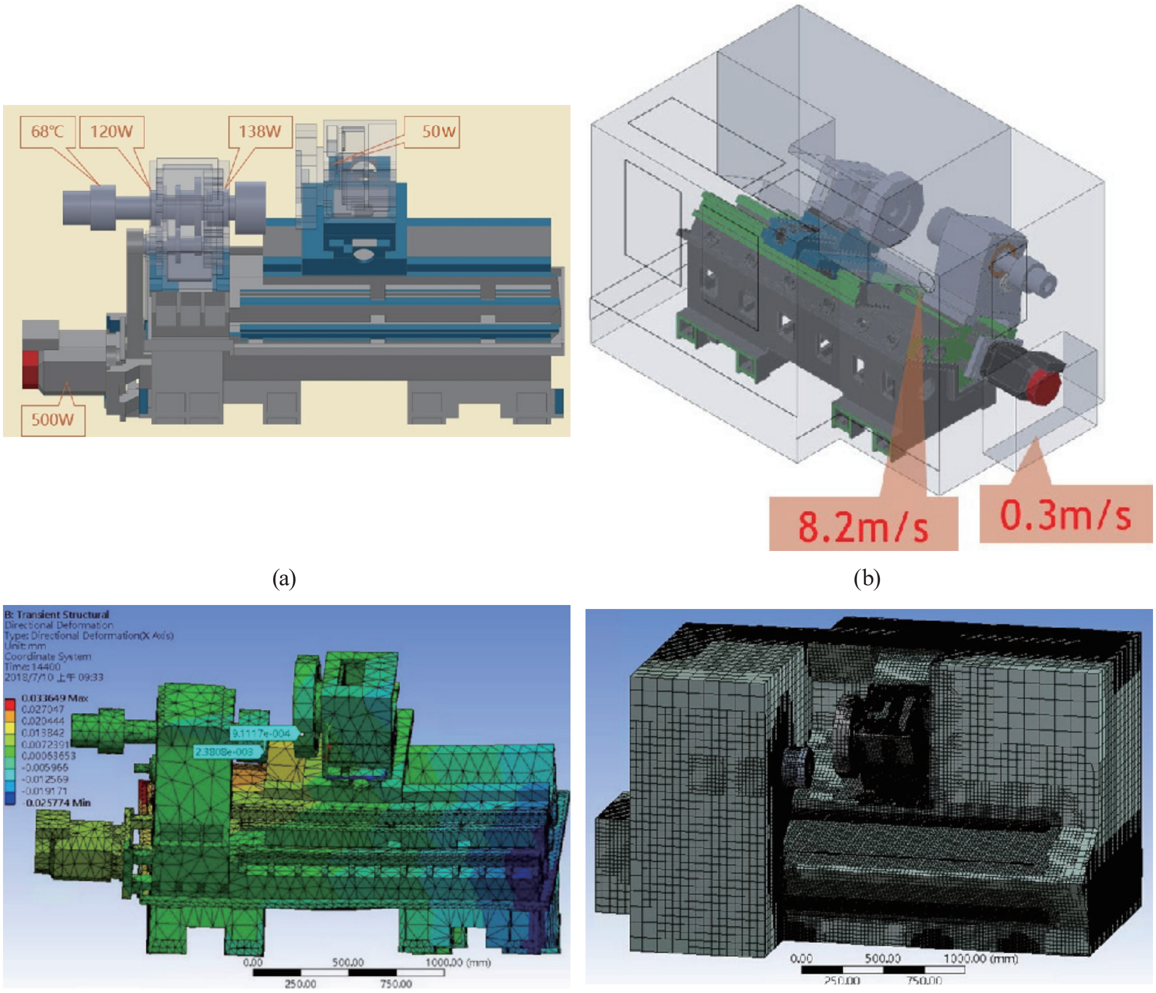
where U_j, T, and P are the averages of velocity, temperature, and pressure, respectively. Under the Boussinesq assumption, the buoyancy effect is considered, and β is the thermal expansion coefficient. With a turbulent closure model, the turbulent stress $-\overline{u_i u_j}$ and turbulent heat flux $-\overline{T' u_j}$ can be obtained as

$$-\overline{u_i u_j} = 2\nu_t S_{ij} - \frac{2}{3} k \delta_{ij} - \overline{T' u_j} = \frac{\nu_t}{Pr_t}\left(\frac{\partial T}{\partial x_j} \right), \tag{6}$$

where ν_t and Pr_t are the turbulent kinematic viscosity and turbulent Prandtl number, respectively. k is the kinetic turbulent energy, where $k = u_x^2 + u_y^2 + u_z^2 / 3$, and δ_{ij} is the Kronecker function. The turbulent closure problem is computed using the k-ε model, where the turbulent stress and turbulent heat flux can be obtained using the kinetic turbulent energy and turbulent dissipation equations, respectively.

The conditions for simulation analysis are shown in Fig. 3. The power of the spindle motor measured using the power meter was 500 W. In the study, the heat generated by a hydraulic cylinder, turret, and the front and rear bearings were 68 °C, 50 W, 138 W, and 120 W, respectively, as shown in Fig. 3(a). In Fig. 3(b), the air flow velocity in the environmental flow field measured by the flow meter was 8.2 m/s, and the air flow rate close to the spindle motor end was 0.3 m/s. The number of grids in the simulation analysis was approximately 12.7 million, as shown in Figs. 3(c) and 3(d).

The conditions of the experiments were based on the lathe usage status in the test. The experimental conditions are shown in Table 1 below.



(a) (b)

(c) (d)

Fig. 3. (Color online) Conditions for simulation analysis: (a) heat generated, (b) air velocity, (c) mesh, and (d) simulation.

Table 1
Experimental conditions.

	1	2	3
Experimental test conditions	No operation Room temp.+15 °C Constant temp. measurement Spindle area/fan ON	Spindle operation/stop 8/2 h Constant room temp. Constant temp. measurement Spindle area/fan ON	Spindle operation/stop 8/2 hours Room temp.+15 °C Constant temp. measurement Spindle area/fan ON
Sensor	Eddy current PT100	Eddy current PT100	Eddy current PT100

2.4 Equipment monitoring and accuracy estimation

The machining industry has already begun moving toward a digital smart production and manufacturing model, and manufacturers can add value to systems through a wide range of software services that replace human behaviors with sensors and communication technologies and thus enhance the performance and lower the costs by reducing the demand for labor. A system for monitoring the precision and condition of metal cutting equipment, which can effectively aid operators in diagnosing equipment condition and enhancing machining accuracy, was developed in this study. The modules of this system include transmission shaft and rotating axis condition detection functions, enabling the user to estimate and compensate for abnormalities, component stress, backlash, straightness, and axial thermal expansion without needing to install additional sensors. The machine tool controller is employed to acquire the servo feedback information necessary for digital estimation, thus overcoming the limitations of sensors and effectively lowering the barriers to entry for operators wanting to upgrade their machinery intelligence. The condition monitoring and precision self-care modules of the developed system perform immediate monitoring and failure prevention by capturing signals, computing features, and determining conditions on site and in real time. This enables the daily assessment of a machine's condition during its warm-up, proactive maintenance scheduling, compensation for backlash, and real-time monitoring of temperature and thermal displacement (including rotating axis extension and transmission shaft straightness variations) during the machining process to maintain stable quality and prevent overheating failures. The three main functions of the proposed system are as follows.

- Precision Estimation and Compensation: The transmission shaft backlash, straightness variation, and thermal extension of the rotary shaft are estimated to assist the user in precision compensation and thereby maintain stable machining precision and reduce the machine warm-up time.
- Cutting Depth Parameter Assistance: Real-time estimates and displays of motor, bearing, and nut loads are provided, enabling the user to adjust the maximum cutting depth for rough machining on the basis of the degree of component stress, enhancing machining efficiency and maintaining machining quality.
- Prevention of Sudden Failures: The transmission and rotating axis temperature and abnormality estimation modules can be implemented to prevent overheating failures during machining and provide early warnings of abnormalities (indications of future failure even if the machine remains operational) to help the user schedule maintenance.

These modules do not require the installation of sensors in machines, which can be impossible because of the difficulty in placing sensors in older machines or other reasons, and instead draw upon feedback information from the machine tool controller to perform state monitoring, precision estimation, and compensation. The modules can help operators maintain consistent quality and reduce waste. The development of these modules began with the acquisition of basic component parameters through experiments or from the components' mechanical designs. Input and output relationships were then simulated under various conditions (environmental and operational) using finite element analysis software. The extensive digital simulations were then sampled in several experiments in which the accuracy of the simulation analysis was evaluated, providing feedback regarding how the simulation conditions should be adjusted such that the simulation results would more closely match the actual state of the machinery. This process facilitated the creation of a large-scale database. Finally, the sensitivity analysis of the estimation targets (temperature, thermal displacement, rigidity, and health state) was performed using servo feedback information such as stator temperature, speed, current, and torque, and the results revealed the parameters that have the strongest impact for regression analysis. The predictive model was converted into mathematical polynomials suitable for real-time calculations. The transmission and rotating axis estimation technology developed in this study assumes that the transmission and rotating axis primarily comprise motors, bearings, and nuts. The first step in this study was the establishment of methods of estimating the condition of these three individual types of component; these methods were then integrated into the evaluation of the transmission and rotating axis.

3. Results and Discussion

3.1 Motor state detection technology

In this section, we describe in detail the development of the motor state prediction technology. The process was as follows. First, the copper loss, iron loss, transient temperature, and efficiency (torque–rotational speed–efficiency relationship) of a motor were plotted in accordance with the mathematical relationship between electromagnetism and heat. Second, the plot was employed as the basis for establishing a technique for motor heat effect analysis; the motor efficiency plot was used to illustrate the efficiency for various rotational speeds and torques, enabling the calculation of the heat generated by the motor while it was in operational and the heat transmitted to the surroundings. Motor heat calculations can help operators protect their motor from overheating, which would otherwise cause thermal displacement in the screws and structure of the machine tool. The developed module for motov status self-detection was modeled as follows (as shown in Fig. 4).

1. The basic parameters of the motor were acquired from the manufacturer or measured by the researchers. The current, voltage, resistance, and power factor (PF) under no-load and load conditions were then obtained using a power analyzer (a digital oscilloscopic power meter) and employed to establish a model of the motor.
2. Data were imported into ANSYS for analysis and to obtain theoretical curves for rotational speed, torque, and efficiency.

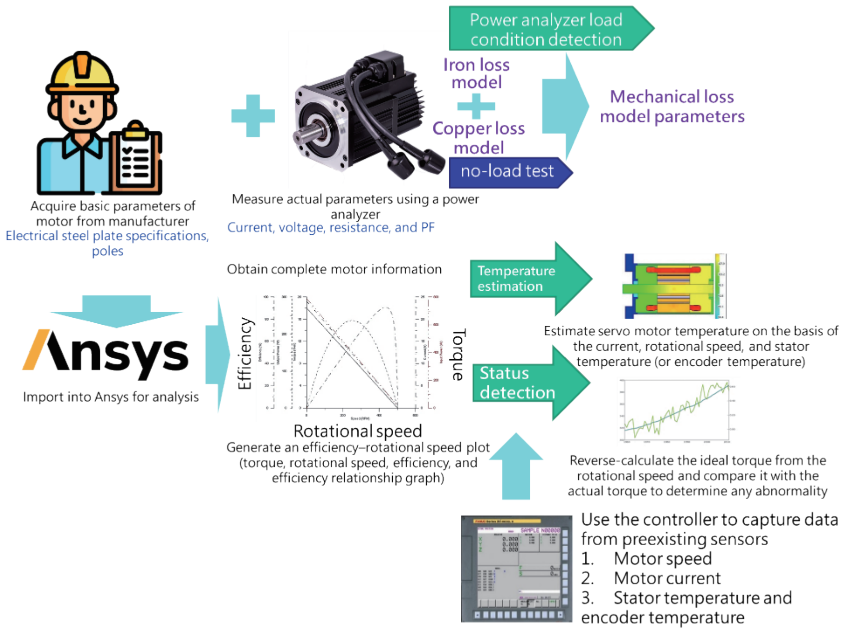


Fig. 4. (Color online) Motor status self-detection module: model construction process.

3. The data obtained by preexisting sensors—such as motor speed, motor current, and stator temperature data—were received through the controller and used as inputs to improve the prediction accuracy.
4. The servo motor temperature was estimated from the current, rotational speed, and stator temperature. During model verification, multipoint temperature sensors were installed on the outside of the motor to ensure the accuracy of the motor temperature simulation results and to provide feedback that could be used to correct the simulation conditions and improve the prediction accuracy.
5. During fault diagnosis, the ideal torque was reverse-calculated from the motor speed and compared with the measured torque. Abnormalities in the motor status were detected from the difference between the ideal and actual torques. The accuracy of the motor abnormality determinations made by the model was verified by adding an accelerometer to the motor.

Once large amounts of simulation data had been acquired and the sampling verifications and revisions had been performed, the simulation and measured data were subjected to sensitivity analysis to evaluate the relationship between the servo feedback and the surface temperature of the motor flange. The five-axis machine tool developed by the Industrial Technology Research Institute's Smart Machinery Technology Center was employed as the model of interest in this study. The results revealed that the surface temperature of the motor flange could be expressed as the following function of the stator temperature:

$$T_{Motor} = C_{ST0} + C_{ST1} T_{stator} , \tag{7}$$

where T_{Motor} is the surface temperature of the motor flange, C_{STi} is the ith-order temperature constant of the motor stator in relation to the flange surface, and T_{stator} is the motor stator temperature. The relationship expressed in Eq. (1) is illustrated in Fig. 5.

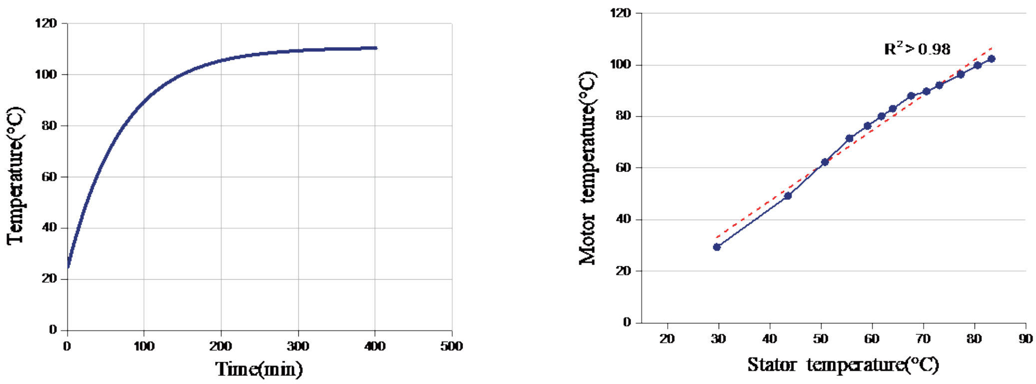
3.2 Bearing and nut status detection

Most bearings and nuts on the market are not equipped with sensors; consequently, information about their movement cannot be acquired directly. However, once they have been connected to a motor, their movement can be estimated using sensor information from the servo motor. Simulation software was employed to analyze the torque conditions of the bearing and nut corresponding to different motor torques, currents, and stator temperatures under normal preload conditions; sensitivity and regression analyses were then performed. The results revealed that the bearing and nut torque ratio could be expressed as a polynomial of the motor torque; thus, the motor torque obtained through servo feedback could be split into bearing and nut torques (as shown in Fig. 6):

$$r_{BN} = C_{BN3}\tau_M^{\ 3} + C_{BN2}\tau_M^{\ 2} + C_{BN1}\tau_M + C_{BN0}\,, \tag{8}$$

where r_{BN} is the nut torque τ_N divided by the bearing torque τ_B, C_{BNi} is coefficient i of the torque ratio polynomial, and τ_M is the motor torque. The machine bearings could be divided into the front and back bearings, and their torques could be calculated separately by decoupling the bearings by the same method.

Once the motor torque had been split into the bearing and nut torques, the status of the bearing and nut was estimated. According to bearing torque theories, the preload value of the bearing can be estimated from the actual machine bearing torque and used in fault diagnoses; the possibility of failure due to a reduction in bearing preload or a sharp increase in friction caused by wear and tear on the bearing could be determined. Moreover, on the basis of the bearing torque status, machining businesses can increase or decrease the cutting depth to maximize the machining efficiency and prevent damage to components. Regarding temperature



(a) (b)

Fig. 5. (Color online) Motor temperature graphs: (a) surface temperature and (b) stator temperature.

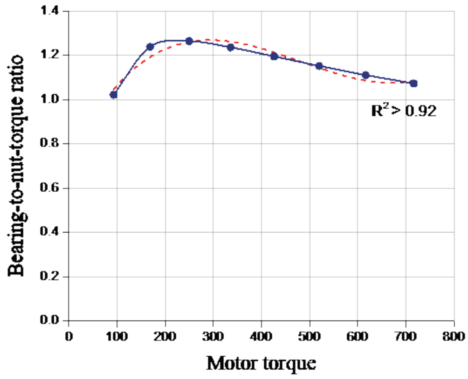


Fig. 6. (Color online) Relationship between motor torque and bearing-to-nut torque ratio.

predictions, by using bearing heat effect simulation and analysis technology, the current bearing heat could be calculated from the bearing torque and added together with the previously accumulated bearing heat to determine the total bearing heat. Predictions of bearing temperature can be employed in displacement prediction and monitoring, improving the accuracy of a machine tool. Sensitivity analysis showed that the relationship between the initial bearing temperature and the stator temperature could be expressed as

$$T_{Bearing} = C_{SB1} T_{stator} + C_{SB0}, \tag{9}$$

where $T_{Bearing}$ is the initial bearing temperature and C_{SBi} is the ith-order constant in the relationship between the bearing and the motor stator.

The total heat generation of the bearing is

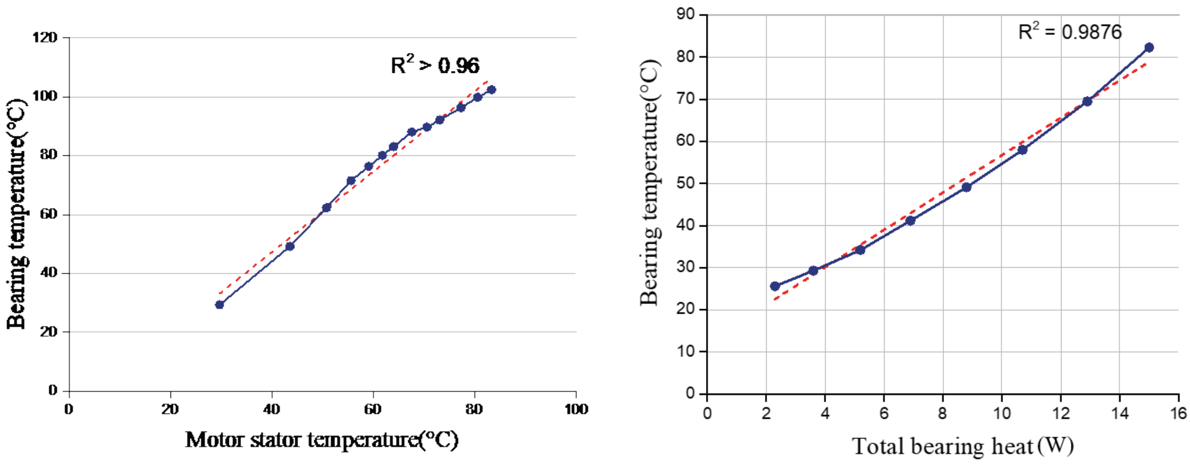
$$H_B = H_B\left(1 - C_{BH}\right) + H'_B\left(C_{BH}\right), \tag{10}$$

$$H'_B = C_{HB'} \tau_B n_B, \tag{11}$$

where H_B is the cumulative heat of the bearing, H'_B is the current bearing heat, τ_B is the bearing torque, n_B is the rotational speed of the bearing, C_{BH} is the regression coefficient of the cumulative bearing heat at each regular sampling time until the total heat is achieved, and C_{HB} is the coefficient of bearing heat at the time of sampling. The values of these coefficients could be obtained through regression analysis. When the machine sampling frequency was not consistent with that in the regression analysis (as shown in Fig. 7), C_{BH} had to be adjusted using the ratio of the two sampling frequencies. The bearing temperature could then be calculated as

$$T_{Bearing} = C_{BH1} H_B + C_{BH0}, \tag{12}$$

where C_{BHi} is the *i*th-order constant of the bearing heat and temperature.



(a) (b)

Fig. 7. (Color online) Relationship between bearing heat and temperature: (a) stator temperature and (b) total bearing heat.

The process of detecting the nut status is similar to that of bearing status monitoring. (1) First, the nut torque was decoupled from the motor torque of the servo drive, and the preload value was obtained using nut torque theories. This preload value was employed to determine whether the status was abnormal and to offer suggestions for adjustments to the cutting depth parameters. (2) Temperature predictions involved the use of nut heat effect simulation and analysis technology: the current nut heat was calculated from the nut torque and added together with the previously accumulated nut heat to determine the total nut heat. Predictions of nut temperature can be used in displacement prediction and monitoring to improve the accuracy of a machine tool. The sensitivity analysis results and regression analysis formulae for nut temperature were similar to those for bearing temperature.

3.3 Estimation of transmission shaft straightness and backlash

A transmission shaft (also known as a linear or feed axis) primarily comprises a motor, a front bearing, screws, nuts, and a back bearing. The motor rotates and drives the screws supported by the front and back bearings, resulting in the linear motion of the nuts on the screw and the moving platform above them. The movement of these components generates heat, which is transferred to the structure through heat conduction. The resulting heat deformation of the structure causes slight deviations in the horizontal and vertical directions of the moving platform while it is moving, and these deviations reduce machining precision. Currently, most machining businesses conduct regular shutdowns for maintenance and repairs, during which they use laser interferometers to measure the linear movement deviation of moving platforms. However, such offline measurements do not enable the immediate detection and correction of abnormalities, and a large number of defective products are thus produced before the deviations have been discovered. Additionally, laser interferometers are expensive, and operators of these devices must receive training on them. Most machining businesses cannot afford the associated in-house equipment and staff and therefore outsource this work; consequently, when an abnormality occurs, a plant must be shut down until it has been inspected by the contracted service provider. To address this issue, thermal fluid–solid coupling analysis was employed in this study to estimate the linear deviations of a transmission shaft, with the temperature estimation technology described in the previous section employed to analyze the impact of component heating on the deformation of a transmission shaft structure. In the simulation analysis, first, the transmission shaft was segmented into multiple nodes, and the amount of deformation of each node under various movement conditions was simulated and predicted separately. Horizontal and vertical changes in axis straightness were analyzed in accordance with the geometrical product specification standard ISO 1101. The proposed approach overcomes the issue of product defects caused by excessive straightness changes due to the inability of machines to dynamically predict the straightness changes caused by thermal displacement.

Once large amounts of simulation data had been gathered and the data had been validated against laser interferometer measurements, sensitivity analysis was performed on the simulation and measured data. The results indicated that the vertical and horizontal straightness changes could be expressed as functions of the motor and front and back bearings. This is because the motor and bearings are directly connected to the structure (whereas the screws and nuts are only indirectly connected through the bearings), and the heat can thus be directly conducted to the structure, producing thermal deformation. The equations are as follows:

$$\delta_{Hi} = \sum_{j=1}^{3} C_{HFBij} T_{FBearing}{}^{j} + \sum_{j=1}^{3} C_{HBBij} T_{BBearing}{}^{j} + \sum_{j=1}^{3} C_{HMij} T_{Motor}{}^{j} + C_{Hj}\,, \tag{13}$$

$$\delta_{Vi} = \sum_{j=1}^{3} C_{VFBij} T_{FBearing}{}^{j} + \sum_{j=1}^{3} C_{VBBij} T_{BBearing}{}^{j} + \sum_{j=1}^{3} C_{VMij} T_{Motor}{}^{j} + C_{Vi}\,, \tag{14}$$

where δ_{Hi} and δ_{Vi} represent the horizontal and vertical straightness deviations of node i, respectively; C_{HFBij} and C_{VFBij} are the coefficients of the impact of the front bearing temperature on the jth-order horizontal and vertical straightness deviations of node i, respectively; C_{HBBij} and C_{VBBij} are the coefficients of the impact of the back bearing temperature on the jth-order horizontal and vertical straightness deviations of node i, respectively; C_{HMij} and C_{VMij} are the coefficients of the impact of the motor temperature on the jth-order horizontal and vertical straightness deviations of node i, respectively; C_{Hj} and C_{Vi} are the constant coefficients of the horizontal and vertical straightness deviations, respectively; $T_{FBearing}$ is the temperature of the front bearing; $T_{BBearing}$ is the temperature of the back bearing; and T_{Motor} is the temperature of the motor. The estimation model is illustrated in Fig. 8.

Regarding backlash in the transmission shaft, wear from the prolonged use of a machine tool results in the deformation of the backlash, compromising the machining accuracy. Presently, most inspections are conducted using laser interferometers, which also involve the risks of machining defects and delayed repairs, similar to those of straightness compensation. To address this issue, a backlash detection method that employs servo feedback data to determine the backlash of a transmission shaft was developed. First, reciprocating movement commands were given to the transmission shaft; this was begun with the minimum movement unit, and the

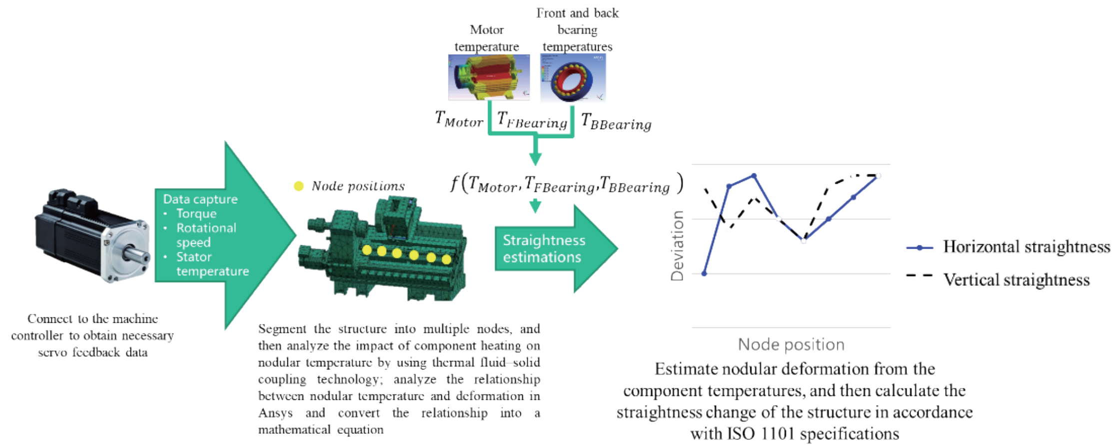


Fig. 8. (Color online) Model for estimating straightness changes in the transmission shaft.

movement range was then gradually expanded. The results demonstrated that when the movement command was smaller than the backlash, only the motor rotated, and the moving platform on top of the transmission shaft was not driven. Consequently, the motor current remained low. When the movement range was greater than the backlash, the moving platform began to move, which caused the motor current to increase or decrease depending on the direction of the movement. This enabled the detection of the transmission shaft backlash under nonmachining conditions and the inference of the backlash value for different rotational speeds. The proposed approach reduces the backlash measuring time from the 15 min required when using a laser interferometer to below 10 min while also improving machining precision. The current under the reciprocating movement is illustrated in Fig. 9.

3.4 Estimation of rotational axis thermal elongation

Another key component in a machining center is the rotational axis, which may constitute a spindle or rotating platform. The interior of the rotating axis mainly comprises transmission components such as a motor, bearings, or nuts, and the backlash of each component can be estimated and compensated by the methods described in Sect. 2.3. Whereas the transmission shaft transmits linear movement, the rotational axis produces rotational movement; therefore, the thermal deformation of the rotational axis primary takes the form of axial elongation. The amount of deformation affects the parameters for correcting the machine tool length. If thermal elongation of the rotational axis is not compensated in a timely manner, finished workpieces will be larger or smaller than the target size, depending on whether the rotational axis has elongated or shortened. Currently, most machining businesses ensure that a rotational axis is thermally stable (its elongation has a certain stable value with only microscale changes being possible) by warming up the machine first (e.g., through continuous rotation for 30 min or longer) and then measuring the tool length and using the controller to compensate for this length to maintain machining accuracy. However, if a machine has been on standby for a long period (for reasons such as workers going on a break or changing molds), the machine must be warmed up again,

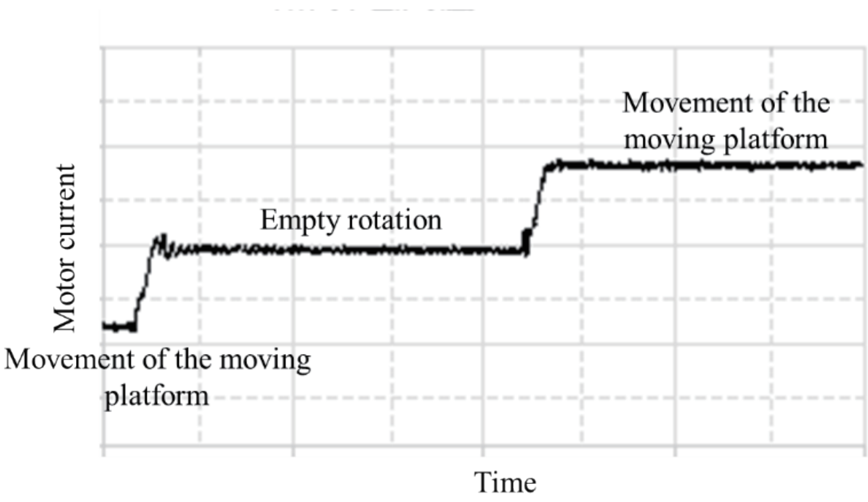


Fig. 9. Motor current during backlash inspection

which wastes time and compromises production capacity. To address this issue, we developed a technology for estimating the thermal elongation of the rotational axis. The heat dissipation and thermal displacement of a rotational axis were analyzed by examining the heat generated by a motor and bearings; finite element analysis software was then employed to establish the relationship between the servo feedback and the thermal displacement. The proposed technology enables machining businesses to periodically estimate the elongation of the rotational axis and thus predict the thermal displacement of the shafts; with this information, the businesses can rapidly compensate the tool length and improve machining accuracy.

Large amounts of simulation data were gathered, and these data were verified against eddy-current detector measurements. Sensitivity analysis was then performed on the simulation and measured data. The results revealed that the thermal displacement of the rotational axis could be expressed as a function of the motor's load, rotational speed, and temperature difference:

$$\delta_R = C_{RT}\Delta T + C_{RM}S_M + C_{RL}L_M + C_{RC}, \quad (15)$$

where δ_R is the thermal elongation of the rotational axis; C_{RT}, C_{RM}, C_{RL}, and C_{RC} are constants derived through regression analysis; ΔT is the difference between the current stator temperature and the stator temperature at the time of tool calibration; and L_M is the motor load. Entering data on the motor's rotational speed, load, and temperature into Eq. (15) enabled the calculation of the amount of elongation. The accuracy of the thermal elongation of rotational axis is shown in Fig. 10.

3.5 On-site β-site system validation

To validate its appropriateness, β-site validation was conducted by introducing the proposed technology in an actual machining plant that performs turbine bush milling. The test machining process is illustrated in Fig. 11. Each hour, the manufacturer can produce six turbine bushings on

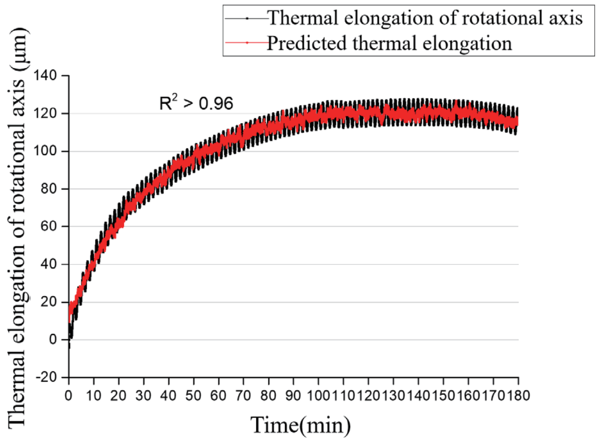


Fig. 10. (Color online) Relationship between rotational axis temperature and thermal displacement.

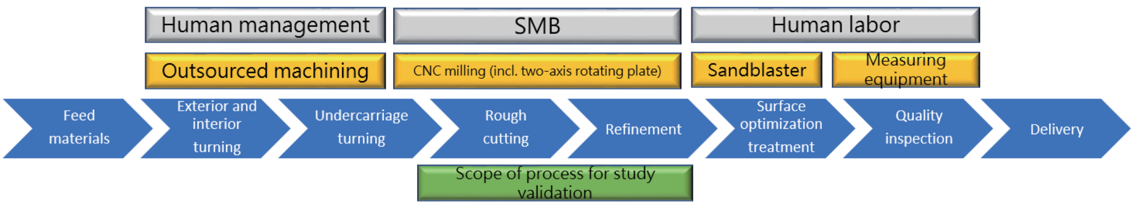


Fig. 11. (Color online) Machining process of the plant used for β-site validation.

each machine. However, Taiwan's declining birth rate has led to a labor shortage and an inability to pass on production line experience. Consequently, the manufacturer hoped to improve their machining accuracy and efficiency through the introduction of digital technologies and the prevention of sudden failures. The verification conditions in this study are shown in Table 1, and the results are shown in Table 2. Using the results in Table 2 for regression analysis, the predicted and actual thermal displacements of the rotational axis were obtained, as shown in Fig. 12.

The equipment status monitoring and precision estimation technology developed in this study was introduced to the machining process in the following manner.

- Routine machine warmup monitoring: An onsite operator revised the routine machine warmup task so that it would be executed by the transmission and rotational axis status monitoring module developed in this study. The software module automatically monitored the statuses of the transmission and rotational axis and provided a fault warning system that could prevent sudden failures. Furthermore, the transmission shaft backlash was calculated during the machine warmup process, and the compensation values were displayed on the human–machine interface, enabling managers to decide whether parameters should be entered into the machine controller.
- Trial machining and adjustments: During the cutting process, the on-site manager ran the software module to monitor the machine tool status. Once the machining program was

Table 2
Experimental results.

		1	2	3
Operation conditions and thermal deformations	Operation 3 h	−21	−33	−34
	Stop 1 h	−26	−19	−37
	Run 1.5 h	−28	−26	−45
	1 h Lunch break errors (μm)	5	14	3
	Max. (μm)	0	0	0
	Min. (μm)	−29	−33	−45
	Difference (μm)	29	33	45

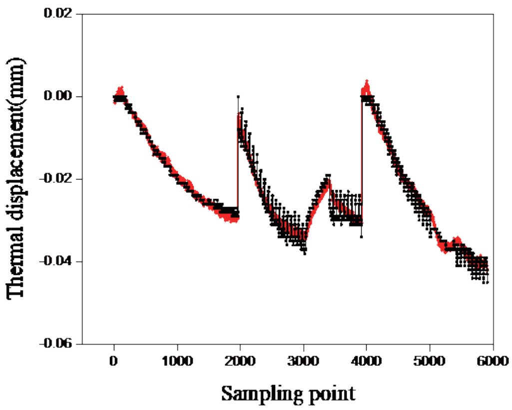


Fig. 12. (Color online) Predicted and actual thermal displacements of the rotational axis.

complete, the software module displayed the recommended adjustments to the depth of cut (to be applied to the rough cutting). The manager could calibrate the machining program in accordance with the displayed results to improve the machining efficiency.

- Machining process monitoring: During the machining process, the developed software module was kept running so that it could automatically monitor changes in transmission shaft straightness and thermal elongation in the rotational axis. The statuses of the axis were displayed on the software interface, enabling managers to enter the necessary parameters into the machine tool controller to compensate for any thermal displacements and thus improve the machining accuracy.

The accuracy of the model estimations was verified by employing actual machining practices with a five-axis machining center developed by the Industrial Technology Research Institute; instruments such as thermometers, load cells, and a laser interferometer were irregularly employed to take measurements and verify the accuracy of the estimations. Using the elongation of the rotational axis as an example, during validation, the controller provided feedback about the rotational speed, torque, and stator temperature. The axial thermal elongation history was taken into consideration when the temperature and thermal elongation of the rotational axis were being estimated, and the actual thermal displacement was derived from the displacement measurements and compared with the predictions. Lastly, all the measurements and predictions were analyzed to determine the coefficient of determination (R^2), which described the accuracy of the model estimations. The results are illustrated in Fig. 9.

The estimation accuracy for each technology is detailed in Table 3.

The experimental results indicate that when the sensor signal is close to the estimation target and the sensing data can be used to predict the state, a higher estimation accuracy can be achieved (such as for motor temperature estimation). However, if more than two sets of regression equations are required for state prediction, the prediction accuracy decreases as the number of equations increases (such as for bearing and nut temperature estimation). Practically, owing to mechanical design constraints, it is often difficult to place sensors directly at the measurement location, making it hard to detect the state of parts. Compared with the current detection difficulties, we provide a simple method to directly estimate the state of parts that are difficult to measure using servo feedback, thereby preventing unexpected failures. Additionally, in this study, we primarily use multiple regression analysis to conduct sensitivity analysis on multiple input and one output parameters from a small number of experiments and a large amount of finite element analysis simulation results, producing corresponding regression equations. According to the equations obtained in this study, state estimation through multiple linear regression equations can generally achieve an estimation accuracy of more than 90%. However, practically, the linear regression analysis method cannot be applied to all machines. The thermal deformation prediction equations of machine tools are related to machine design. Considering conditions such as thermal symmetry, the thermal deformation equations can usually be simplified into linear regression equations. If the thermal effects are not considered in the machine design, it is generally difficult to achieve good estimation results using regression analysis. Many researchers have also invested in the prediction and compensation methods for the thermal deformation of such types of machines using neural networks such as LSTM, GRU, and RNN. However, the estimation calculations are much more complex and cannot be embedded into the machine tool controller for real-time compensation. The results of our study also align with those in Okuma's technical white paper:[21] regression analysis is an effective method for thermal compensation, and if the results are inaccurate, it may indicate a problem with the machine tool design. Therefore, the results of this study further demonstrate the effectiveness of regression analysis in machine tool thermal compensation and a thermal compensation method that can be embedded into the machine tool motion controller is developed, which will be introduced into end-processing plants for actual machining verification. The benefits to the machining business from the introduction of these technologies can be summarized as follows.

Table 3
Status monitoring accuracy

Estimation target	Estimation accuracy
Motor temperature	$R^2 \approx 0.92$
Bearing temperature	$R^2 \approx 0.88$
Nut temperature	$R^2 \approx 0.90$
Transmission shaft straightness	Horizontal straightness $R^2 \approx 0.93$ Vertical straightness $R^2 \approx 0.94$
Transmission shaft backlash	$R^2 \approx 0.97$
Rotational axis thermal elongation	$R^2 \approx 0.92$

- The validation of machining accuracy and yield rate was performed through random inspections of the turbine bushings produced when following the original quality control protocols of the collaborating manufacturer. The original tolerance was approximately 0.05 mm. Following the introduction of the thermal displacement estimation technology, the compensation was improved to 0.03; furthermore, the tolerance was exceeded for no more than one item per 100 samples. Hence, the technology was shown to effectively improve machining accuracy and yield while addressing the impact of misaligned lubrication holes on the lubrication of turbine bushings.
- Regarding adjustments to the machining parameters, the machining center status and component stress could be automatically estimated using status estimation technology and a visual interface, and recommendations for the maximum cutting depth could be provided. The user could modify the machining program in accordance with the recommendation, and the number of trial cuts was reduced by more than 30%.
- No unforeseen shutdowns occurred during the technical validation period of this study. Furthermore, the equipment status detection performed by the warmup program and using the technology developed in this study reduced the time taken to inspect three-axis milling beds by 60%.

4. Conclusions

In this study, systems that use servo feedback data were developed for status estimation, precision estimation, and the compensation of the machine tool transmission and rotational axes. The proposed technologies do not require the installation of sensors and can perform estimations using only the servo feedback information obtained from the machine tool controller. Compared with existing sensorless estimation techniques, this approach improves the estimation accuracy, avoids incorrect estimations due to sudden changes in machine tool status, and eliminates the need for additional sensor installations at specific positions, which would require modifications to the mechanical design. The proposed method was practically introduced into a β-site for machining verification. The verification results indicate that, with the proper mechanical design of the machine tool, the accuracy of estimating mechanical part temperatures and thermal deformation through regression analysis can reach a value above 88%. This method is easier to integrate into the machine tool controller for real-time compensation than existing neural network methods, and the results are consistent with those in Okuma's technical white paper. The validation results indicate the following benefits to machining businesses:

- Improving the value added to products: Machining accuracy can be improved by equipping machine tools with intelligent machining application functions to carry out efficient and intelligent machining and production; in addition, defect rates can be reduced, and trial machining parameter adjustment and machine status detection times can be shortened.
- Establishing smart manufacturing capabilities: Small-batch, diverse, and customized requirements will become the norm for customer orders in the future, and the stability and efficiency of machining will affect manufacturing capabilities. Establishing smart manufacturing capabilities by using the status detection technologies developed in this study

would enable the digital and visual management of the equipment status. As well as reducing time-consuming and inaccurate manual operations, the developed technologies enable quality monitoring, production progress querying, and customer feedback in real time. Overall, these technologies can effectively improve product quality and lead times while lowering product costs, thereby improving a company's competitiveness.

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