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Hierarchical explicit–implicit combined sensing-based real-time monitoring method for the service performance of complex equipment

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Abstract

Purpose – Real-time monitoring of the critical physical fields of core components in complex equipment is of great significance as it can predict potential failures, provide reasonable preventive maintenance strategies and thereby ensure the service performance of the equipment. This research aims to propose a hierarchical explicit–implicit combined sensing-based real-time monitoring method to achieve the sensing of critical physical field information of core components in complex equipment.

Design/methodology/approach – Sensor deployable and non-deployable areas are divided based on the dynamic and static constraints in actual service. An integrated method of measurement point layout and performance evaluation is used to optimize sensor placement, and an association mapping between information in non-deployable and deployable areas is established, achieving hierarchical explicit–implicit combined sensing of key sensor information for core components. Finally, the critical physical fields of core components are reconstructed and visualized.

Findings – The proposed method is applied to the spindle system of CNC machine tools, and the result shows that this method can effectively monitor the spindle system temperature field.

Originality/value – This research provides an effective method for monitoring the service performance of complex equipment, especially considering the dynamic and static constraints during the service process and detecting critical information in non-deployable areas.

Keywords Real-time monitoring, Complex equipment, Service performance, Sensor layout, CNC machine tools

Paper type Research paper

1. Introduction

With the rapid development of manufacturing, typical complex equipment such as CNC machine tools and nuclear power equipment plays a vital role in modern industrial production. Among them, core components such as the spindle of CNC machine tools and the surge line of nuclear power equipment significantly impact their service performance (Bae *et al.*, 2021; Cai *et al.*, 2017). Real-time monitoring of the critical physical fields of core components can

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predict potential failures in complex equipment, provide reasonable preventive maintenance strategies, and thereby ensure the service performance of the equipment (Hao *et al.*, 2023; Zhao *et al.*, 2022). However, how to monitor these critical physical fields of complex equipment core components in real time using sensing technology is an urgent scientific problem that needs addressing. In recent years, there has been a surge of research focused on the optimization of sensor layout and the extraction of key sensor information.

Tao *et al.* (2018) collected acceleration signals on the gearbox of wind turbine, integrating physical signals and virtual device simulation signals, achieving accurate fault identification of wind turbine gearbox. Hosamo *et al.* (2022) proposed a predictive maintenance framework for air handling unit (AHU), which included temperature, pressure, and flow sensors, and combined performance evaluation rules and machine learning to achieve fault detection of AHU. These methods have achieved certain success in using sensors to monitor equipment performance. However, these methods lack exploration of the association between sensor layout and monitoring quantities, relying more on experience than on explicit layout rationale.

Sun *et al.* (2024) divided the sensor areas through finite element simulation analysis, and selected a set of temperature measurement points to achieve the migration prediction of thermal errors. Kong *et al.* (2022) proposed a sensor number and location optimization method based on the discrete particle swarm algorithm, aimed at state monitoring and fault diagnosis of hydraulic control systems, effectively improving diagnostic efficiency while avoiding resource waste. These methods have achieved certain effectiveness, but overlook the issue that sensors cannot be deployed due to constraints imposed by geometric structures, service processes, and environmental factors in complex equipment.

Chen *et al.* (2014) considered mechanical structure constraints on sensor layout in gate machines and proposed a primitive motion and interference analysis algorithm, which optimized sensor layout in gate machines. Yuan *et al.* (2015) designed an optimized layout method for aircraft fuel measurement sensors, introducing a settable boundary distance factor to solve the interference issues between sensor positions and the fuel tank walls. These methods have achieved certain results. However, they fail to capture critical information from non-deployable areas, leading to incomplete equipment sensor information collection.

In response to the existing research problems, this research proposes a real-time monitoring method for the service performance of complex equipment. The method optimizes sensor layout through hierarchical means and detects critical information in both deployable and non-deployable areas, achieving real-time reconstruction of the critical physical fields of core components. The main contributions are as follows: (1) A complex equipment virtual-real prototype considering dynamic and static constraints related to the real service process is built, and the sensor deployable and non-deployable areas are accurately divided through a combination of physical experiments and numerical simulations; (2) An integrated method of measurement point layout and performance evaluation is utilized to optimize sensor placement, and an association mapping between information in non-deployable and deployable areas is established, thereby achieving hierarchical explicit-implicit combined sensing of key sensor information for core components; (3) The critical physical fields of core components is reconstructed based on the sensing of key sensor information, and real-time monitoring of the service performance of complex equipment is achieved through visualization tools.

2. Overall framework

The overall framework of this research is shown in Figure 1, which mainly involves three parts: complex equipment, virtual-real prototype, and functional module. Firstly, a virtual-real prototype of the core component is constructed based on the geometry, materials, and structural information of the complex equipment, and the sensor deployable and non-deployable areas are divided based on the dynamic and static constraints experienced during the service process. Based on the sensor areas divided in the virtual-real prototype, a

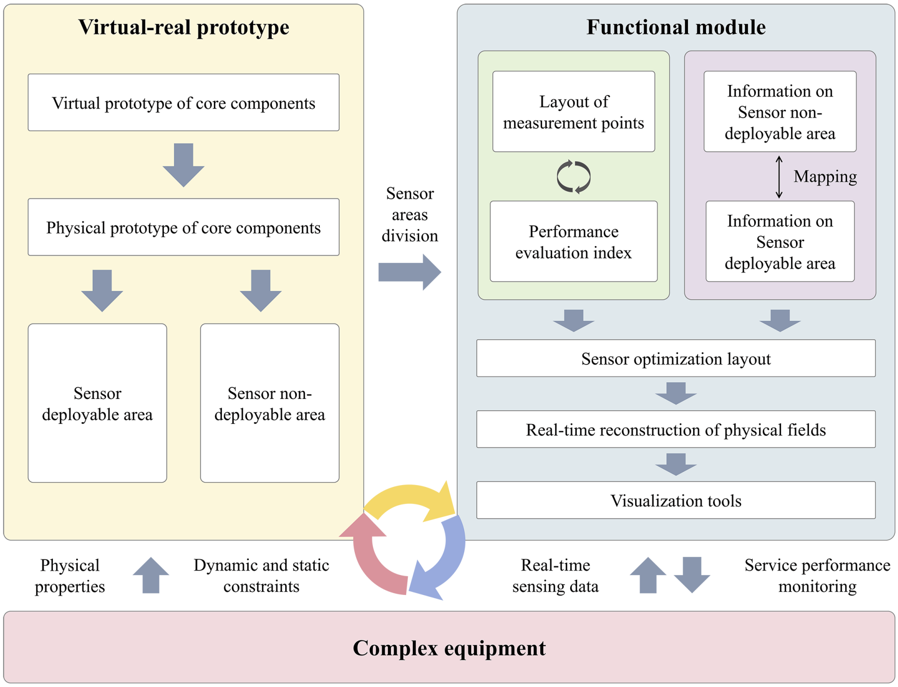

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Figure 1. Overall framework of the method

hierarchical approach is used to achieve sensor optimization layout and information exploration, guiding the sensor placement on the actual complex equipment. The physical field is reconstructed based on the real-time collected key sensor data of the complex equipment, and performance monitoring is achieved through visualization tools.

3. Method and principle

3.1 Division of sensor areas considering dynamic and static constraints

Constructing a virtual-real prototype of complex equipment that correlates with the dynamic and static constraints of the actual service process is the foundation for accurately dividing the sensor deployable and non-deployable areas. The virtual-real prototype includes both virtual and physical prototypes. The virtual prototype, based on finite element analysis (FEA), performs high-precision simulations of the core component of complex equipment. It includes the geometric shapes, material properties, internal structures, and various physical parameters related to the actual service process, enabling simulating the behavior and critical physical fields of component during the actual service process. The physical prototype, built based on the real core component of complex equipment, not only reproduces the geometric and structural features of the equipment but also embeds the necessary sensors and measurement systems to collect operational data for further analysis.

The virtual-real prototype integrates the dynamic and static constraints of complex equipment during the actual service process. Dynamic and static constraints refer to a series of moving and stationary conditions that affect the normal use of sensors during their deployment. Dynamic constraints involve the limitations and conditions encountered during the operation of the equipment, such as the movement of components and changes in the surrounding environment. Static constraints focus on the conditions for sensor deployment when the equipment is not in motion or affected by external dynamics, such as the dimensions and shapes of the installation space. Evaluating the sensor deployability in various regions of the core component based on these dynamic and static constraints ensures that the sensors do not interfere with the normal operation of the sensors themselves or the core component due to spatial limitations or environmental impacts, thereby dividing the sensor deployable and non-deployable areas.

3.2 Hierarchical explicit-implicit combined sensing of key sensor information

Based on the integrated method of measurement point layout and performance evaluation and explicit-implicit measurement points association mapping modeling, an optimized sensor layout scheme for monitoring the physical fields of core components in complex equipment is obtained, as shown in Figure 2.

3.2.1 Integrated method of measurement point layout and performance evaluation for sensor layout optimization. The placement of sensors is crucial for monitoring the performance of complex equipment, as it affects the accuracy and coverage of the monitoring data, and consequently the quality of the data. Since the ultimate goal of sensor placement and data collection is to monitor the performance of core component, a performance evaluation index of the core component can be used to measure the effectiveness of the sensor layout. An integrated method of measurement point layout and performance evaluation is proposed to optimize the sensor layout, with specific steps as follows:

Step 1: Measurement points are uniformly selected along predetermined lines or grid patterns on the virtual prototype of complex equipment, and the data of the physical quantities to be monitored by these measurement points over time are exported.

Step 2: A performance evaluation index for the core component, such as the deformation of a component in a critical direction or the wear of a specific part of the component, is chosen,

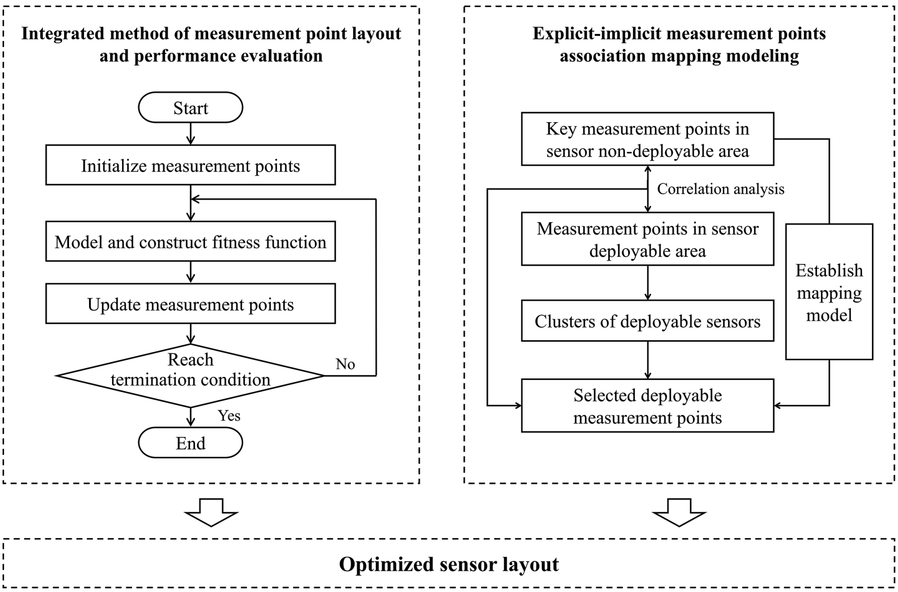

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Figure 2. Hierarchical explicit-implicit combined sensing of key sensor information

and the performance evaluation index data of the core component of the complex equipment over time are exported.

Step 3: The correlation coefficient between the physical quantities of each measurement point and the performance evaluation index is calculated. When the correlation coefficient of a physical quantity measurement point and the performance evaluation index exceeds a set threshold, that measurement point is marked as a principal factor measurement point, and the area formed by connecting the principal factor measurement points is designated as the principal factor zone.

Step 4: Sensors are uniformly placed along predetermined lines or grid patterns in the principal factor zone of the physical prototype of complex equipment. The service process of the actual equipment is simulated, and the data of these measurement points over time are collected, while the performance evaluation index data of the core component of the complex equipment over time are simultaneously measured.

Step 5: Different combinations of measurement points are used as the input for modeling, and the performance evaluation index is used as the model output to establish a model.

Step 6: The root mean square error (RMSE) between the predicted results and the actual values is calculated as the objective function for the combination of measurement points, and the particle swarm optimization (PSO) algorithm is used to iteratively optimize and select the combination of key measurement points that best represent the performance evaluation index.

3.2.2 Explicit-implicit measurement points association mapping modeling. In the complex equipment, many critical measurement points often exist in non-deployable areas, which can reflect important physical fields information. Without obtaining the critical information from non-deployable areas, it is challenging to achieve comprehensive physical fields calculations. Therefore, based on the physical prototype of complex equipment, an association mapping between information in non-deployable areas and deployable areas is established, with specific steps as follows:

Step 1: The real-world deployability of sensors is simulated on the physical prototype of the core component, dividing the sensor deployable and non-deployable areas. In the physical prototype, sensor information from both parts can be conditionally obtained.

Step 2: Sensors are placed at key measurement points in the sensor non-deployable areas of the physical prototype of the core component, and multiple sensors are placed in the sensor deployable areas to collect sensor data during the operational process.

Step 3: K-means clustering analysis is performed on the measurement points in the sensor deployable areas, dividing the measurement points into several internally similar clusters.

Step 4: The correlation between the key measurement points in the sensor non-deployable areas and the measurement points in the sensor deployable areas is analyzed using correlation analysis methods, and the measurement points in the sensor deployable areas are ranked based on the correlation magnitude.

Step 5: In each cluster formed by the measurement points in the sensor deployable areas, the measurement point with the highest correlation to the key measurement point in the sensor non-deployable areas is selected.

Step 6: Based on specific requirements and data characteristics, an appropriate modeling method is chosen. The selected measurement points in the sensor deployable areas are used as inputs and the key measurement points in the sensor non-deployable areas are used as outputs to establish the association mapping model.

3.3 Reconstruction of critical physical field of core component

On actual complex equipment, sensors are deployed according to the optimized measurement point layout scheme, and sensor data of the core component during the service process is collected in real time. Based on the characteristic and precision requirement of the data, an appropriate interpolation method is selected to perform interpolation calculations on the known data points. The results of the interpolation calculations are then mapped to the entire component area, forming a complete distribution of the physical field.

The real-time calculated physical field result is visualized in the form of a heatmap. Heatmaps represent data values through color gradients, allowing for an intuitive display of the spatial variation and distribution of the data. The key to using heatmaps for visualization lies in mapping the physical quantity values to colors. Typically, the maximum and minimum values of the physical field are first mapped to specific colors, and then the physical quantity is mapped across the entire color spectrum to achieve the visualization of the physical field.

4. Case verification

Taking the spindle system of a certain model of CNC machine tools as an example, the service performance is monitored in real time using hierarchical explicit-implicit combined sensing method. During the service process of CNC machine tools, temperature field changes in the spindle system caused by environmental temperature variations, bearing heat generation, and other factors can lead to thermal deformation of components, thereby affecting machining accuracy and reducing service performance. Therefore, it is necessary to monitor the temperature field of the spindle system of CNC machine tools and make timely adjustments to ensure machining accuracy.

Firstly, a virtual-real prototype of the spindle system is established, including an FEA model and a physical prototype. The temperature field simulation result is shown in Figure 3.

A physical prototype consistent with the actual spindle system is constructed, and necessary sensors are embedded, as shown in Figure 4(a). Based on the dynamic and static constraints such as internal geometric structures, coolant interference, and cutting sparks encountered during the actual processing, the sensor deployability is simulated on the physical prototype of the spindle system. The sensor deployable and non-deployable areas are divided accordingly. In the physical prototype, sensor information from both areas can be conditionally obtained. To facilitate distinction, an acrylic cover is added to the sensor non-deployable areas on the physical prototype, as shown in Figure 4(b).

The integrated method of measurement point layout and performance evaluation is employed to optimize the sensor layout. Since temperature field variations lead to thermal errors, which directly affect the machining performance of the machine tools, the thermal error of the spindle is chosen as the performance evaluation index for monitoring. Firstly, the

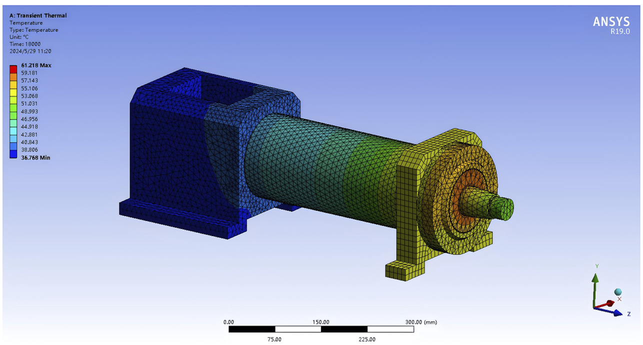

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Figure 3. FEA result of the spindle system temperature field

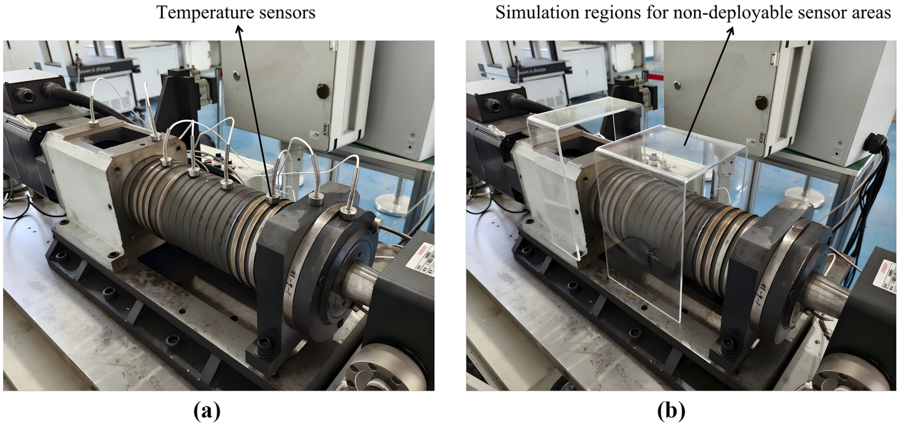

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Figure 4. Physical prototype of the spindle system: (a) spindle system, (b) division of sensor areas

principal factor zone that has a strong correlation with thermal error is identified based on data from FEA. Multiple temperature sensors are deployed in the principal factor zone of the physical prototype and an eddy current displacement sensor is placed at the front end of the spindle to collect sensor data during operation. Then, different combinations of measurement points are used as inputs, and thermal error is used as the output to establish a model and calculate the fitness of each combination of measurement points. To extract the temporal characteristics of temperature and thermal error data, a Long Short-Term Memory (LSTM) network is used to establish the model. LSTM is a deep learning model commonly used for processing sequential data. To address the limitation of traditional recurrent neural networks (RNNs), which struggle to retain information from earlier in a sequence, LSTM utilizes three gate controllers to selectively retain and forget inputs and states. This enables LSTM to better capture long-term dependencies in time series data. The LSTM unit is illustrated in Figure 5, and the functions of the three gate controllers are given by the following formulas:

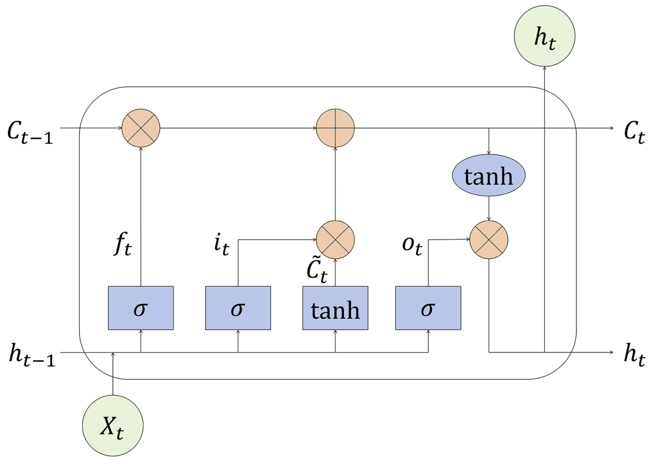

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Figure 5. LSTM unit

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{3}$$

where W_f、 W_i、 W_o and b_f、 b_i、 b_o are the weight matrices and biases of the forget gate, input gate, and output gate, respectively.

Finally, the PSO algorithm is employed to iteratively optimize and select the combination of measurement points that best represent the thermal error. Sensor data at multiple rotational speeds are collected, and a thermal error prediction model is established using the selected measurement points. The prediction results at rotational speeds of 1,200 RPM and 1,500 RPM are shown in Figure 6, with R^2 values of 99.5 and 99.6%, respectively.

For sensor non-deployable areas, K-means clustering analysis and Pearson correlation analysis are initially used to select several measurement points in the deployable areas that can represent the critical measurement points in the non-deployable areas. An LSTM network is used to establish an association mapping model between the selected measurement points in the deployable areas and the critical measurement points in the non-deployable areas. The test results of the trained association mapping model at rotational speeds of 1,200 RPM and 1,500 RPM are shown in Figure 7, with R^2 values both reaching 99.5%, demonstrating that the selected measurement points in the deployable areas can effectively predict the temperature information of the critical measurement points in the non-deployable areas. This provides guidance for sensing information in difficult-to-deploy sensor locations on the actual spindle system.

Combining the sensor layout schemes for both sensor deployable and non-deployable areas, temperature sensors are deployed on an actual CNC machine tool to collect real-time temperature data during operation, as shown in Figure 8.

Taking the temperature sensor data from a specific region of the spindle system at a certain moment as an example, the temperature field is reconstructed using linear interpolation and visualized in the form of a heatmap, as shown in Figure 9.

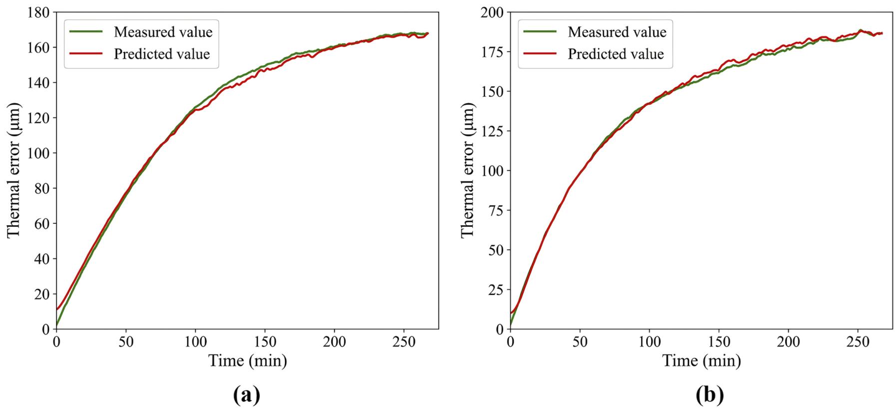

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Figure 6. Modeling effect of performance evaluation index: (a) 1,200 RPM, (b) 1,500 RPM

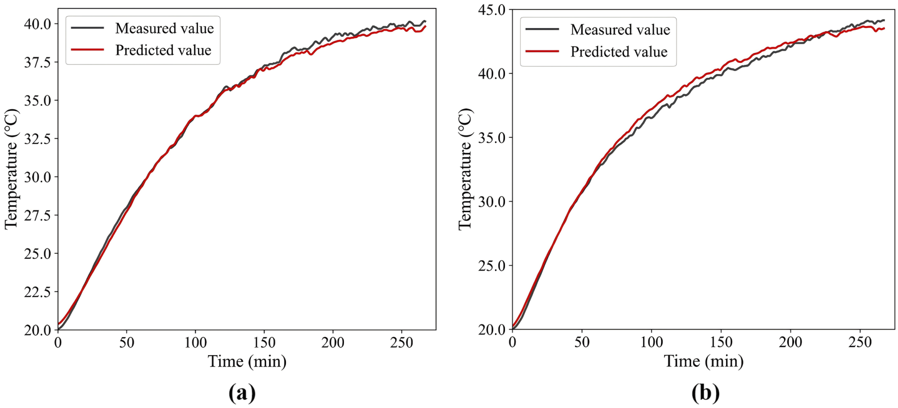

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Figure 7. Modeling effect of association mapping: (a) 1,200 RPM, (b) 1,500 RPM

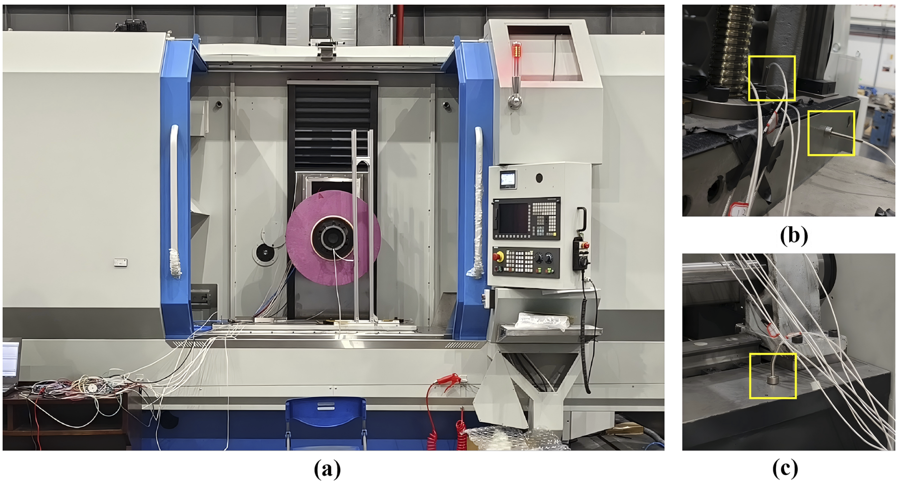

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Figure 8. Data collection from CNC machine tool: (a) CNC machine tool, (b) temperature sensors near the *Z*-axis ball screw, (c) temperature sensor on the table base

As mentioned earlier, there are certain limitations in the existing methods for acquiring critical sensing information in complex equipment, including: a lack of exploration of the correlation between sensor layout and monitoring performance; neglecting the challenges of sensor placement difficulties due to dynamic and static constraints during actual operation when planning sensor layout; and the inability to obtain sensing information from areas where sensors cannot be placed. To address these shortcomings, the method proposed in this study optimizes sensor layout and enables the acquisition of sensing information from hidden areas through an integrated method of measurement point layout and performance evaluation, along with explicit-implicit association mapping modeling.

The method has been validated and applied on a typical piece of complex equipment, CNC machine tools, and can be extended to other types of complex equipment. For different types of

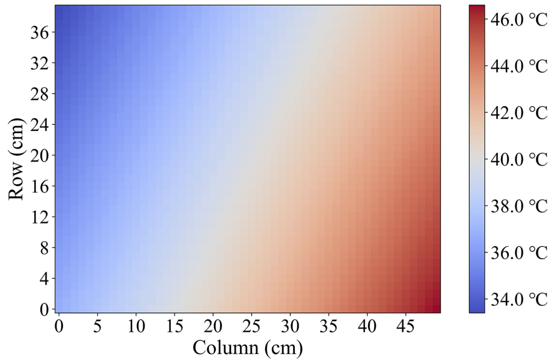

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Figure 9. Heatmap of the temperature field in a section of the spindle system

complex equipment, the first step is to construct virtual-physical prototypes of the core components based on information such as the geometry, materials, and structure of the equipment. Next, the sensor deployable and non-deployable areas are defined based on the dynamic and static constraints experienced during operation. Sensor layout optimization and information acquisition are subsequently achieved through an integrated method of measurement point layout and performance evaluation, along with explicit-implicit association mapping modeling. Finally, the physical field is reconstructed based on the real-time data collected from critical sensors in the complex equipment.

5. Conclusion

This research proposes a real-time monitoring method for the service performance of complex equipment by optimizing sensor layout through hierarchical means and detecting critical information in both deployable and non-deployable areas, ultimately achieving real-time reconstruction of the critical physical fields of core components. The research results are summarized as follows:

(1) A virtual-real prototype that includes finite element analysis and a physical prototype is constructed based on actual complex equipment, and the sensor deployable areas are divided based on the dynamic and static constraints during the service process.

(2) Hierarchical explicit-implicit combined sensing of key sensor information for core components is achieved using an integrated method of measurement point layout and performance evaluation, and explicit-implicit association mapping modeling.

(3) The method is validated on the spindle system of CNC machine tools. The temperature sensor layout scheme is determined, and the temperature field is reconstructed using the collected real-time sensor data to achieve performance monitoring of the spindle system.

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