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Condition monitoring of three-axis ultra-precision milling machine tool for anomaly detection

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Abstract

Accurately and continuously monitoring ultra-precision machining (UPM) process is the foundation for subsequent diagnosis and optimization, then facilitating energy-saving, efficient production, and high-quality machining. However, comprehensive monitoring of UPM process has hardly been investigated systematically in previous studies. To cover the gap, this study examined the linkages among these parameters monitored in UPM process using a five-layers network for the first time. Subsequently, we proposed an advanced monitoring platform that integrates G-code command, installation sensors, and controller interface. This proposed platform incorporated with anomalies detection algorithm was finally employed and validated on a three-axis ultra-precision milling machine tool. Results showed that this proposed platform could successfully achieve anomaly identification using power consumption and X/Y/Z components force signals.

Keywords: Ultra-precision machining; Condition monitoring; Anomaly detection

Nomenclature

UPM	Ultra-precision machining
IoT	Internet of Things

1. Introduction

Ultra-precision machining (UPM) is capable of fabricating micro-components with less than 0.2 μm forming accuracy and 10 nm surface accuracy, therefore widely applied in various high-tech fields such as optics, electrics, and semiconductors. In accordance with the market analysis report, the global UPM market size was valued at USD 11.8 billion in 2020 and is expected to expand at a compound annual growth rate of 9.6 from 2021 to 2028 [1].

However, the production capacity of current UPM sector cannot constantly fulfill the rapidly expanding market demand due to its low machining efficiency. Additionally, the large volume of UPM has emitted as much CO_2 as that of the conventional machining sector, raising environmental concerns from both academia and industries [2]. Despite various efforts to promote the machining efficiency and energy efficiency of UPM industry, most studies conducted were patchy with limited improvement due to the inadequate monitoring signals of UPM [3]. It is well-known that accurate estimation of UPM process not only directly reflects the machine's working state but is also crucial for determining the specific parameters in these optimization strategies, consequently influencing the optimization effect. It is, therefore, imperative to accurately and simultaneously capture these parameters in the UPM process.

To monitor the machining process, a high-resolution power analyzer was adopted to collect the power, the current, and the voltage of the three-phases power supply, which was then used to identify the axis moving feedrate using the 1-dimensional convolutional network model [4]. Additionally, an energy-efficient monitoring system for machining workshops comprising serval devices with the newly emerging Internet of Things (IoT) technology was proposed to calculate electricity consumption [5]. The vibration signal of the spindle installed on the conventional CNC machine tool was sensed by the accelerometers to identify the tool failure [6], but both were designed for the conventional machining

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process, and the measurement accuracy was insufficient for UPM process. The acoustic sensor was installed on the tool holder to detect the contact between the workpiece and the diamond tool in UPM [7]. The detection accuracy of this method, however, was unacceptable due to large errors. Additionally, in efforts to determine the range of surface roughness of the UPM workpiece, the accelerometers, 3-axis dynamometers, and acoustic sensors were integrated together, resulting in the prediction of surface roughness with a mean R^2 value of 0.83 using signals-fusion methods [8]. Similarly, on the ultra-precision diamond turning machine, three miniature accelerometers, 3-axis piezoelectric dynamometers, and acoustic sensors were used for the real-time identification of incipient surface morphology variations. The experimental findings showed that the prediction error was about 5~25 *nm* using a recurrent predictor neural network [9].

Recently, the quantitative measurement of tool wear has become a hot topic due to its significance in affecting surface quality [10]. The indirect way to determine the cutting tool wear is from the cutting force. Previous study findings indicated that the cutting force increases dramatically as the cutting tool severely wears or fractures [11-13].

The straightforward approach is to adopt the high-resolution CCD camera capable of capturing the image of the cutting tool geometry, morphology, and crack. Compared to the initial state of the cutting tool, the tool wear degree can be detected in quantity through the image-processing algorithms [14，15]. Also, this CCD camera can facilitate checking the surface quality of the UPM workpiece. However, this approach is limited in on-machined measurement as the movement or rotation of the tool or workpiece makes capturing photographs more difficult. Plus, mounting the big-sized CCD camera is a significant issue.

According to the aforementioned analysis, there are numerous UPM process parameters to be monitored, and comprehensive solutions for monitoring numerous parameters were barely investigated. To narrow the gap, this work proposed a practical monitoring platform for UPM process by mining the linkage among these monitored parameters in depth. This proposed platform was verified on the 3-axis ultra-precision machine tool for anomaly detection with promising results.

2. Correlations of UPM monitoring parameters

Numerous factors in the UPM process will impact machining quality and power consumption, both directly and indirectly. Herein, as shown in Figure 1, we summarized these factors called monitored physical parameters. According to the component's type, these parameters can be classified into five categories: external environment, machine status, cutting tool status, workpiece status, and machining process status. As shown in Figure 1, the numbers of physical parameters reach 30, and it is challenging to install extra sensors for the acquisition of all of these signals due to high cost, installation complexity, and manpower consumption. Some ultra-precision machine tools provide the controller interface that can produce some signals to debug the machines. However, the amount of available signals is limited and difficult to retrieve unless the manufacturer's unique communication protocol is accessible. On the other hand, ultra-precision machine tools are under the control of the command G-code. The G-code will determine the ideal working status of equipment, like axis feedrates, axis position, spindle rotation speed, etc. However, the error between the ideal and the actual status will generate due to various uncertainties of the dynamic system of the machine. In reference [11], the running G-code was interpreted into the working status matrix, involving axis feedrates, axis position, and components ON/OFF status through experimental time error setoff. Notably, if the command G-code can be interpreted with accurate error compensation considering the dynamic characteristic of machines, more contributions, such as real-time toolpath generation and digital twin model development of machine tools, can be made.

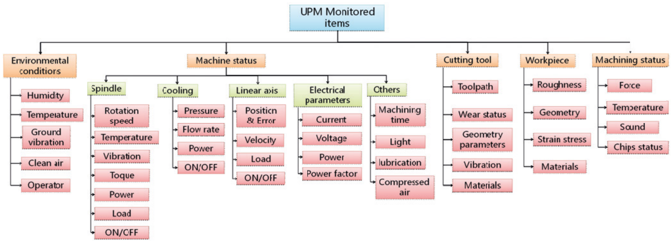


Fig. 1. Physical parameters to be monitored in UPM process.

To summarize, the primary methods for collecting real-time UPM signals are through installation sensors, controller interface connection, and G-code interpretation. A comparison of three approaches from different perspectives is presented in Table 1.

Table 1. Comparison of three approaches: installation sensors, controller interface connection, and command G-code interpretation

Methods	Available signals	Difficulty	Accuracy	Cost
Installation sensors	Many	High	High	High
Controller interface	Depending on manufacturer	Low	High	Low
G-code	Few	Middle	Middle	Extremely low

Table 1 shows that the controller interface has the highest priority for collecting real-time signals of these monitored parameters due to its obvious advantages in low difficulty and high accuracy. Because of its incredibly low monitoring cost, the G-code interpretation is a viable alternative for collecting these less significant signals. As the available signals from the controller interface and G-code are rather restricted, external sensors should be installed to get these important parameters, such as machining forces, machining temperature, instantaneous power consumption, and so on.

Additionally, multiple-signals data fusion methods were adopted to identify tool failures by employing acoustic sensors, and tests suggested that this method might produce more accurate prediction results than the simple combination [16, 17]. From this, data fusion approach is helpful to contribute to the comprehensive monitoring of UPM process by offering more valuable insight into these difficult-to-monitored parameters, like tool wear and life, machining roughness and accuracy, etc. Many studies have been undertaken to determine the tool remaining life, machining roughness and accuracy, and power consumption of the UPM process. The majority of them sought to map the relationship between various processing parameters, such as axis feedrates, cutting depth, tool parameters, etc. However, the selection of these processing parameters for predicting the target items is frequently influenced by their prior experience. Serious redundancy or insufficiency for constructing the mapping model frequently happens, increasing the monitoring cost and lowering prediction accuracy, respectively. In order to avoid this and provide systematic instruction, the correlations between these monitored parameters and the evaluation index in UPM are analyzed and mapped in Figure 2 using a five-layers network.

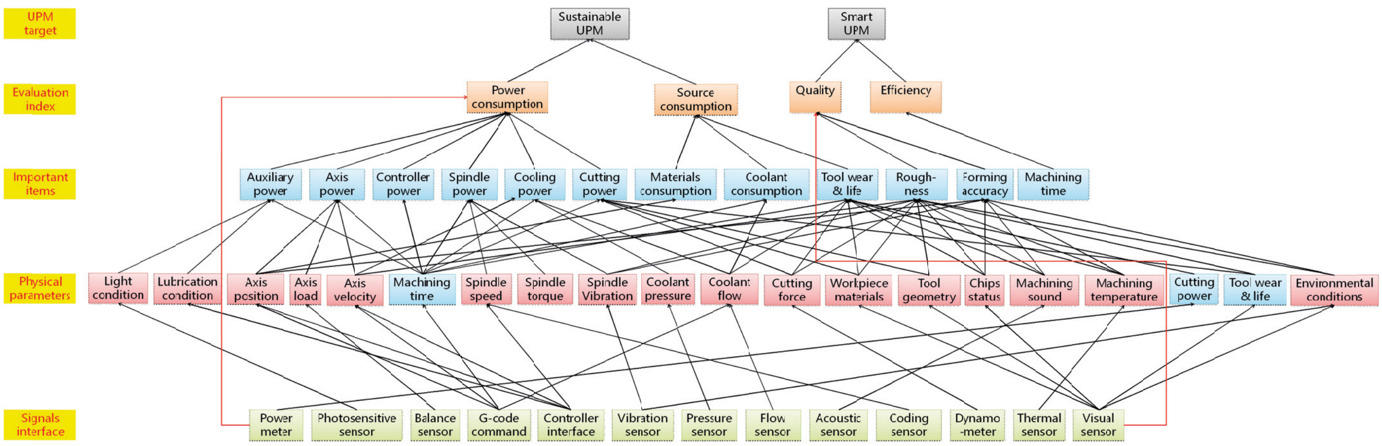


Fig. 2. Correlations between these monitored parameters and evaluation indexes.

Current UPM is developing toward a more sustainable and smart tendency, called sustainable UPM and smart UPM. As shown in the first and second layers, sustainable UPM focuses on lowering energy and source consumption, whereas smart UPM enhances machining quality and efficiency. The energy consumption and machining efficiency can be measured by the power meter and the machining time. Whereas the source consumption and machining quality are difficult to be measured in real-time, the commonly used method is to use these relevant items in the third layer to predict. These items are linked with those influenced items in the fourth layer with arrow lines. In the third layer, cutting power consumption, tool wear and life, machining roughness, and machining accuracy are linked by the high-density arrow lines from the fourth layer. This suggests that these four items are influenced by more physical factors. In other words, the modeling complexity of predicting these four items using relevant physical parameters will skyrocket. In the fifth layer, accessible ways are provided to obtain these physical parameters based on Table 1. This can help the operators determine the best way to obtain monitored parameters in practice.

To summarize, this section thoroughly explored the accessible ways to real-time acquire large quantities of UPM process signals, then compared Pros and Cons of these three ways, and finally analyzed the correlations between monitored parameters and these evaluation indexes in UPM process. This work will significantly contribute to the development of the optimal monitoring system for UPM process.

3. Engineering application

In the case study, a 3-axis ultra-precision milling machine tool was taken as the research objective, as shown in Figure 3. Three-axis X/Y/Z is driven by the linear servo motors, ranging from [-50 *mm*, 50 *mm*], [-50 *mm*, 50 *mm*], and [0, 100 *mm*] at a resolution of 1 *nm*. On the Z axis, the electrical spindle with a rotation speed of 100,000 *r/min* is stalled. On the electrical spindle, the air bearing is driven with 9 *bar* compressed air. The coolant chiller is equipped with 20 *L/min* of pure water to cool the copper coil of the electrical spindle. This machine adopts single-phase at 220V, 16A, and three-phase at 380V and 30A as power sources. The former one serves the PC controller, the display screen, the servo drivers, the chiller, and three linear axes. The latter one powers the electrical spindle to rotate. Correspondingly, single-phase and three-phase power analyzers are used to measure the instantaneous consumption power of the machine. Additionally, the milling forces during the milling process are measured by the three-dimensional dynamometer. Based on section 2, the important monitored parameters - consumption power, X/Y/Z components forces, axis feedrates, axis positions, and servo motor states are selected as the monitored parameters. The monitoring system is presented in Figure 4.

These selected monitored parameters can be measured using installation sensors, controller interface connection, and G-code interpretation. Herein, different communication protocols, I^2C, Modbus RTU, special Modbus, and G-code interpreter, are adopted. Then the Raspberry Pi hardware transfers these collected data to the data storage server after synchronizing data sampling frequency and filtering anomalous points. The anomaly detection algorithm is also deployed on the Raspberry Pi hardware.

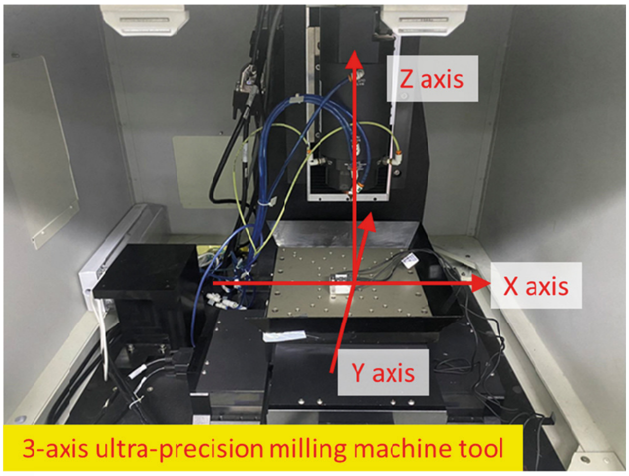


Fig. 3. Three-axis ultra-precision milling machine tool.

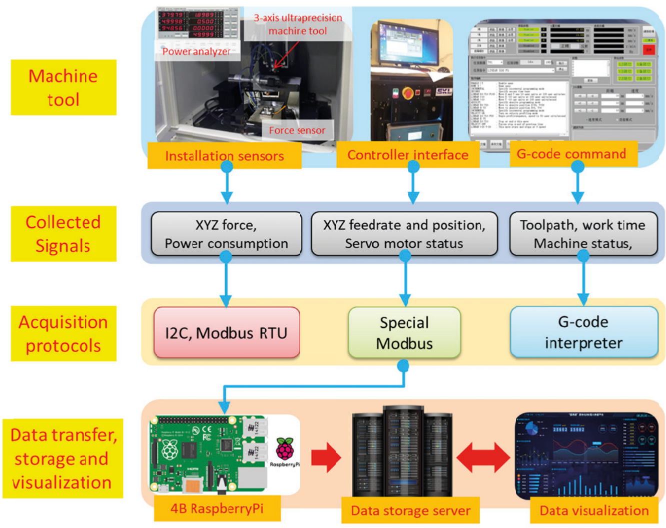


Fig. 4. Monitoring system of three-axis ultra-precision milling machine tool.

In this platform, an anomaly detection algorithm was developed to achieve failure detection during UPM process using the force and power signals. The working principle of the proposed anomaly detection algorithm is presented in Figure 5. The core of the proposed algorithm is to determine the specific value of the power and force signals during the non-milling and milling process model through calibration experiments. In experiments, X/Y/Z component's forces greater than zero indicated that the milling process happened. This enables us to distinguish between the milling process and no-milling process. Then, the real-time X/Y/Z components forces and the power consumption were compared to the experimental criterion. If both parameters meet the judgment conditions, this indicates the machine tool is working at normal status in the milling process. Otherwise, there is an abnormal incident. During the non-milling process, real-time power consumption was the only criterion to judge the work status of the machine tool.

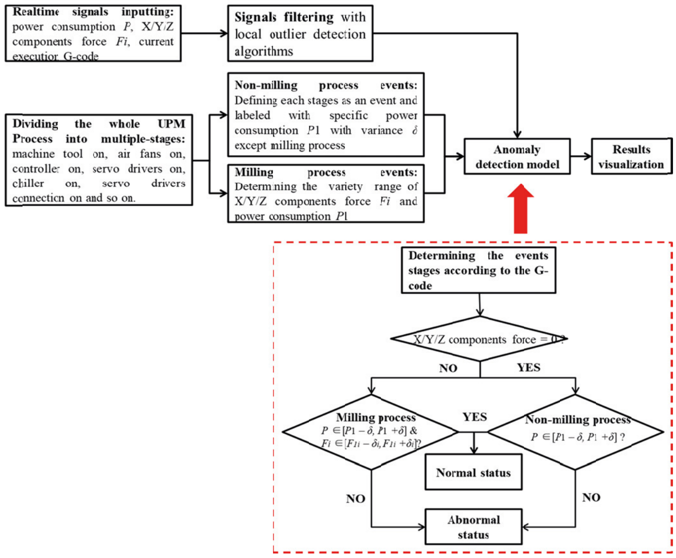
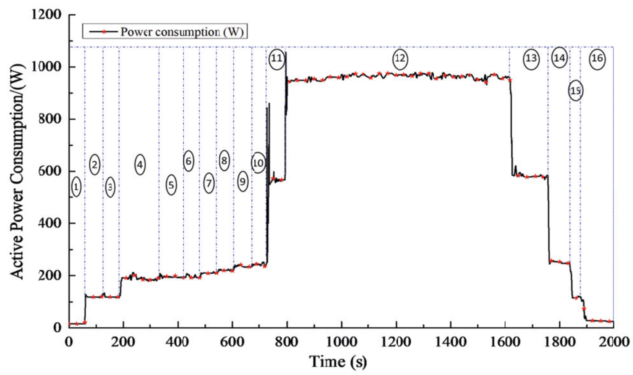


Fig. 5. Working principle of anomaly detection algorithm in UPM process.

4. Results and discussions

Figure 6 presents the power profile of three-axis ultra-precision milling machine tool working at normal status. A complete working cycle of UPM process follows the sequential operations: power off, air fans ON for cooling the servo drivers, PC controller ON for running the G-code, servo drivers ON for the electrical linear and rotated motors, chiller ON for cooling the electrical spindle, X/Y/Z linear axis enabled, and spindle enabled for the preparation of milling, milling process ON for machining the workpiece, after that turning off these components until power off. During each transition phase of two operations, the power profile sharply increases, which can be used as the mark for segmenting these operations.



1- Machine tool OFF, 2- X/Y/Z Axis servo driver ON, 3- Spindle servo driver ON, 4- PC controller ON, 5- Monitoring screen ON, 6- Controller system ON, 7,8,9- X/Y/Z Axis enabled, 10- X/Y/Z Axis return reference point, 11- Chiller ON, 12- Milling process, 13- Milling process end, 14- Chiller off, 15- PC controller OFF, 16- All servo drivers OFF

Fig. 6. Power consumption profile at normal status.

The profiles of X/Y/Z components forces in the milling process were measured as shown in Figure 7.

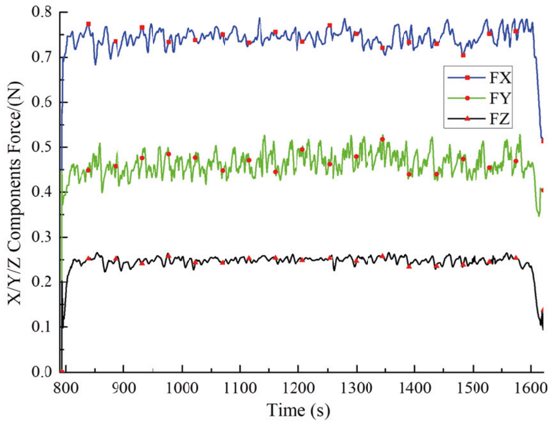


Fig. 7. Profile of X/Y/Z components forces.

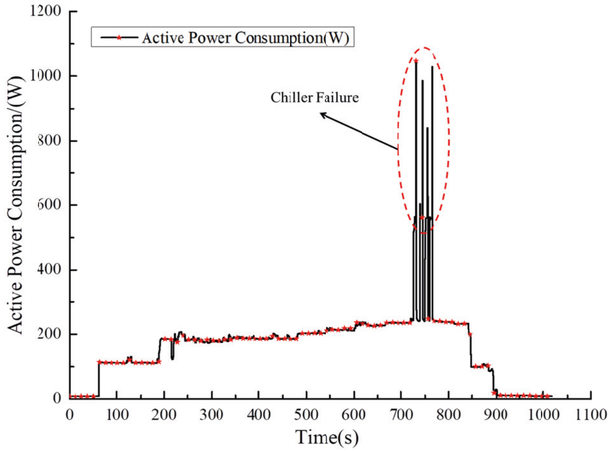


Fig. 8. Power profile of chiller failure detected by the proposed platform.

The calibration experiments of power consumption and X/Y/Z components forces were conducted three times to eliminate accidental errors. The variation ranges of the above parameters were calculated in Table 2.

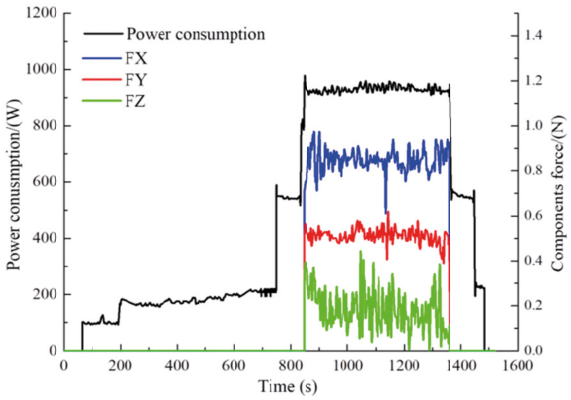


Fig. 9. Power profile and X/Y/Z component's forces profiles under serious tool wear conditions in the milling process.

Figure 8 presents the power profile in case of a chiller failure of UPM process, and Figure 9 presents the power and X/Y/Z component's force profiles under serious tool wear in the milling process. In Figure 8, as the coolant chiller suffered from rotational speed abnormality, the power consumption profile of the coolant chiller fluctuated dramatically, and the peak power exceeded the normal range. In Figure 9, the cutting tool was worn, and the power consumption in the milling process was little affected and just increased slightly compared with that of the normal status, while X/Y/Z components forces fluctuated greatly and exceeded their normal ranges obviously. In the experiments, both types of failures were successfully detected by the proposed system with anomaly detection algorithms. This demonstrated the feasibility and accuracy of this proposed platform.

Table 2. Range of power consumption and X/Y/Z components forces during each operation

	Non-milling process							Milling process
Operation	Power OFF	X/Y/Z servo driver ON	Spindle servo driver ON	PC controller ON	Spindle enabled	X/Y/Z motor enabled	Chiller ON	Milling
Power (*W*)	0	117~118	5~10	73~74	8~10	30~32	323~332	393~396
X forces (*N*)	0	0	0	0	0	0	0	0.65~0.80
Y forces (*N*)	0	0	0	0	0	0	0	0.40~0.50
Z forces (*N*)	0	0	0	0	0	0	0	0.2~0.26

5. Conclusions

Comprehensive monitoring of UPM process is essential for high-quality and energy-efficient UPM production. In this work, the linkages of these monitored parameters in UPM process were investigated to help develop a practical monitoring strategy. Under the guidance of this, two significant monitored parameters, power consumption and milling force were selected in the proposed monitoring system. To validate the effectiveness and benefits, the proposed monitoring system was successfully used to detect the failures with anomaly detection algorithms. To the authors' knowledge, no research has been conducted to discuss the comprehensive monitoring system for UPM process like the work presented here. With the applications of this proposed research, the operators can easily optimize UPM processing parameters for better milling performance. Notably, this research can be extended in several directions, such as the digital twin of UPM process, cooling strategy optimization, etc. Significantly, this work is also beneficial to these designers to optimize their blueprint for designing UPM products.

This study focuses on developing a condition monitoring system for a three-axis ultra-precision milling machine tool. This system uses various sensors to monitor the machine's condition and detect anomalies or deviations from normal operating conditions. This research can promote engineering design by informing the development of new and improved machine tools with built-in condition monitoring systems, leading to more robust and reliable machines. By implementing such a system, engineers and manufacturers can identify potential problems or malfunctions in the machine tool early on, allowing for preventive maintenance and reducing the risk of costly downtime. The developed system can also provide valuable data on the performance of the machine, which can be used for further optimization of the design. By incorporating the anomaly detection system into the machine design, engineers can ensure that the machines are operating within their optimal conditions, which can improve the quality of the final product.

This study uses a statistical model with fixed threshold values of power and forces for anomaly detection that cannot be generalized to other types of machines due to the low robustness. Future research will compare the performance of different types of signals for anomaly detection and explore the possibility of using multiple signals for enhanced detection and diagnosis. Furthermore, some ML/DL models will be adopted to build data-driven models for predicting these difficult-monitored items with high accuracy. Finally, we will evaluate and investigate the possibility of integrating ML/DL models with the proposed approach for higher prediction accuracy.

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