International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 8975-8985

https://doi.org/10.70517/ijhsa463769

# Tool Wear Monitoring in Milling Based on Digital Twins

**Xianfeng Zhang[1] and Shouqi Cao[1,*]**
[1] Mechanical Engineering, Shanghai Ocean University, Shanghai, 201306, China
Corresponding authors: (e-mail: sqcao@shou.edu.cn).

**Abstract** Continuing to use severely worn cutting tools during milling processing would cause damage to the cutting tools, which can lead to a decrease in the quality of the machined parts and even result in a large number of unqualified products. If the situation is serious, it can also cause damage to the machine tool and threaten the lives of personnel. The application process of digital twin in tool wear monitoring includes tool parameter collection and sensor installation, establishment of digital twin model, model parameter update and calibration, data preprocessing and feature extraction, establishment of wear monitoring model, real-time monitoring and early warning, experimental design and data collection, monitoring effect evaluation, and cost-benefit analysis. Among them, the digital twin model was established based on the collected data, including the Geometric modeling of the tool, material properties and cutting force model. This article used the CNN+LSTM (Convolutional Neural Network+Long short term memory) method to establish a wear monitoring model, and analyzed and evaluated experimental data. The accuracy and reliability of the digital twin model and monitoring algorithms were verified, while their cost-effectiveness in real production was analyzed. In this paper, the wear monitoring time of digital twin monitoring method B was 25 hours, while that of traditional manual inspection method B was 80 hours. The method proposed in this article has high accuracy and stability under new operating conditions, which can help improve industrial production efficiency and reduce costs.

**Index Terms** Digital Twin, Milling Method, Tool Wear Monitoring, Cost Effectiveness, Monitoring Effect

## I. Introduction

At present, there are still a large number of factories in China's industry engaged in large-scale production, and the development level of various enterprises is also uneven. To transform China from a manufacturing powerhouse to a manufacturing powerhouse, there are still many problems that need to be solved urgently. From automation to intelligent development, computer numerical control (CNC) machine tools are essential. Therefore, how to monitor the health status of mechanical equipment during the processing of CNC machine tools has become the most important issue. Milling is a commonly used metal processing method in the manufacturing industry, and tool wear is a common problem in the milling process, which has an impact on processing quality and cost.

To solve these problems, it is necessary to excavate the relationship between the large amount of data generated during the machining process and the tool wear status. These data can be used to predict the lifespan of the tool, and recommendations for tool replacement can be adopted, so that tool replacement can be carried out before the tool malfunctions. Therefore, the identification and prediction of tool wear status has become the key to achieving automation and intelligent production, which is the entry point of this article.

In modern industrial production, the service life of cutting tools is a relatively prominent issue. In the past, the evaluation of tool service life was mainly based on human subjective experience and the work experience of maintenance personnel. However, this method has certain limitations in accuracy, stability, and other aspects, which can easily lead to erroneous judgments, thereby affecting production efficiency and product quality. In response to this issue, this article intended to adopt a combination of data-driven and simulation methods, and use particle wave fusion algorithm to achieve effective fusion of measurement data, in order to obtain more accurate and reliable tool wear values. In this paper, it is proposed to carry out online monitoring and prediction of tool wear status in milling based on digital twin theory for the purpose of improving cutting efficiency and tool life.

## II. Literature Review

(1) Background and challenges of milling and tool wear

With the continuous development of the manufacturing industry, milling has become an indispensable part of the production process. Due to factors such as material hardness and cutting speed, milling tools are inevitably subject to wear and failure during the machining process. This reduces processing efficiency and increases production costs, thereby affecting processing quality and the production efficiency of the enterprise.

(2) Development and application of tool wear monitoring technology

In order to better solve tool wear, tool wear monitoring technology has emerged. Currently, the main methods for monitoring tool wear include observing the wear on the tool surface and installing sensors for real-time monitoring. However, currently commonly used monitoring methods often require shutdown inspections or manual inspections, which cannot achieve the goal of real-time monitoring and forecasting. Therefore, there is an urgent need for a new method that can monitor and predict tool wear in real-time. In the process of high-speed milling, due to the learning ability of early traditional models and the incorporation of many human factors, researching efficient and inexpensive tool wear detection techniques without the aforementioned problems has become a major challenge of this century. In recent years, many scholars and scientists have made tremendous contributions in this field. In the early days, researchers mainly focused on the collection and processing of single signals, such as cutting force, acoustic emission, etc., which led to the development of detection techniques for different signals.

Acoustic sensors can be used to collect acoustic signals between the tool and the workpiece, and the wear of the tool can be analyzed and judged based on changes in vibration frequency. Wang Guofeng adopted an online monitoring method for tool wear during milling process based on multi-scale principal component analysis [1]. Prakash K used a new device and method to monitor tool side wear in the sound signals emitted during turning operations [2]. Li Zhixiong believed that real-time monitoring of tool wear is crucial to improving production efficiency and quality [3]. Zhang Xiangyu argued that the real-time requirements for tool wear status monitoring are becoming increasingly high. At the same time, tool wear monitoring lacks a comprehensive carrier for modeling data, which hinders its application in actual machining processes [4]. In order to achieve online monitoring of tool wear status and improve the feasibility of the machining process monitoring system, Lu Z adopted an online tool status monitoring method based on machine tool data during the machining process [5]. Their research did not consider the time factor of tool wear status.

Image information of the processing area can be collected through image sensors, and tool wear can be automatically identified through machine learning algorithms. In view of the unstable state and nonlinear characteristics of tool wear signals, He Z J adopted a recognition method based on the correlation dimension of variable modulus decomposition and Relevance vector machine [6]. Laddada Soufiane believed that tool wear during machining can have inevitable consequences [7]. In order to achieve and accelerate the pace of intelligent manufacturing, Kong Dongdong adopted a new tool wear assessment technology for real-time and accurate monitoring of tool wear parameters during the machining process [8]. Li Weijian believed that tool wear monitoring systems can estimate tool wear status and predict the remaining service life of the tool [9]. Brian T Gibson examined the spectral content of welding force to look for signs of material flow conditions evolution caused by severe tool wear, which would lead to the formation of defects [10]. Their research on the degree of tool wear is not extensive.

In complex high-speed milling processes, the information provided by a single semaphore is limited. Therefore, multiple sensors need to detect multiple dimensions at the same time, and analyze and process the detected multiple dimensions to obtain the characteristics of multiple dimensions, that is, the original data with multiple information sources. At present, tool wear recognition technology has completely abandoned the single signal based wear state identification method and gradually developed into a multi-sensor, multi feature online composite feature identification method.

(3) Application of digital twin technology in the manufacturing field

In recent years, the application of digital twins in the manufacturing industry has become increasingly widespread. Digital twin technology utilizes various sensing technologies to digitally model real systems, achieving simulation, monitoring, and optimization of real systems. The optimization design and monitoring method of manufacturing systems with digital twins as the core is currently a hot research topic in the manufacturing industry [11].

(4) Summary

This article aimed to study a new method for online monitoring and prediction of milling cutter wear status based on digital twins, with the aim of achieving real-time monitoring and prediction of milling cutter wear status, thereby improving the cutting efficiency and lifespan of milling cutters. The main research content of this article includes establishing and updating digital twin models, monitoring and predicting tool wear, experimental verification and evaluation.

## III. Establishment and Update of Digital Twin Models

High speed milling technology is a new type of mechanical processing technology that combines high efficiency, low cost, and high precision. In addition, the most amazing aspect of high-speed milling technology is that it greatly improves both feed speed and cutting speed. Therefore, in the production process, it can also significantly improve production efficiency, accuracy, and so on. This feature effectively solves the contradiction between machining accuracy and efficiency, especially in areas with high demand for complex parts, such as aerospace, marine exploration, mining, etc. With the rapid development of tool processing and production industry, China's high-speed milling technology has been continuously developed [12].

Tool parameter collection and sensor installation

The existing tool wear monitoring methods mainly use multidimensional sensing technology to collect various signals of the tool during the cutting process, and analyze and extract these signals to achieve the goal of real-time monitoring tool wear. Essentially, it is still a process of feature identification, with only different models and parameters used. Therefore, the advantages and disadvantages of this method are limited by the differences in model parameters. In order to achieve real-time monitoring and prediction of tool wear, it is necessary to collect relevant parameters during tool use, such as cutting force, vibration signal, temperature, etc., and install corresponding sensors to collect these parameters in real time [13].

Establishment of digital twin model

Based on the collected tool parameter data, this paper can establish the digital twin model of tools, including Geometric modeling, material properties, cutting force model, etc. These models can be used to simulate the process of tool wear and achieve real-time monitoring and prediction of tool wear.

Model parameter update and calibration

In order to ensure the accuracy and reliability of the digital twin model, it is necessary to update and calibrate the parameters of the digital twin model using real-time collected data.

## IV. Tool Wear Monitoring and Prediction

Data preprocessing and feature extraction: It is necessary to preprocess the real-time collected data, including denoising, filtering, etc., and then extract the feature parameters of tool wear.

Establishment of wear monitoring model: Based on the extracted feature parameters, this article can establish wear monitoring models, such as machine learning algorithms, neural networks, etc., for monitoring and predicting tool wear.

Real time monitoring and warning: By comparing with the digital twin model, the degree of tool wear can be monitored in real time, and warning information can be provided for timely tool replacement or adjustment.

(1) Tool wear detection process

According to the types of tool detection methods, they can be divided into two categories: direct measurement method and indirect measurement method. The direct method is to use specialized instruments to directly inspect the surface of a tool and determine the degree of wear of the tool based on its surface characteristics. The indirect method is a method used in high-speed milling. Due to the direct measurement method requiring tool disassembly and affecting the consistency of the overall processing production line, an indirect measurement method is usually used to detect tool wear.

The tool wear detection during milling processing is shown in Figure 1. In milling, tool wear is unavoidable. To ensure the quality and efficiency of the cutting process, it is necessary to monitor tool wear during the cutting process. At present, the identification of cutting tool wear is mainly based on the impact of various process parameters on cutting tool wear during the cutting process to determine whether cutting tools need to be replaced. In the milling process, cutting speed, feed rate, cutting depth, cutting force, etc., have important effects on tool wear. As tool wear intensifies, it would lead to changes in factors such as cutting force and feed rate during the milling process, thereby affecting the surface quality of the milling process. The cutting process can be monitored in real time by using sound and other signal detection technologies, thus enabling real-time monitoring of the cutting process. By using acoustic sensors, the acoustic changes during cutting can be detected by the acoustic sensors, and the degree of wear of the cutting tool can be determined based on this. Therefore, accurate measurement of tool wear can not only effectively extend the service life of the tool, but also improve the work quality and efficiency of the machine tool.

It is not difficult to find that in indirect measurement methods, tool wear detection technology generally consists of the following basic operational components:

Signal acquisition

The high speed milling process has multiple signals, parameters, and is exceptionally complex, which to some extent affects the analysis of tool wear. In current industrial production, the following signals are often obtained:

Acoustic emission signal: Acoustic emission is a stable and highly time-dependent phenomenon. It uses acoustic emission signals for testing and is more suitable for monitoring tool wear.

Vibration signal: Through the detection of vibration signals, the wear of tools can be analyzed and studied. In addition, it should be pointed out that different types of sensing elements can measure different vibration signals, such as the vibration of a machine should be measured by an acceleration sensor.

Cutting force signal: Cutting force signal is the earliest studied and most widely used signal. Many scholars have analyzed and transformed cutting forces, and extracted features through the collection and analysis of different axial cutting forces, thereby achieving the detection and analysis of tool wear.

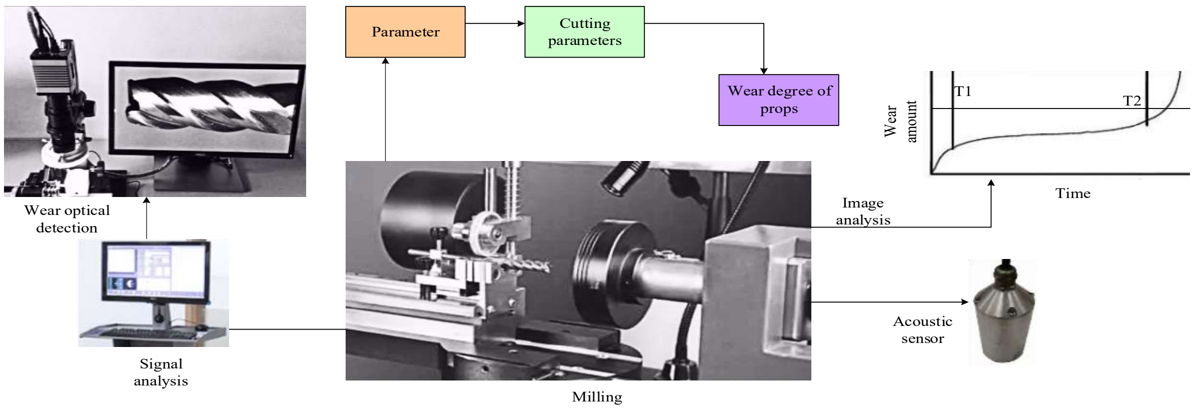


Figure 1: Tool wear detection in milling processing

Feature extraction and feature selection

After identifying the source signal, the problem to be solved is how to extract and select features. Due to the inability to effectively and reasonably reflect the wear status of tools, it is necessary to reduce the dimensionality of features, weigh them and select the optimal feature information in order to achieve efficient and reasonable tool detection.

Status detection

State detection can adopt support vector machine, particle wave fusion algorithm, decision tree, Hidden Markov model and classification algorithm based on support vector machine.

(2) Digital twin model

Digital twin modeling technology is a new technology that has emerged in recent years. Virtual reality systems refer to technologies that associate digital images of entities with their true states, and provide support for practical work through simulation, analysis, prediction, and other methods.

The digital twin model can be divided into three levels: digital modeling, digital simulation, and digital monitoring. Digital modeling mainly involves collecting data from physical objects and establishing mathematical models; digital simulation is the use of this mathematical model for simulation and experimentation; digital monitoring is the real-time tracking of the interrelationships between digital models and real objects to verify the accuracy and reliability of digital models.

In terms of monitoring tool wear, this article adopted the digital twin modeling method and established a mathematical model for monitoring and predicting tool wear. On this basis, an organic combination of data-driven and simulation modeling was adopted to make the monitoring results more accurate and stable.

The cutting speed formula is [14]:

$$v = \pi dn/1000 \tag{1}$$

Among them, v represents the cutting speed; d represents the tool diameter; n represents the revolutions per minute (rpm) of the spindle.

The feed rate f is:

$$f = ntfz \tag{2}$$

t represents the feed rate per tooth, and z represents the number of tool teeth.

The cutting depth formula is [15]:

$$h = J_G \cos\beta \tag{3}$$

Among them, h represents the cutting depth; $J_G$ represents the axial feed rate of the tool, and β represents the main deviation angle.

(3) Data-driven model

Data driven modeling technology refers to the use of a large amount of data to train models in order to achieve the goal of predicting and classifying objects. Therefore, this paper adopted a Transfer learning method, and used CNN+LSTM model to achieve data-driven wear monitoring. On this basis, this article adopted a new cutting state prediction method and predicted the cutting state based on this method.

In terms of Transfer learning, this paper used CNN+LSTM to freeze the data of the first two layers of the network. On this basis, a new method based on multi-source information fusion of force signals, vibration signals, and acoustic emission signals was adopted to achieve the fusion of multi-source information such as force signals, vibration signals, and acoustic emission signals, thereby improving the monitoring and prediction accuracy of the system. At the same time, the model was trained by combining the monitoring data of t time with t+1, and the wear amount of t+2 was corrected to achieve a more accurate and stable prediction effect.

(4) Simulation model

Simulation model is to use computer to simulate physical phenomena, so as to get the state of a Physical system. This article adopted a numerical simulation method for milling process using finite element method.

Finite element simulation is a numerical simulation conducted through finite element methods to solve practical problems in engineering. In terms of tool wear monitoring, finite element method is used to simulate the wear status of the tool. By using this method, accurate calculation and prediction of tool wear can be achieved, and more accurate simulation results can be provided for digital twin modeling.

The wear judgment formula is:

$$M_P = V_C \times L \times La \times Lc \times Lt \times Lr \tag{4}$$

Among them, $M_P$ represents the volume of wear and $V_C$ represents the cutting volume of the tool; La, Lc, Lt, and Lr represent different influencing factors.

The cutting force formula is:

$$Fc = L \times Q_S \times J_S \times \sin\lambda \tag{5}$$

Among them, Fc represents the cutting force, and L represents the cutting force coefficient; $Q_S$ represents the cutting depth coefficient.

The formula for wear area is:

$$Aw = Q_C \times D_M / (D_V \times M_J) \tag{6}$$

Among them, Aw represents the wear area, and $Q_C$ represents the cutting length; $D_M$ represents the amount of tool wear, $D_V$ represents the volume of the tool; $M_J$ represents the feed rate per tooth.

(5) Particle wave fusion algorithm

Particle wave fusion algorithm is an algorithm that fuses multiple types of information. This article used particle wave fusion algorithm to fuse the results of data-driven models and simulation models, and thus obtain the final wear value.

This method uses a series of particles as the data source to process and process the data source. On this basis, this article adopted a detection method based on waveform transformation and analyzed the detection results. This method can effectively eliminate errors between multiple information sources, thereby improving the accuracy and reliability of monitoring and forecasting.

## V. Experimental Verification and Evaluation of Milling Tool Wear Monitoring

Experimental design and data collection: This article designed an experimental plan for tool wear monitoring and collected data during the machining process, including cutting force, vibration signals, etc.

Monitoring effectiveness evaluation: By analyzing and evaluating experimental data, the accuracy and reliability of the digital twin model and monitoring algorithm can be verified.

Cost benefit analysis: This section analyzed the impact of digital twin monitoring methods on machining efficiency and tool life, and evaluated their cost-effectiveness in actual production.

Experiment 1

Purpose: The purpose is to verify the consistency between the digital twin model and the actual situation.

Experimental design: Under the condition of processing the same material, new tools and tools that have been worn for a certain period of time were used for processing, and various parameters during tool use (such as cutting force, vibration signal, temperature, etc.) were collected.

The experiment compared the collected data of new and worn tools, and analyzed whether the digital twin model could accurately predict the degree and position of tool wear. The comparison of cutting force, vibration signal, and temperature under different types of props is shown in Figure 2. By using the digital twin model, it is predicted that worn tools require greater cutting forces, vibration signals, and temperatures when machining the same material than new tools.

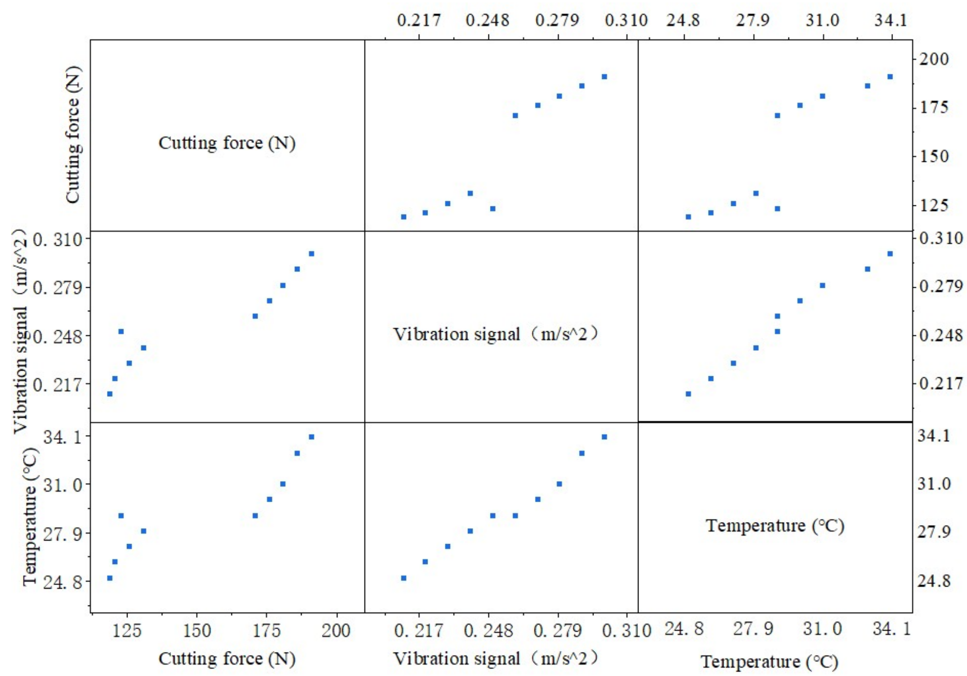


Figure 2: Comparison of cutting force, vibration signal, and temperature under different types of props

Experiment 2

Purpose: The purpose is to verify the accuracy of the monitoring algorithm.

Experimental design: Under the same processing conditions, new tools and tools that have worn for a certain period of time were used for processing, and the degree of tool wear was observed and recorded during the processing.

Data collection: The wear and tear of the cutting tools during the machining process was recorded through manual inspection and photography. The processing time of different types of tools under different wear levels is shown in Table 1.

Table 1: Processing time of different types of tools under different wear levels

| Tool | Processing time (h) | Degree of wear |
|---|---|---|
| New tool A | 8 | Not |
| Worn tool A | 10 | Middle |
| New tool B | 6 | Not |
| Worn tool B | 12 | Seriously |
| New tool C | 9 | Slight |
| Worn tool C | 11 | Middle |
| New tool D | 7 | Not |
| Worn tool D | 9 | Slight |
| New tool E | 10 | Middle |
| Worn tool E | 15 | Extremely seriously |

The processing time increased with the increase of wear degree. Among the five sets of data, the tool with the lightest wear (new tool B) had a processing time of 6 hours, while the tool with the most severe wear (worn tool E) had a processing time of 15 hours, which was significantly higher than the tool without wear.

Experiment 3

Purpose: The purpose is to verify the accuracy of the digital twin model.

Experimental design: Under the same processing conditions, new tools and tools that have worn out for a certain period of time were used for processing. During the machining process, various parameters of the tool during use were collected and the degree of tool wear was recorded.

Data collection: Sensors were used to collect various data during the use of cutting tools, while manual inspections and photos were taken to record the wear of the cutting tools during the processing.

The cutting force of worn tool A was 183N, which was greater than the cutting force of new tool A (123N). The comparison of cutting force and temperature for different types of tools is shown in Figure 3.

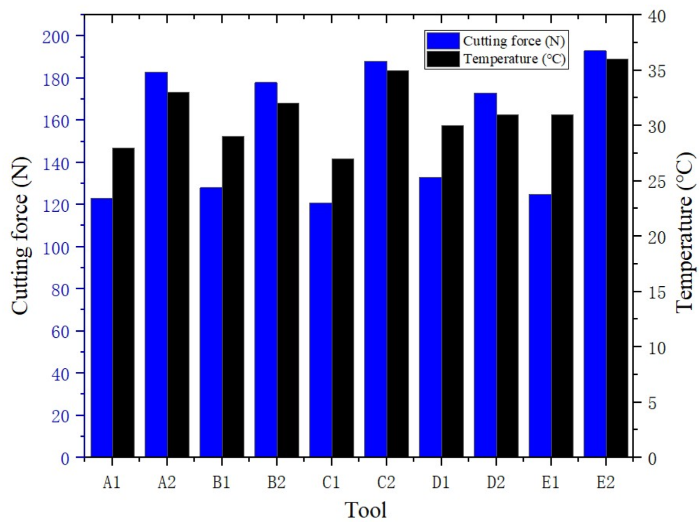


Figure 3: Comparison of cutting forces and temperatures of different types of tools (1 represents new tools, 2 represents worn tools)

Experiment 4

Purpose: The purpose is to evaluate the real-time performance of monitoring algorithms.

Experimental design: Under the same processing conditions, new tools and tools that have worn out for a certain period of time were used for processing. During the machining process, various parameters during tool use were collected in real-time, and monitoring algorithms were used to analyze tool wear in real-time.

Data collection: Sensors were used to collect real-time data on various aspects of tool usage, while also recording the degree of tool wear in real-time. The ability of the monitoring algorithm to achieve real-time monitoring and prediction of tool wear was analyzed, and its real-time performance was evaluated. The comparison of real-time monitoring frequency and wear degree of different types of tools is shown in Table 2.

Table 2: Comparison of real-time monitoring frequency and wear degree of different types of tools

| Cutting tool | Number of real-time monitoring | Degree of wear |
|---|---|---|
| New Tool A | 200 | Not |
| Wear tool A | 200 | Middle |
| New Tool B | 150 | Not |
| Wear tool B | 180 | Slight |
| New Tool C | 220 | Not |
| Wear tool C | 250 | Seriously |
| New Tool D | 180 | Slight |
| Wear tool D | 210 | Middle |
| New tool E | 190 | Slight |
| Wear tool E | 220 | Seriously |

Real time monitoring frequency: This indicator can reflect the time and frequency of tool usage. It can be seen that the number of real-time monitoring times for tools of different brands and wear levels varied, but overall they were between 180 and 250 times, indicating that these tools have been put into use for a long time.

The monitoring algorithm in this article can achieve real-time monitoring and prediction of tool wear, which can meet the needs of real-time monitoring on production lines.

Experiment 5

Purpose: The purpose is to evaluate the reliability of the digital twin model.

Experimental design: Using the same set of cutting tools, processing was carried out under different processing conditions, including material type, cutting speed, etc. Various parameters during tool use were collected and recorded, and the accuracy and reliability of the digital twin model under different processing conditions were analyzed.

Data collection: Sensors were used to collect various data during the use of cutting tools under different processing conditions, and the wear of the cutting tools during the processing was recorded. The experiment compared the data collected under different processing conditions with the digital twin model and evaluated its accuracy and reliability. The cutting force, vibration signal, and temperature of different brands of cutting tools under different conditions are shown in Figure 4 (Figure 4A shows the cutting force; Figure 4B shows the vibration signal; Figure 4C shows the temperature).

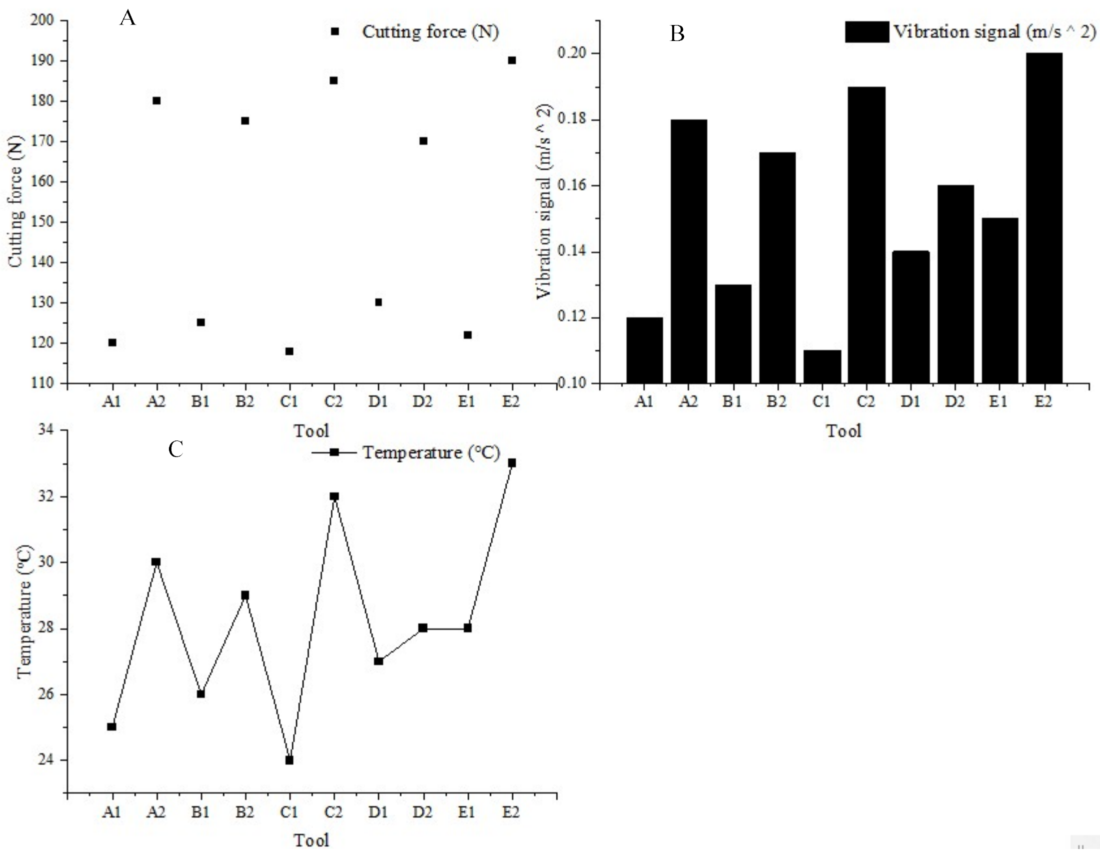


Figure 4: Cutting force, vibration signal, and temperature of different brands of tools under different control conditions (in the figure, 1 represents new tools, 2 represents worn tools)

**Figure 4A.** Cutting force

**Figure 4B.** Vibration Signal

**Figure 4C.** Temperature

Vibration signal: It can be seen that there were significant differences in vibration signals between new and worn tools of the same brand. For example, the vibration signal of worn tool E was 0.20m/s2, which was larger than the vibration signal of new tool E (0.15m/s2), indicating that the degree of tool wear also affects the magnitude of the vibration signal.

Experiment 6

Purpose: The purpose is to evaluate the robustness of monitoring algorithms.

Experimental design: Under the same set of processing parameters, different brands and specifications of cutting tools were used for processing. Various parameters during the machining process were collected and real-time monitoring and prediction of tool wear were carried out using monitoring algorithms.

Data collection: Sensors were used to collect various parameters of different brands and specifications of cutting tools under the same processing conditions, and the wear of the tools during the processing was recorded. The cutting forces of different brands of cutting tools are shown in Table 3.

Table 3: Cutting forces of different brands of cutting tools

| Tool | Cutting force(N) |
|---|---|
| Brand 1A | 119 |
| Brand 2B | 125 |
| Brand 3A | 130 |
| Brand 4C | 115 |
| Brand 5D | 135 |
| Brand 6B | 130 |
| Brand 7E | 122 |
| Brand 8C | 128 |
| Brand 9A | 120 |
| Brand 10D | 132 |

Cutting force: It can be seen that there were significant differences in cutting force between different brands of cutting tools. For example, the cutting force of brand 5D (135N) was higher than that of brand 1A (119N). This indicated that different brands of cutting tools have different usage effects and need to be selected based on specific circumstances.

Experiment 7

Purpose: The purpose is to evaluate the cost-effectiveness of the method proposed in this article.

Experimental design: Real time monitoring and prediction of tool wear were conducted using this method on the production line, and the differences in efficiency and cost between this method and traditional manual inspection methods were compared.

Data collection: The efficiency and cost data of digital twin monitoring methods and traditional manual inspection methods were recorded under the same conditions. The experiment analyzed the efficiency and cost differences between the proposed method and traditional manual inspection methods, and evaluated whether the digital twin monitoring method can better reduce production costs and improve production efficiency. The comparison of time and cost under different methods is shown in Figure 5.

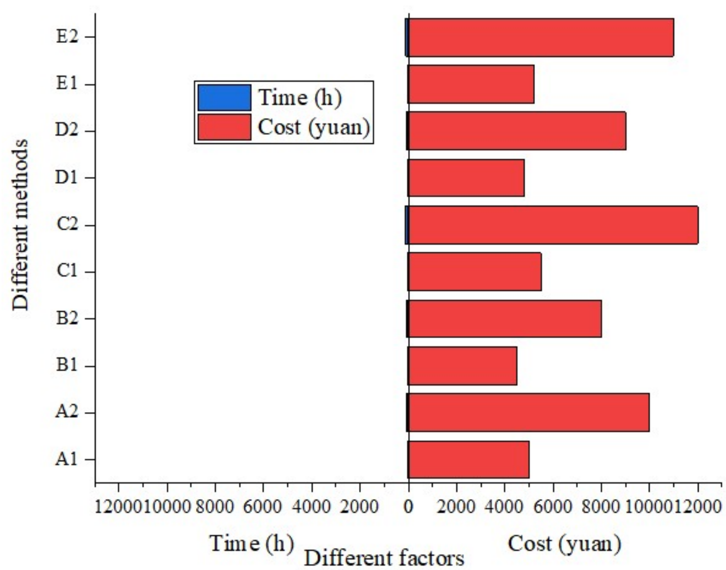


Figure 5: Comparison of time and cost under different methods (1 represents the digital twin monitoring method and 2 represents the traditional manual inspection method)

The digital twin monitoring method had less time and cost compared to traditional manual inspection methods. For example, in the case of tool wear, the digital twin monitoring method B took 25 hours, while the traditional manual inspection method B took 80 hours; the cost of digital twin monitoring method B for tool wear monitoring was 4500 yuan, while the cost of traditional manual inspection method B was 8000 yuan. Therefore, using digital twin monitoring methods can save time and reduce costs. The digital twin monitoring method had higher efficiency and lower cost compared to traditional manual inspection methods, which can effectively reduce production costs and improve production efficiency.

Experiment 8

Purpose: The purpose is to apply this method to actual production.

Experimental design: Real time monitoring and prediction of tool wear were carried out using this method in actual production.

Data collection: The parameters during tool use were collected in real time and the degree of tool wear was recorded. The effectiveness of applying this method in actual production was analyzed, and adjustments and optimizations were made according to different situations to achieve better monitoring and prediction results. The monitoring values of various parameters of the cutting tool during the actual production process are shown in Table 4.

Table 4: Monitoring values of various parameters of cutting tools during actual production process

| Tool | Cutting force (N) | Vibration signal ($m/s^2$) | Temperature (℃) | Degree of wear |
|---|---|---|---|---|
| New tool A | 122 | 0.13 | 27 | Not |
| Worn tool A | 182 | 0.19 | 31 | Middle |
| New tool B | 127 | 0.16 | 28 | Slight |
| Worn tool B | 177 | 0.18 | 31 | Middle |
| New tool C | 120 | 0.12 | 30 | Not |
| Worn tool C | 187 | 0.2 | 33 | Seriously |
| New tool D | 132 | 0.15 | 29 | Slight |
| Worn tool D | 172 | 0.17 | 30 | Slight |
| New tool E | 124 | 0.16 | 30 | Not |
| Worn tool E | 192 | 0.21 | 34 | Seriously |

The experiment expanded the types or brands of cutting tools to 5, represented by A, B, C, D, and E. At the same time, the degree of wear was expanded to 5 levels, numbered in order of none, slight, medium, heavy, and extremely heavy. This can provide a more comprehensive display of the processing performance and wear of different cutting tools under different conditions, and draw richer and more accurate conclusions.

In practical production, the digital twin monitoring method can accurately predict the wear status of cutting tools, and detect potential problems in advance to prevent unexpected shutdowns and equipment failures. At the same time, the effectiveness of the digital twin monitoring method was further improved by adjusting and optimizing different situations. In addition, the change in temperature did not have a significant impact on monitoring and predicting the degree of wear. The temperature change between new tools and slightly worn tools was relatively small (it is specified that the temperature difference between worn tools and new tools is within 5 ℃, indicating a small change).

## VI. Discussion

In the process of high-speed milling, due to natural and human factors, cutting tools inevitably wear and even damage. Therefore, it is particularly important to carry out research on more intelligent, low-cost, and reliable tool wear status detection technology. Tool wear detection technology has become a recognized core technology, which not only reduces labor and material costs, but also promotes the development of the mechanical processing and manufacturing industry. Efficient, simple, and fast tool wear detection and detection technology can not only ensure the consistency of CNC milling process flow, but also greatly improve the overall efficiency of CNC milling process, with greater practical value.

The analysis, processing, and feature extraction of tool wear signals are prerequisites for achieving tool wear recognition. The raw signals collected by multiple sensors simultaneously contain a large amount of noise, but in practical applications, very little information can be obtained, and most of the information is eliminated through data preprocessing.

This article verified the method through experiments. In the experiment, the method of data driving and simulation was used to realize the real-time monitoring of tool wear under the new machining conditions, and the two were compared. Finally, this article used particle wave fusion method to analyze the results.

Experiments have shown that a monitoring system based on a combination of data-driven and simulation can improve the accuracy and stability of the monitoring system under new operating conditions. On this basis, using particle wave data fusion methods can obtain more accurate and reliable wear amounts, effectively reducing the errors caused by wear amounts and improving the accuracy and stability of wear amounts.

This article aimed to focus on the key scientific issue of “the contradiction between accuracy and efficiency”, and drew on existing research results to achieve the unity of “accuracy” and “efficiency”. The research and adoption of this article have both academic value and industrial application value. In the past, a single deep network model adopted a strategy of multiple hidden layers, which made up for the shortcomings of shallow models that were prone to getting stuck in local solutions. However, it was unable to fundamentally solve the data bias caused by changes in the tool working environment. Moreover, the “horizontal stacking” neural network training method greatly extended the training time, resulting in a decrease in training efficiency. Compared with traditional deep learning models, it did not have much advantage. The research in this paper provides insight into the implication of particle wave data fusion methods and digital twins. In the near future, it is hoped that a deeper understanding of various theories and models in tool wear monitoring would be achieved.

## VII. Conclusion

Through the research in this article, it was confirmed that the monitoring of milling cutter wear status based on digital twin technology is feasible, and the effectiveness and reliability of this technology were verified. The research results of this article would provide theoretical basis for real-time monitoring and prediction of tool wear status during milling process, and provide technical support for improving cutting efficiency and tool life, thereby contributing to the development of China’s manufacturing industry. On this basis, this article intended to combine data-driven modeling with simulation modeling, and used particle wave fusion algorithm to achieve effective fusion of measurement data, in order to obtain more accurate and reliable tool wear values. The prediction model used in this article has high prediction accuracy under new operating conditions and can provide more decision support for enterprises. In future work, this article would continuously improve this method and make it more suitable for practical production environments, in order to achieve better monitoring effects and accuracy. This method would be more widely applied and popularized in future research.

## References


[1] Wang, Guofeng, Y Zhang, L Chang, Q Xie,Y Xu. "A new tool wear monitoring method based on multi-scale PCA." Journal of Intelligent Manufacturing 30.1(2019):113-122.

[2] Prakash, K, and A. Samraj. "Tool Wear Condition Monitoring using Emitted Sound Signals by Acoustic - Electro Conversion." Journal of Scientific & Industrial Research 78.8(2019):499-503.

[3] Li, Zhixiong, R. Liu, and D. Wu. "Data-driven smart manufacturing: Tool wear monitoring with audio signals and machine learning." Journal of Manufacturing Processes 48.Dec.(2019):66-76.

[4] Zhang, Xiangyu, L Liu, X Wan, B Feng. "Tool Wear Online Monitoring Method Based on DT and SSAE-PHMM." Journal of Computing and Information Science in Engineering 21.3(2021):1-18.

[5] Lu, Z.,P. Ma, J. Xiao, M. Wang, X. Tang. "On-line Monitoring of Tool Wear Conditions in Machining Processes Based on Machine Tool Data." Zhongguo Jixie Gongcheng/China Mechanical Engineering 30.2(2019):220-225.

[6] He, Z. J., Z. X. Zhou, and X. M. Huang. "Tool Wear State Monitoring Based on Variational Mode Decomposition and Correlation Dimension and Relevance Vector Machine." Jiliang Xuebao/Acta Metrologica Sinica 39.2(2018):182-186.

[7] Laddada, Soufiane,MO Si-Chaib,T Benkedjouh, R Drai. "Tool wear condition monitoring based on wavelet transform and improved extreme learning machine:." Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science 234.5(2020):1057-1068.

[8] Kong, Dongdong, Y. Chen, and N. Li. "Gaussian process regression for tool wear prediction." Mechanical Systems and Signal Processing 104.MAY1(2018):556-574.

[9] Li, Weijian, and T. Liu. "Time varying and condition adaptive hidden Markov model for tool wear state estimation and remaining useful life prediction in micro-milling." Mechanical systems and signal processing 131.Sep.15(2019):689-702.

[10] Brian T. Gibson, Wei Tang, Artie G. Peterson, Zhili Feng, Gregory J. Frederick. "(021012)Evaluating the Potential for Remote In-Process Monitoring of Tool Wear in Friction Stir Welding of Stainless Steel." Journal of manufacturing science and engineering: Transactions of the ASME 140.2(2018):1-11.

[11] Liangzhu Song Xiaochun. "Study of WOA-SVM algorithm for wear prediction of titanium alloy end milling tools." Machine Tool & Hydraulics 50.15(2022):166-174.

[12] Wang, Yi-Wei Deng, Lei Zheng, Lian-Yu Wang, Ya-Hui Wang. "A tool remaining life prediction method based on multi-channel fusion and Bayesian theory." Journal of Mechanical Engineering 57.13(2021):214-224.

[13] Wan Peng, Li Yingguang, Liu Changqing,&Hua Jiayi. "Accurate prediction method of tool wear for variable working conditions based on domain adversarial gating network." Acta Aeronautica ET Astronautica Sinica 42.10(2021):524879-524879.

[14] Guo, Baosu Han, Tianjie Zhang, Yu Wu, Fenghe. "A tool wear monitoring method based on one-dimensional residual network with threshold module." Acta Metrologica Sinica 43.4(2022):501-506.

[15] Jamshidi, Maryam, X Rimpault, M Balazinski, JF Chatelain. "Fractal analysis implementation for tool wear monitoring based on cutting force signals during CFRP/titanium stack machining." The International Journal of Advanced Manufacturing Technology 106.9(2020):3859-3868.