Tool Condition Monitoring and Maintenance Based on Deep Reinforcement Learning

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Abstract. Tool status monitoring requires collecting a large amount of data to complete analysis, and different types of tools may exhibit different wear and failure modes during processing, making tool status monitoring more difficult. Therefore, a tool condition monitoring method based on deep reinforcement learning is proposed. The feature of tool wear is extracted by wavelet packet analysis. Introduce regression network into deep reinforcement learning network, and complete tool condition monitoring by combining regression algorithm with deep reinforcement learning network algorithm. Finally, specific suggestions for tool status maintenance are provided. To verify the effectiveness of the proposed method, comparative experiments were designed. The results show that the accuracy of tool condition monitoring is high, the monitoring decision coefficient can be maintained above 0.95, and the mean absolute percentage error is smaller.

Keywords: Deep Reinforcement Learning · Tool Status · Monitoring Methods · Regression Algorithm

1 Introduction

With the development of modern manufacturing, the requirements for product accuracy and quality are becoming increasingly high. As a key component in machining, the state of cutting tools has a significant impact on the entire machining process. Therefore, studying tool condition monitoring and maintenance can improve processing efficiency and product quality, reduce processing costs and mechanical failures, and have important industrial application value. At present, the technology of tool condition monitoring and maintenance has been widely applied. For example, using sensors, digital signal processing, artificial intelligence and other technologies, real-time monitoring and diagnosis of tool wear, fracture, temperature, vibration and other conditions can be realized, and timely warning and maintenance can be carried out to improve the utilization and life of machine tools and tools, shorten downtime and production cycle, and reduce maintenance costs and losses. However, existing tool condition monitoring and maintenance technologies still face some challenges and shortcomings, such as low sensor accuracy and reliability, immature data processing methods, and insufficient standardization and intelligence. Further research and improvement are needed to meet the needs of different processing fields.

L. Yun et al. (Eds.): ADHIP 2023, LNICST 547, pp. 16–28, 2024.
https://doi.org/10.1007/978-3-031-50543-0_2

Yang et al. [1] proposed a recognition method of tool wear state based on one-dimensional depth convolution automatic encoder, selecting the effective value of three-phase current of motor under different working conditions and doing normalization. Utilize a one-dimensional deep convolutional autoencoder to perform unsupervised training on the processed values and extract feature information. Using sample labels for secondary supervised recognition of different wear states of cutting tools. Dong et al. [2] proposed a woodworking tool wear condition monitoring method based on discrete wavelet transform and genetic BP neural network. The main shaft power signals under different spindle speeds, milling depths and tool wear conditions are collected, their approximate coefficients are extracted by discrete wavelet transform, sample data sets are established, and they are input into BP neural network model training, and optimized by genetic algorithm to achieve accurate monitoring of woodworking tool wear conditions. Wu et al. [3] proposed an indirect monitoring method for tool wear based on the spindle current signal and particle swarm optimization support vector machine model. The main shaft signal characteristic parameters related to tool wear are extracted as the input feature vector, and the parameters are optimized through the particle swarm optimization algorithm, and the model is established to complete the tool state detection.

Deep learning is a machine learning method that simulates the information processing mechanism of human brain neural networks. It is built on the basis of artificial neural networks and gradually constructs high-level abstractions from local features to global semantics through multi-level nonlinear transformations. However, there are certain shortcomings in current deep learning, such as the need for a large amount of data for training, so data acquisition and organization are very difficult tasks.Due to the use of a series of neurons in deep learning, and the complex interactions between each neuron, the interpretability of deep learning models is poor, making it difficult to distinguish which features ultimately determine the output of the model [4]. Therefore, this article proposes a deep reinforcement learning method, which has the ability to handle continuous actions and state spaces, and performs better than traditional reinforcement learning methods.

2 Feature Extraction of Tool Wear

The number of sensor output signals collected on site by machine tools is not only large, but most of them do not have availability. If the collected signal data is directly used as a prediction basis, it will not only prolong the training time but also increase hardware costs. Therefore, it is necessary to extract the signal characteristics of tool wear from the initial signal data. Tool wear signal includes high and low frequency bands. The frequency resolution of high frequency band information is small, which usually causes information loss. In order to make the high-frequency part of the signal more refined and the high-frequency information more complete, the wavelet packet analysis method [5, 6] is used to divide the frequency band into multiple levels, and the signal characteristics are used as the reference basis for selecting the frequency spectrum and frequency band to accurately extract the tool wear characteristics.

Given the high frequency band D and low frequency band A of tool wear signal, wavelet packet S divides the frequency band into layer n, so the decomposition expression of wavelet packet is as follows:

$$\begin{aligned} S &= A^n n + DA^n n + ADAn + D^{n-1}An \\ &\quad + A^{n-1}Dn + DADn + AD^{n-1}n + D^n n \end{aligned} \tag{1}$$

In the process of decomposing high-frequency information, if the following equation relationship exists between Hilbert space $L^2(R)$ and wavelet function closure W_j, it indicates that the main basis of wavelet packet decomposition is scale factor j:

$$L^2(R) = \sum_j^n W_j \tag{2}$$

Let the decomposition level be 0 to simplify the calculation complexity of wavelet function[7, 8], then the following simplified formula is obtained:

$$\begin{cases} u_1(x) = \sum_j h_j u_0\left(\sqrt{2}x\right), \{h_j\} \in L^2(R) \\ u_0(x) = \sum_j g_j u_0\left(\sqrt{2}x\right), \{g_j\} \in L^2(R) \end{cases} \tag{3}$$

If the solved wavelet functions $u_1(x)$ and $u_0(x)$ degenerate to scale function and wavelet basis function respectively, then there is a double scale equation set as shown in the following formula:

$$\begin{cases} \phi(x) = \sum_j h_j \phi\left(\sqrt{2}x\right) \\ \varphi(x) = \sum_j g_j \varphi\left(\sqrt{2}x\right) \end{cases} \tag{4}$$

In conclusion, the characteristics of tool wear are constructed by using the two scale equations:

$$\begin{cases} u_{L^2}^{j,2n}(x) = \sum_j h_{j-2L^2} d_j^{2j+1,n^2} \\ d_{L^2}^{j,2n+1}(x) = \sum_j g_{j-2L^2} d_j^{2j+1,n^2} \end{cases} \tag{5}$$

$$d_{L^2}^{j+1,n}(x) = \sum_j \left(h_{L^2-2j} d_j^{j,2n^2} + g_{L^2-2j} d_j^{j,2n^2+2}\right) \tag{6}$$

3 Tool Condition Monitoring Based on Deep Reinforcement Learning

In the past, tool status detection was mostly achieved through deep learning methods. Although tool status monitoring can also be achieved, a large number of candidate areas are needed for status monitoring operations, which undoubtedly reduces the efficiency of tool status monitoring. Compared with deep learning methods, deep reinforcement learning has significant efficiency advantages in tool condition monitoring, and has been widely used in tool condition monitoring for a period of time [9, 10]. However, deep reinforcement learning algorithms only perform region search operations based on the specifications of the current candidate region, which reduces the accuracy of state monitoring to a certain extent. Introducing regression networks into deep reinforcement learning networks can significantly improve the accuracy of tool state monitoring. Based on this, this article introduces regression networks into deep reinforcement learning networks and uses motion state monitoring methods based on regression and deep reinforcement learning networks to complete tool state monitoring.

A regression network has been added to the existing network of deep reinforcement learning. The newly added reinforcement learning network consists of a VGG network for feature extraction, a DQN network responsible for performing path search, and a regression network capable of performing regression operations on candidate regions. After introducing the regression network, joint optimization is carried out on the regression network and DQN network in the following two ways to output better tool condition monitoring results.

(1) Loss function. Generally, root mean square error and smoothL1 are regarded as the loss function of DQN and regression network respectively. Since the network based on regression and deep reinforcement learning only adds regression network on the basis of the original deep reinforcement learning network, correspondingly, as long as the DQN and the loss function of regression network are combined together, the loss function of the learning network in this paper can be obtained by weighting. The solution process can be described by the formula:

$$A(s, a, t) = \frac{1}{N_{dpn}} \sum_{j} \left(y_i - Q\left(s_j, a\right)\right)^2 + \lambda \frac{1}{N_{reg}} \sum_{j} R\left(t_j - t_j^*\right) \tag{7}$$

In the above equation, the sample index value is represented by j; Output from DQN network to y_j; The weighted parameters and the size of regression losses are described by λ and $R\left(t_j - t_j^*\right)$; The number of input samples and expected output values of the DQN network are described by N_{dpn} and $Q\left(s_j, a\right)$ respectively;SmoothL1 loss function is represented by R; The candidate area coordinates and actual area coordinates t and t_j^* after parameterization meet the following equation:

$$\begin{cases} t = \left(t_d, t_y, t_w, t_h\right) \\ t_j^* = \left(t_d^*, t_y^*, t_w^*, t_h^*\right) \end{cases} \tag{8}$$

Use b to represent the coordinates of the candidate region, satisfy $b = (d, y, w, h)$, and perform parameterization operations on it. The parameterization process can be expressed as:

$$\begin{cases} t_x = \frac{d - d_a}{w_a}, t_y = \frac{y - y_a}{h_a} \\ t_w = \log\left(\frac{w}{w_a}\right), t_h = \lg\left(\frac{h}{h_a}\right) \end{cases} \tag{9}$$

$$\begin{cases} t_x^* = \frac{d^* - d_a}{w_a}, t_y^* = \frac{y^* - y_a}{h_a} \\ t_w^* = \log\left(\frac{w^*}{w_a}\right), t_h^* = \lg\left(\frac{h^*}{h_a}\right) \end{cases} \tag{10}$$

In the above equation, the center points and width/height of the candidate regions output by the regression network and obtained by the DQN network are described by d, y, w, h and d_a, y_a, w_a, h_a respectively; The center point and width height of the actual target area are described by d^*, y^*, w^*, h^* and respectively.

(2) Model training. In order to enable the DQN network to better complete path search work and perform action search and decision operations using probabilities ε and $1 - \varepsilon$, the value of ε is set to 1 in this process. Use *epoch* to represent the training cycle. As *epoch* increases, ε will continue to decrease until its value decreases to 0.1.

In order to ensure the accuracy of regression network training, $I_O U$ with a target area and a real area higher than a certain threshold is sent to the regression network for network training operations.

For a tool image, define the entire tool image as the initial candidate area, perform size normalization on it, normalize it into a tool image with size, and then send it to VGG for image feature extraction. Then, action search and decision-making are carried out with probabilities ε and $1 - \varepsilon$. After the action is completed, new image candidate regions and rewards will be obtained accordingly. Then, normalization operations will continue on the newly obtained image candidate regions [11], which will be sent to VGG to obtain the new state. Repeat the above process continuously. When the search step reaches the upper limit or the action is completed, use a regression network to adjust the image candidate regions reasonably to obtain the final tool status monitoring results.

4 Tool Wear Status Maintenance Suggestions

Tool wear refers to the gradual loss of sharpness and functionality of a tool due to factors such as friction, abrasion, and chemical reactions during its usage. Tool wear can lead to various hazards, and here are some common ones:

① Decreased machining quality: Tool wear can result in increased surface roughness, larger dimensional deviations, and irregular shapes. When a tool loses its original sharpness and geometry, it cannot effectively cut the material, leading to burrs, cracks, or other defects. This directly affects the appearance and functionality of the products, reducing machining quality.
② Reduced production efficiency: Worn-out tools require more time and energy to complete the same machining tasks. The increased friction generated during cutting with worn-out tools slows down the machining speed, thus reducing production efficiency. Additionally, worn-out tools need to be replaced or repaired more frequently, leading to increased downtime and maintenance costs.
③ Shortened tool life: Tool wear significantly shortens the lifespan of a tool. When a tool becomes too worn to perform effective cutting, it needs to be replaced. Frequent tool changes not only increase costs but also disrupt production schedules and workflow. Moreover, frequent tool changes pose challenges for tool inventory management.

④ Increased safety hazards: Worn-out tools can generate high temperatures, splattering metal chips, or other hazardous substances during cutting. These substances can cause harm to operators, such as burns, cuts, or eye injuries. Additionally, worn-out tools are prone to breakage or detachment, which can create safety hazards in the workplace.
⑤ Increased costs: Tool wear not only increases the costs of tool replacement and repair but also raises production costs. Ineffective cutting by worn-out tools can result in material waste and extended machining time. Furthermore, worn-out tools require more frequent maintenance and adjustments, adding to operational costs.

In summary, tool wear poses significant hazards to machining quality, production efficiency, tool lifespan, work safety, and costs. Therefore, mitigating the hazards associated with tool wear becomes crucial.

When a tool is used for a period of time, wear is inevitable. How to maintain the good condition of the tool to ensure its good cutting performance and lifespan is a key issue. The following are suggestions for maintaining tool wear status.

① Timely tool replacement: For tools under high pressure, high speed and other processing conditions, timely replacement is very important. Once the tool experiences wear and cracks, it must be replaced in a timely manner. Timely tool replacement can ensure the cutting performance and lifespan of the tool [12, 13].
② Clean the tool: The tool is prone to contamination such as oil and dust during processing, which can lead to increased wear of the tool. So it is necessary to regularly clean the cutting tools, keep them dry and tidy, and use appropriate lubricants to reduce friction and wear.
③ Tool maintenance [14]: Pay attention to the tool maintenance during use, regularly apply anti rust oil and cutting fluid, and do other necessary maintenance work to ensure the normal operation of the tool.
④ Choose the correct cutting conditions: While selecting the machining tool, it is also necessary to choose the correct cutting conditions based on the specific processing conditions, such as cutting speed, feed speed, etc. The correct cutting conditions can not only improve cutting performance, but also extend the service life of the tool [15].
⑤ Shockproof measures: when using high-speed rotating cutting tools, vibration and noise will often occur due to their high-speed operation, which will lead to increased tool wear and reduced processing quality. Effective shockproof measures should be taken to reduce tool wear and ensure machining accuracy.

In short, for enterprises, maintaining the condition of cutting tools is very important. It can significantly improve the efficiency of machine use, reduce production downtime, reduce production costs, and improve the overall production efficiency and competitiveness of the enterprise.

5 Experimental Design and Result Analysis

Set the parameters as shown in Table 1 to construct a deep reinforcement learning model. On the CK6180 large CNC lathe provided by a certain CNC machine tool factory, a simulation experimental environment was established using three way dynamic piezoelectric force measuring equipment, kistler high-precision charge amplifier, acquisition card, and wear measurement microscope to simulate the status monitoring results of 20 1mm titanium alloy cutting tools (Fig. 1 and Table 2).

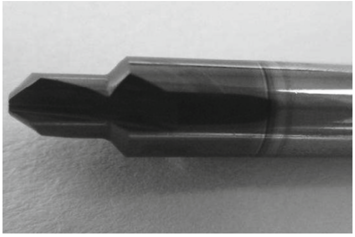

Fig. 1. Schematic diagram of hard alloy cutting tools

Table 1. Experimental setup details

Set Content	Details
Cutting	The cutting speed is 16 m per minute and the cutting depth is 11 μ m
Laser	The diameter of the light spot and the distance between the light spot and the tool tip are set to 0.9 mm and 5 mm respectively. Set the incident angle to 61° and the laser power to 351 W
Tool structure	Set the tip arc to 0.9 mm
Measuring instrument	DVM5000 HD Ultra Depth of Field Microscope
Ultrasonic	The frequency range of ultrasonic vibration is 36 kHz, with an amplitude of 5 μ m

Table 2. Setting of parameters related to deep reinforcement learning

Indicator Name	Specific parameters
Number of network structure layers	4
Number of input layer nodes	16
Number of hidden layer nodes	16
Number of output layer nodes	10
Training frequency	800
Training error	0.0001
Learning rate	0.1
Momentum factor	0.2

5.1 Monitoring Accuracy

According to the preset experimental plan, the overall monitoring accuracy of different methods was compared using a holistic analysis method during the analysis process of the experimental indicators. The specific experimental results are shown in Fig. 2.

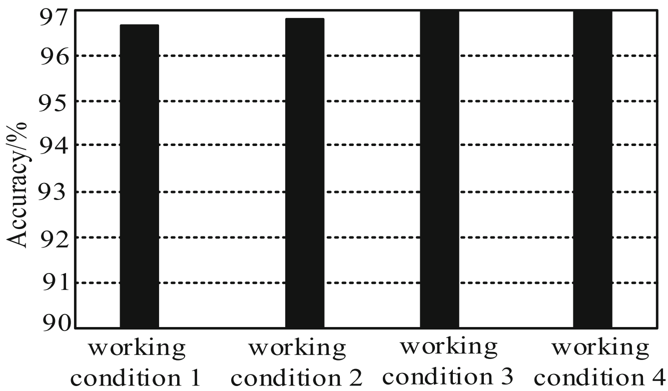

Fig. 2. Experimental Results of Tool Status Monitoring Accuracy

From Fig. 2, it can be determined that from an overall perspective, the wear monitoring accuracy of the methods in the following four working conditions is between 96% and 97%, and the monitoring ability and sensitivity of the methods in the article to tool condition are relatively ideal.

5.2 Test Using the Mean of Determination Coefficient and Absolute Percentage Error

To better demonstrate the application advantages of the method, the determination coefficient R^2 and the mean absolute percentage error *MAPE* are used as evaluation indicators to demonstrate the universality of the method from different levels. The determination coefficient R^2 represents the fitting level between the output wear value and the actual wear value. The closer the R^2 value approaches 1, the better the fitting level between the two, and the more accurate the monitoring results. The calculation process is as follows:

$$R^2 = 1 - \frac{\sum \left(\psi_i - \hat{\psi}_i\right)^2}{\sum \left(\psi_i - \overline{\psi}\right)^2} \tag{11}$$

Among them, $\overline{\psi}$ represents the mean of all true values, ψ_i is the true value calculated for the i-th time, and $\hat{\psi}_i$ is the monitoring value calculated for the i-th time.

MAPE can effectively highlight the true situation between the wear monitoring value and the actual wear value, and use it as a cost function to statistically analyze the operational performance of the three methods, recorded as:

$$MAPE = \sum_{i=1}^{n_w} \left| \frac{\psi_i - \overline{\psi}}{\psi_i} \right| \times \frac{100}{n_w} \tag{12}$$

Among them, n_w is the number of calculated iterations.

The number of experiments is set to 700, and the mean coefficient of determination for every 100 experiments is used as the analysis object. The comparison methods are the tool state monitoring method based on deep convolutional automatic encoder proposed in reference [1] (referred to as deep convolutional automatic encoding method) and the tool state monitoring method based on discrete wavelet transform and genetic BP neural network proposed in reference [2] (referred to as discrete wavelet transform and genetic BP neural network method). The comparison results of tool wear output value determination coefficients of the three methods are shown in Fig. 3.

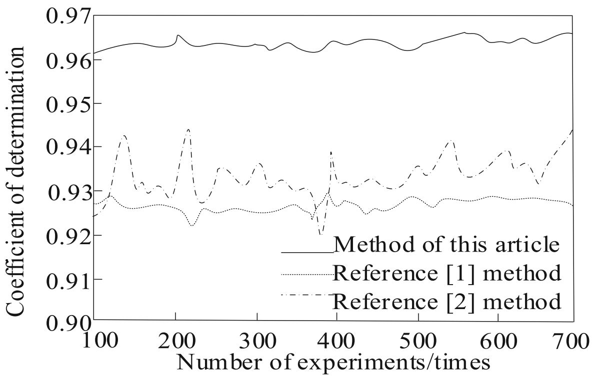

Fig. 3. Comparison Results of tool wear Output Value Determination Coefficient

Observing Fig. 3, it can be seen that under the same experimental operation, the determination coefficient value of the method in this paper is always higher than that of the deep convolutional automatic coding method and the discrete wavelet transform and genetic BP neural network method. The value of the research method is always stable above 0.95, while the curve fluctuation amplitude of the two literature methods is relatively large, indicating that their computational stability is not strong and they are prone to deviation from the true value.

The trend of cost function changes for the three methods is shown in Fig. 4.

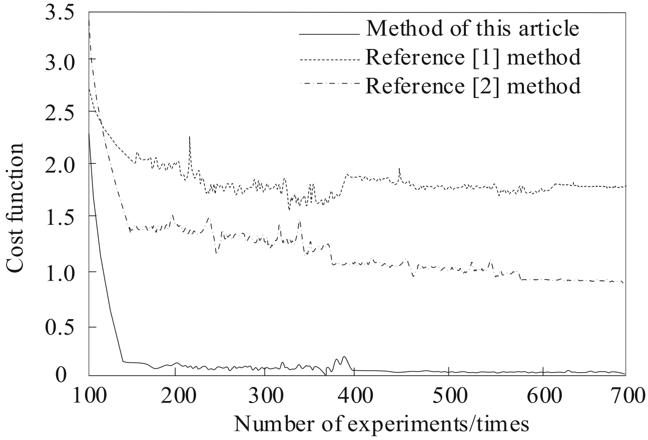

Fig. 4. Comparison of the Trend of Cost Function Changes

According to Fig. 4, as the number of iterations increases, the cost function value gradually decreases, and the mean absolute percentage error between the wear detection value and the actual value decreases, ultimately tending to converge smoothly. The two reference methods may generate gradient dispersion effects during calculation, resulting in high cost function values and slow optimization rates; Compared with this method, this method has the fastest convergence rate, can complete high-quality tool wear monitoring tasks in the shortest time, has strong generalization ability, and has more significant application advantages.

5.3 Application Accuracy Testing of the Method in This Paper Under Different Turning Environments

(1) Conventional turning environment

In the turning environment, the tool wear is measured by the method in this paper when the tool passes through different cutting paths. The results are shown in Table 3.

From the analysis of Table 3, it can be seen that in the conventional turning environment, the measurement results of the tool wear of the method in this paper are highly consistent with the actual value when the tool passes through different cutting paths. The measurement error of the method in this paper is 0.01 mm when the cutting path is 301 m, but the measurement accuracy still meets the requirements of tool wear measurement.

(2) Laser ultrasonic composite ultra precision turning environment

Divide the details of tool wear into four parts: the width, area, perimeter, and depth of the wear range, and then randomly extract the cutting paths in sequence of 151 m, 451 m, 573 m, 301 m, 73 m, and 523 m. The measurement results of this method are shown in Table 4.

Table 3. Measurement results of this method

Cut path/m	Actual value/mm	The measurement value of the method in this article/mm	Error value/mm
73	0.03	0.03	0
151	0.11	0.011	0
223	0.12	0.12	0
501	0.15	0.15	0
573	0.14	0.14	0
451	0.17	0.17	0
523	0.19	0.19	0
301	0.21	0.22	0.01

Table 4. Measurement results of this method in laser ultrasonic composite ultra precision turning environment

Cut path/m	Maximum width of the wear range/mm	Actual value/mm	Maximum area of wear range/	Actual value/mm	Perimeter of wear range/mm	Actual value/mm	Maximum depth in the z-direction of the wear range/mm	Actual value/mm
73 m	0.43	0.43	0.22	0.22	1.95	1.95	0.53	0.53
151 m	0.43	0.43	0.21	0.22	1.94	1.95	0.41	0.421
573 m	0.43	0.43	0.22	0.22	1.96	1.95	0.55	0.53
451 m	0.43	0.43	0.23	0.22	1.95	1.95	0.44	0.42
301 m	0.43	0.43	0.22	0.22	1.92	1.95	0.41	0.41

In the laser ultrasonic composite ultra precision turning environment, the measurement accuracy of the method in this paper for tool wear is 0.99. Therefore, the method in this paper is applicable to the measurement task of laser ultrasonic composite ultra precision turning tool wear.

6 Conclusion

The increasingly popular CNC machine tools have greatly improved processing efficiency and quality, and vigorously promoted the automation process in the industrial production field. However, during mechanical processing, due to factors such as continuous processing at a single station, lagging or overshoot of tool holders at multiple stations, and varying positions of tool tips during tool clamping, the tools used are bound to experience varying degrees of wear.

Once the tool wear reaches a certain degree, it will lead to machine tool failure and even workpiece scrap, and the machining will be interrupted for a long time, which will increase the time cost and production cost. Therefore, in order to ensure the continuous operation of machine tool processing, improve production efficiency and machine tool utilization, and create economic benefits, a tool condition monitoring and maintenance method based on deep reinforcement learning is designed. By using wavelet packet analysis method to process tool signals and extract tool wear features. The regression network is introduced into the Deep reinforcement learning network to learn the mapping relationship between tool wear characteristics and tool status, so as to complete tool status monitoring.

The experimental results of this study indicate that the research method has a high level of accuracy in monitoring tool status, and the monitoring determination coefficient can be maintained above 0.95. The mean absolute percentage error is close to 0, indicating better application performance. According to the experimental results, the proposed method can achieve accurate monitoring of tool status. Future research will further enhance the performance and application scope of tool condition monitoring and maintenance methods, explore their applicability and effectiveness in different fields, and contribute to intelligent manufacturing and industrial automation.

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