Summary of the Prediction Methods of Tool Remaining Life Based on Data Collection

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Abstract: According to different starting principles, this article has advanced the prediction methods of tool remaining life in FMS. It focuses on the physical model method and the method of collecting data based on specific signals and using it as the tool life prediction feature quantity. Then they showed their research status and summarized the corresponding advantages and disadvantages.

1. Introduction
With the rapid development of the production economy, the transformation and upgrading of the manufacturing industry from manual to automation has become an inevitable trend. The flexible manufacturing system (FMS) that is suitable for multi-variety, small-batch production mode has been developed rapidly, the domestic manufacturing industry is mostly small and medium-sized enterprises. The high cost, low efficiency and poor quality caused by the multi-variety, small-batch production model promote the rapid development of flexible manufacturing system (FMS). At the same time, the production demand of enterprises has also caused more and more types and quantities of CNC tools. FMS takes the realization of unmanned processing and production as its goal, which can greatly improve equipment utilization and economic benefits. For this reason, FMS must have the function of automatic detection and monitoring, and the monitoring of tool status is particularly important. Tools have become an important part of the entire processing system, and the proportion of tool investment (especially the cost of high-speed cutting tools and special tools) is increasing [1], tool life is an important indicator to measure the performance of a tool system and evaluate the reliability of the tool. It can provide a basis for the design of the tool, improve the utilization rate of the tool, and save the purchase cost of the enterprise. Real-time tracking of tool life has a profound impact on FMS. Precise tool remaining life prediction is an important basis for realizing adaptive optimization of the machining process. When the tool fails and cannot be replaced in time, it will not only directly affect the processing quality of the product, but also cause damage to the machine and the personal safety of the operator. According to the actual production engineering statistics of enterprises, more than 75% of failures of mechanical equipment are caused by tool failure [2]. If the remaining service life of the tool cannot be determined reasonably and accurately, the following two problems are likely to occur: One is that the remaining service life of the tool is too low, so that the tool has not reached the failure form of reimbursement and it is judged as failure, this will increase the frequency of tool change, extend the machine's downtime, affect the production efficiency of the company, waste tool resources, and increase the investment cost of the company's tools; The second is that the remaining service life of the tool is too high, so that the tool has reached the reimbursement condition and is still working. It is easy to cause the quality of the
processed workpiece to be unqualified, and even cause damage to the machine tool and threaten personal safety. Especially in some special fields, such as the aerospace field, the requirements for the processing quality of workpieces are high, and the cost of this situation is relatively high, which seriously affects the production and economic benefits of enterprises [3].

Therefore, accurate tool remaining life prediction is of great significance to the production of manufacturing enterprises. Studies have shown that if the remaining life of the tool can be accurately predicted, the downtime can be effectively reduced by 75%, the production efficiency will be increased by 10% to 40%, and the production cost will be reduced by 10% to 30% [4,5,6]. With the development of industrial intelligence, real-time tool life prediction methods based on data acquisition have received more and more attention.

2. The concept of remaining service life of the tool

Remaining Useful Life (RUL), broadly speaking, refers to the time that a system can operate normally after a period of normal operation. In a narrow sense, it refers to the time interval from the current moment to the failure moment of a component or subsystem of the system. Therefore, the remaining service life of the tool can be defined as:

\[ F = N - n \]

In the formula, \( F \) represents the remaining life of the tool, reflecting the remaining machining time of the tool; \( N \) is the available machining time specified by the rated life of the tool; \( n \) represents the use time of the tool. Therefore, the judgment of whether the tool fails is the key technology for accurate tool remaining service life prediction.

The remaining tool life prediction can use physical model methods and prediction methods based on tool availability. The tool RUL prediction based on tool availability is based on whether the tool can continue to be used as the failure criterion. The main cause of tool damage is wear and breakage, when the tool material and processing parameters are selected appropriately, the main physical phenomenon that determines the tool life is tool wear. It is usually judged as tool failure when the wear amount reaches a certain threshold. Judgment methods can be divided into direct measurement methods and indirect measurement methods. The direct method uses direct mechanical measurement [7], contour tracer [8], optical [9] and pneumatic [10] to measure, used to measure actual tool wear, these are often offline measurements, and it is not easy to implement automatic tool wear monitoring. Indirect detection, through indirect measurement of various signals (such as cutting force, vibration and sound, etc.) in the process of tool processing, to analyze the relationship between the measured data and tool wear.

3. Prediction of remaining tool life based on physical methods

Generally speaking, the physical method mainly regards the way of tool damage behavior as a physical model, the model is combined with the measured tool data to determine model parameters and predict future trends. The model focuses on the experimental verification of the calculation model to describe the changing trend of tool life, in 1907, based on a large number of tool life experiments, Taylor concluded the Taylor formula to calculate tool life.

\[ T = k \frac{C}{V^{x}f^{y}a^{z}} \]

In the formula, \( T \) is the tool durability, \( V \) is the cutting speed during processing, \( f \) is the tool feed, \( a \) is the depth of cut, and \( C, x, y, \) and \( z \) are all constants, but Taylor's formula simply studies the exponential relationship between tool life and tool cutting speed, so the actual application range of the modified formula is limited [11].

British John F. Archard et al. proposed the Archard model, by predicting the future change trend of the tool wear value and predicting the remaining service life of the tool based on the predicted change, the formula is:

\[ W = \int k \frac{P^{a}V^{b}}{H^{c}} dt \]

In the formula, \( W \) is the tool wear, \( P \) is the interface pressure, \( V \) is the relative sliding speed, \( H \) is the hardness of the tool material, \( t \) is the time, and \( K, a, b, \) and \( c \) are all correction coefficients, But the
Archard model only predicts the trend of tool wear, and the remaining service life of the tool cannot be directly obtained.

In the actual production and processing process of the enterprise, the processing process of the tool is not stable, tool life will also be affected by other effects. For example, the impact cutting force between the tool and the workpiece during cutting will cause fatigue damage to the tool, another example is the friction and heat generated during cutting will also affect the wear of the tool [12]. However, because the traditional physical method model only describes the functional relationship between cutting parameters, time and tool life prediction, it has relatively high limitations, which will make the error between the result predicted by the empirical formula and the actual value larger.

4. Prediction of remaining tool life based on signal analysis

Due to the random nature of the tool and the workpiece in the production and processing process, relying solely on the physical model method to predict the remaining service life of the tool cannot meet the work requirements of the manufacturing enterprise. Therefore, the precise mapping relationship between a certain feature extracted and the tool wear state is established through the method of data collection, so as to predict the remaining life of the tool. The most important issues for automated processing in the actual environment are: The machine operator cannot be freed from the CNC machine tool, the tool wear is monitored manually, and then the tool is changed. Therefore, since the late 1980s, research on the status monitoring system of development tools has been carried out in earnest [13]. At present, the commonly used features are: acoustic emission signal, vibration signal, power signal, cutting force signal and so on.

4.1. Acoustic emission signal

Acoustic emission (AE) signals contain potentially valuable information, it can be used to monitor and detect tool wear and breakage. However, the AE stress wave generated in the cutting area is distorted due to the transmission path and the measurement system. And it is difficult to obtain effective results from these raw acoustic emission data.

Xiaozhi Chen [14] et al. proposed a tool condition monitoring technology based on wavelet analysis of AE signals. Through wavelet multi-resolution analysis, the local characteristics of the frequency band containing the main energy of the acoustic emission signal are described. The wavelet resolution coefficient is used as the characteristic quantity of tool condition monitoring. Obtain tool life prediction based on tool status; Li Liang [15] used acoustic emission sensors to be highly sensitive to tool damage, the AE signal was used to monitor the breakage of the tool during the micro-milling process. Through the wavelet analysis of the experimental data, the characteristic parameters of the tool breakage are obtained.

Since the AE signal is also sensitive to other processing parameters or machine tool structure in the actual machining process, it is not only sensitive to the tool state, this has high requirements for the working environment, and is greatly affected by cutting noise, machine tool noise and other factors. Unable to withstand the extreme conditions during cutting, for example, the influence of high temperature, large amount of coolant and chips [16], it makes the analysis of the signal more difficult than the sensing of the signal [17].

4.2. Vibration signal

Vibration signals require less peripheral equipment than AE. In addition, vibration signals have the fast response time required to indicate changes in online monitoring [18]. D. E. Dimla [19] uses vibration characteristics to monitor tool wear in metal turning operations. Experiments were carried out by using coated grooved blades, and online vibration signals were collected. Analyze the signal in the time domain and frequency domain, based on the measurement of the cutting tool wear form and the analysis of the vibration signal, the trend of the sensor signal generated as the blade wear length increases can be determined. The characteristics show that the measured wear value has a good correlation with some resonance peak frequencies. It can be effectively used for wear monitoring and wear identification of
cutting tools. Alonso [20] et al. proposed to analyze the structure of tool vibration signals based on the use of singular spectrum analysis (SSA) and cluster analysis. Through SSA, the obtained tool vibration signal is decomposed into an additive set of time series. Then use cluster analysis to group the SSA decomposition to obtain several independent components in the frequency domain. These components are presented to the feedforward backpropagation (FFBP) neural network to determine the flank wear of the tool. Then predict the remaining service life of the tool.

But in the same way, vibration signals are also susceptible to external factors. For example, the vibration signal of the machining process caused by the tightness of the workpiece clamping will lead to the inaccurate results of the tool state prediction. In turn, the prediction of the remaining life of the tool does not match the actual life of the tool.

4.3. Power signal

During the machining process, reliable data can be obtained in a short time to monitor the progress of tool wear and predict its wear and damage. Reminding mechanics in real time to avoid unexpected failures of tools or machines can help companies obtain high-quality products. Spindle power data is easily collected directly from modern machine tools and can be used for real-time data processing in the production workshop.

Raphael [21] et al. studied the relationship between spindle power signal and tool wear/breakage, and conducted drilling research on nickel-based superalloys. Experiment by changing the speed and feed parameters. This experiment collects spindle power data from the machine power meter to verify their relationship with relevant cutting force data. Then the power data is input into the neural network for functional processing, so as to predict the wear progress and life of the tool with a preset threshold. Wan Wenbo [22] proposed that on the basis of the power monitoring method, an adaptive neuro-fuzzy system and support vector regression were used to establish the relationship model between power and processing parameters. Calculate the standard cutting power and perform real-time comparison and analysis with the actual cutting power to determine the machining state of the tool and execute the tool change strategy.

Although the power signal acquisition is convenient and the anti-interference ability is strong, these signal processing technologies are usually computationally expensive and cannot be widely used in the actual production of enterprises.

4.4. Cutting force signal

Letot et al. [23] used force signal, vibration signal, power signal and sound signal to evaluate the remaining service life of the tool under the same model. It is found that the effect derived from the force signal is the best. Bhattacharyya [24] et al. proposed a combination of signal processing techniques for real-time estimation of tool wear in face milling using cutting force signals. Three strategies based on linear filtering, time-domain averaging and wavelet transform techniques are used to extract relevant features from the measured signal. Introduce isotonic regression and exponential smoothing techniques to enhance the monotonicity and smoothness of extracted features. By analyzing the mapping relationship between eigenvalues and tool wear, tool life prediction is realized. Gao Hongli [25] used signal analysis methods such as wavelet transform to extract cutting force signals as tool life prediction features. The principal vector analysis (PCA) method is used to optimize the selection based on the cumulative contribution rate. The monitoring system automatically selects the dynamic monitoring model composed of the life calculation model according to the processing conditions. According to the output accuracy, tool life calculation, online learning and model parameter update are realized, and finally online prediction of tool life is realized.

Studies have shown that cutting force is the most important indicator of machining state and quality [26]. The most commonly used cutting force sensor is a dynamometer. However, the equipment is expensive, the stroke and load are limited, and the machine tool needs to be modified and connected to external equipment, which imposes greater restrictions on the installation location and processing conditions.
5. Conclusion
According to different starting principles, this article has advanced the prediction methods of tool remaining life in FMS. It focuses on the physical model method and the method based on a certain signal as the tool life prediction feature quantity, then they showed their research status and summarized the corresponding advantages and disadvantages.

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