IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received July 6, 2020, accepted July 27, 2020, date of publication August 6, 2020, date of current version August 18, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3014334

Precision Retaining Time Prediction of Machining Equipment Based on Operating Vibration Information

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This work was supported in part by the Technical Foundation Program from the Ministry of Industry and Information Technology of China under Grant JSZL2019601A003 and Grant JSZL2016601A003, and in part by the National Natural Science Foundation of China under Grant 51705015.

ABSTRACT The precision of machining equipment is the main factor that affects the reliability of the manufacturing system. The failure of equipment function which affects the efficiency of manufacturing system is often caused by out-of-tolerance of precision. In this research, the precision degradation was connected to the stress and frequency of the external load, and a method was proposed to predict the precision retention time (PRT) of machining equipment, in which the traditional fatigue theory was combined with the monitoring technology of the operating vibration information. The calculation method of vibration energy was derived based on the principle of mechanical dynamics. Combined with signal processing technology, the complex loads were expressed by energy spectrum in frequency domain. According to the characteristics of *S-N* curve and the historical test data, the *F-E-T* surface reflecting the relationship among load frequency, vibration energy and precision retention time was obtained. The surface was used to predict the PRT of the equipment under a certain processing task, and the effectiveness of the method was verified by a case study.

INDEX TERMS Operating vibration information, machining equipment, complex loads, vibration energy, precision retention time (PRT).

I. INTRODUCTION AND LITERATURE REVIEW

For common machining equipment, especially high-grade CNC machine tools, the loss of equipment function is generally not caused by the reduction of strength and stiffness, but by the decrease of machining precision. In other words, the machining precision is the key factor to determine whether the equipment is scrapped [1]. The decline of the precision indexes of the workpiece is the specific performance of precision degradation, such as the value of dimensional deviation and circular degree. Therefore, it is a significant part of fault prediction and maintenance decision to carry out the study of precision retaining ability based on precision degradation analysis [2].

According to the relevant research, the degradation of precision index is often caused by the performance degradation of equipment. And the performance degradation of equipment and components mainly results from the damage caused by the external load [3]. In addition, there is a common phenomenon in engineering practice, that is, performance degradation is more obvious when the load frequency of the component is close to its own first or several order natural frequencies. Taking rolling bearing as an example, the inner ring, outer ring, cage, rolling body and other parts of the bearing have their respective corresponding failure frequencies [4]. In consequence, the degradation of machining precision index is sensitive to frequency. It is not only related to the load stress, but also has a close relationship with the load frequency. These characteristics have also become the challenge of studying the degradation and precision retaining ability of machining equipment [5].

Precision retaining ability of machining equipment refers to the ability of each precision index to remain within the required range for a long time under normal operating conditions [6]. According to the definition of precision retaining ability, the precision retaining ability of machining equipment

The associate editor coordinating the review of this manuscript and approving it for publication was Md. Moinul Hossain.

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can be evaluated by the length of time for each precision index to be kept within the required range, that is, the precision retention time (PRT) [7]. Therefore, the prediction of PRT is actually the prediction of useful life of machining equipment. The existing life prediction theories mainly include life prediction theories based on model and data-driven life prediction theories. The former is based on the static characteristic values such as the stress amplitude and the average stress value. It is easy to cause estimation error because the effect of load frequency on performance degradation is ignored [8]–[10]. In addition, with the development of computer technology, sensor technology and network technology, the equipment life prediction method based on data-driven has become a research focus. The operating vibration data produced in the manufacturing process contains dynamic information reflecting the state changes. Therefore, the key information of the equipment condition can be determined by monitoring the signals [11]–[13]. Some signal processing methods, such as wavelet packet decomposition and neural networks, have been used to extract features from vibration signals for equipment condition prediction [14]–[16]. However, the above method relies on a large number of historical experimental data and lacks the consideration of failure mechanism. Therefore, when the external load changes, the prediction model will not be suitable for the new environment. Taking the prediction method in [14] as an example, the prediction error of the model is two to three times that of the stable working condition when the operating condition of the tool changes.

The flexibility in the use of equipment is caused by the flexible product structure and customer requirements of contemporary manufacturing. The same machining equipment is often used to perform multiple machining tasks. The degradation law of equipment performance have a difference under different processing tasks. Therefore, the accurate prediction of PRT is inseparable from the consideration of machining tasks. At present, some researches have been carried out to predict the equipment life under various processing tasks. Wang *et al.* [17] proposed a tool life prediction method to solve the problem that tool life is difficult to predict accurately due to the influence of processing tasks. The method was based on the long short term memory network and integrates the online learning module to realize the prediction of tool life under variable working conditions. Huang *et al.* [18] proposed a new multi-condition deep convolutional neural network model (MC-DCNN) to predict the equipment life under multiple working conditions. Although the above life prediction methods based on deep learning consider various processing tasks, they rely on a large number of historical experimental data. This kind of method can accurately predict the equipment life under processing tasks with historical data up to 95%, and the MSE of residual life obtained by methods in [17] is only 2.93156×10^{-3}. For new processing tasks without a large amount of data accumulation, the accuracy of life prediction is usually less than 85%.

Some scholars regard the variation of machining tasks as an uncertain factor affecting the performance of machining equipment and predict the life of equipment based on the stochastic process model. Sun *et al.* [19] proposed a hybrid model combining random process with artificial intelligence model. Aiming at the problem of tool wear, the relationship between signal characteristics and tool wear quantity was constructed by BP neural network. Then, the wear predicted by BP neural network is modeled by wiener process and the tool life can be predicted. This kind of life prediction method based on stochastic process model can give a prediction value with confidence level, considering the change of task load in the process of equipment degradation. The result is more reasonable. However, the parameter estimation in the modeling process has a great influence on the accuracy of the model and the performance degradation data which the model depends on is difficult to obtain. In addition, it is equivalent to simplifying the relationship between processing tasks and equipment performance degradation by considering the influence of machining tasks as an uncertain factor. This will result in a large deviation in the forecast results. The deviation is usually larger than the error of life prediction method based on deep learning.

Based on the above considerations, it is necessary to combine the traditional fatigue theory with the monitoring technology of the operation information to predict the precision retention time of machining equipment. The machining task load can be quantified through the equipment operation signal. And the relationship between task load and equipment precision degradation will be studied to predict the PRT under different machining tasks. The machining equipment is always under the complex alternating load during the processing. The energy information contained in the operating vibration signal can more accurately reflect the stress information and frequency information of the task load. Therefore, it is realistic to take the operating information of equipment as the load information and combine it with the fatigue theory to predict the precision retention time of the equipment. The operation vibration information of machining equipment is composed of simple harmonics at multiple frequencies. The change is random and cannot be expressed by explicit function. In consequence, the task load is treated as complex load in this paper. In the time domain, the change of stress under complex load is irregular, which requires a large number of cycle counting. The amount of data being processed is very large [10]. However, from the perspective of frequency domain, the complex load information is not completely indescribable. In order to reflect the comprehensive influence of load frequency and load stress on equipment damage, a method for calculating vibration energy spectrum based on power spectrum density (PSD) analysis is proposed in this paper. PSD is an important parameter in signal spectral analysis. It is the statistical result of the structure response under the excitation of random dynamic load. It is a relation curve of power spectral density value to frequency value [20]. In the design of random vibration test, the researchers used

PSD to simulate the external load of the product in actual operation [21].

In this paper, a method to predict the precision retention time of machining equipment by considering the action of task load is presented. This method is suitable to solve the problem of equipment precision degradation under the flexible processing task. The rest of this paper is arranged as follows: In section II, the calculation method of vibration energy under simple load is analyzed in detail. In Section III, the calculation method of energy spectrum under complex loads is introduced. In Section IV, the specific process of precision retaining time prediction based on F-E-T surface is presented. In Section V, the proposed method is verified by specific experimental data. Section VI summarizes the article and looks forward to the future research direction.

II. VIBRATION ENERGY UNDER SIMPLE LOAD

A. DYNAMIC MECHANISM OF PRECISION DEGRADATION

A variety of processing tasks need to be undertaken by machining equipment during its life cycle. The processing task load is treated as a complex load. A complex load can be decomposed into a series of simple loads at a single frequency. In this section, the calculation method of vibration energy with physical significance for the simple load is proposed according to the principle of mechanical dynamics [22].

Suppose that $x(t)$ is a simple load related to simple harmonic excitation force $F(t)$, and its form is as follows:

$$x(t) = A\cos(\omega t + \varphi) \tag{1}$$

In which, A is the amplitude of the device response signal and φ is the initial phase Angle. The magnitude of A is determined by the frequency ratio and the damping ratio, as shown in (2) and (3).

$$A = \frac{F}{k}\beta = A_0\beta \tag{2}$$

$$\beta = \frac{1}{\sqrt{(1-r^2)^2 + (2\zeta r)^2}} \tag{3}$$

In which, A_0 is the equivalent static displacement, which represents the displacement generated on the device after the amplitude of the excitation force is statically processed. k is the elastic modulus of the material, which reflects the stress-strain law of the material in the static environment. β is the displacement amplification coefficient. The closer the load frequency is to the sensitive frequency of the structure, the greater the displacement amplification coefficient is. $r = \omega/\omega_n$ is the frequency ratio. ξ is the damping ratio.

Both the stress amplitude and the vibration frequency will affect the precision degradation of machining equipment. Therefore, vibration energy is proposed to reflect the comprehensive effect of stress amplitude and vibration frequency on the equipment. According to the definition, mechanical energy is the sum of kinetic energy and potential energy. So, the mechanical energy of the equipment subjected to the load is:

$$E = \frac{1}{2}kx^2 + \frac{1}{2}mv^2 \tag{4}$$

The elastic coefficient $k = m\omega_n^2$. The velocity v can be obtained by taking the derivative with respect to $x(t)$.

$$v = -A\omega\sin(\omega t + \varphi) \tag{5}$$

By substituting the value of k, v and x into the mechanical energy expression, the instantaneous mechanical energy E can be obtained after simplification.

$$E = \frac{mA^2}{4}\left[\left(\omega^2 + \omega_n^2\right)\left(\omega_n^2 - \omega^2\right)\cos 2(\omega t + \varphi)\right] \tag{6}$$

From the above equation, it can be seen that the mechanical energy borne by the equipment caused by the load is composed of two parts, one is a constant independent of time, the other is a variable with time. The magnitude of the instantaneous energy is proportional to the square of the response displacement $x(t)$.

After a long period of steady-state operation of the equipment, if the time is T, the total mechanical energy of the equipment is the integration of instantaneous energy with time T:

$$\begin{aligned} E_T &= \int_{t=0}^{t=T} E dt \\ &= \int_{t=0}^{t=T} \frac{mA^2}{4}\left[\left(\omega^2+\omega_n^2\right)+\left(\omega_n^2-\omega^2\right)\cos 2(\omega t+\varphi)\right]dt \end{aligned} \tag{7}$$

If the equipment runs for a long time and T is much greater than $\cos 2(\omega t + \varphi)$, the simple harmonic vibration can be neglected in the total mechanical energy of the equipment, which is abbreviated as:

$$E_T \cong \frac{T}{4}mA^2\left(\omega^2 + \omega_n^2\right) \tag{8}$$

The external load is doing work on the equipment all the time and the dissipated energy of the device is constant. Since the energy borne by the equipment is proportional to the time, the energy will gradually accumulate over time. However, the energy bearing capacity of the equipment is limited. When the energy is accumulated to a certain degree, the stability and precision retaining ability of the equipment will be destroyed [23]. Therefore, the dynamic mechanism of equipment precision degradation is also analyzed from the perspective of energy accumulation by the above equations.

B. CALCULATION OF VIBRATION ENERGY

In order to reflect the influence of vibration frequency ω on vibration energy, the expression of displacement amplification coefficient is substituted into the expression of cumulative vibration energy:

$$\begin{aligned} E_T &= \frac{T}{4}mA_0^2 \cdot \beta^2\left(\omega^2 + \omega_n^2\right) \\ &= \frac{T}{4}mA_0^2 \cdot \frac{\left(r^2+1\right)\omega_n^2}{\left(1-r^2\right)^2 + (2\zeta r)^2} \end{aligned} \tag{9}$$

The accumulated energy dissipated in the form of vibration is calculated by the above formula. It can be seen that the vibration energy accumulates linearly with time under the same load. The vibration energy per unit time is more representative of the size of the simple load. Therefore, the vibration energy defined in this paper is the instantaneous energy, as shown in (10):

$$\begin{aligned} E &= \frac{1}{4} m A_0^2 \cdot \beta^2 \left(\omega^2 + \omega_n^2\right) \\ &= \frac{1}{4} m A_0^2 \cdot \frac{\left(r^2+1\right)\omega_n^2}{\left(1-r^2\right)^2 + (2\zeta r)^2} \end{aligned} \tag{10}$$

When the damping ratio ξ is constant, the change curve of vibration energy E with frequency ratio r is shown in Figure 1.

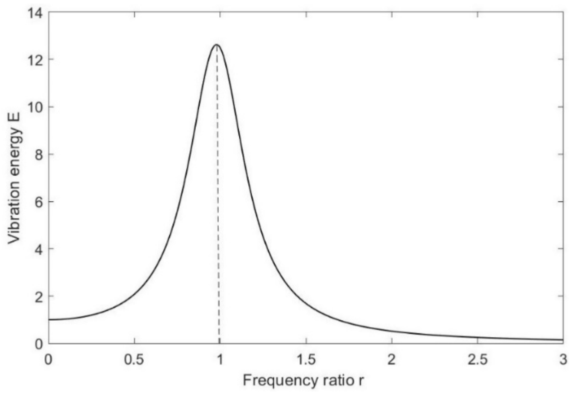

FIGURE 1. The relation between vibration energy and frequency ratio under simple load.

The relation between vibrational energy and frequency ratio can be discussed through the Figure above. Under the initial conditions or when the frequency ratio $r \rightarrow 0$, the displacement amplification coefficient is close to 1. The response displacement of the equipment is close to the initial static displacement. However, with the increase of load frequency, when $r < 1$, the vibration energy borne by the equipment gradually increases. The maximum value is reached at the time point close to 1 but less than 1. When $r = 1$, resonance phenomenon occurs, and the vibration energy is relatively large. When $r > 1$, the vibration energy gradually decreases. And when r is much greater than 1, the vibration energy of the system gradually approaches zero. Therefore, it can be concluded that if the external load has the same amplitude, the excitation effect of different frequency loads on the same equipment failure mode is also different. The closer the load frequency ω is to the sensitive frequency ω_n, the greater the vibration energy of the equipment. Vibration energy is a physical quantity which can reflect the combined action of load amplitude and vibration frequency.

According to the calculation of vibration energy, if the load amplitude A_0, load frequency ω and the sensitive frequency ω_n corresponding to the precision index n are known, the vibration energy causing degradation of the precision index n can be obtained. When the specific form of the response signal $x(t)$ of the load is unknown, the above parameters can be obtained by collecting the operation information of the equipment.

III. ENERGY SPECTRUM UNDER COMPLEX LOADS

A. ESTIMATION OF POWER SPECTRUM

The vibration energy of the above simple load only considers the influence of simple harmonics at a single frequency. In the actual manufacturing process, the processing task is a complex load, which is formed by the simple harmonic superposition of multiple frequencies. Therefore, it is necessary to comprehensively consider the energy of several simple harmonics from the perspective of frequency domain and draw the energy spectrum of the equipment. According to the conclusion of the previous section, the operation information can provide important information for the expression and quantification of the processing task load.

Empirical mode decomposition (*EMD*) algorithm and correlation analysis can be used to select the sensitive frequency ω_n for precision index n. *EMD* is used to decompose the running signal into multiple modes (*IMF*). The decomposition process amplifies the smaller frequency peaks in the original signal and separates different frequency components. Through the correlation analysis of frequency peak and precision index, the frequency that is most sensitive to precision index n is obtained as the sensitive frequency ω_n. With the degradation of equipment precision, the measured values of frequency peaks and precision index will change. Assuming that a signal has M frequency peaks, M sets of variables of the frequency peaks and precision index can be obtained in the process of precision degradation. The correlation coefficients of each set of variables with the same dimension are calculated separately. The calculation formula of correlation analysis is as follows.

$$\rho(a_i, b_n) = \frac{\sum(a_i - \overline{a_i})(b_n - \overline{b_n})}{\sqrt{\sum(a_i - \overline{a_i})^2}\sqrt{\sum(b_n - \overline{b_n})^2}} \tag{11}$$

In which, a_i is a set of variables consisting of the peak frequency of group i; b_n is a set of variables consisting of the measured value of equipment precision index n ; $\overline{a_i}$ and $\overline{b_n}$ are the mean values of the variables a_i and b_n respectively. A certain running signal and the three modes decomposed by *EMD* are shown in Figure 2. The value of the correlation coefficient between the three frequency peaks and precision indexes is calculated respectively. The greater the absolute value is, the more sensitive the frequency band is to the precision index.

In addition, *PSD* is a very important characteristic in the analysis of stationary random signals in the frequency domain. It is similar to the amplitude spectrum. But its calculated value is the amplitude squared [20]. The calculation is:

$$S_X(f) = \int_{-\infty}^{\infty} R_X(\tau) e^{-j2\pi f \tau} d\tau \tag{12}$$

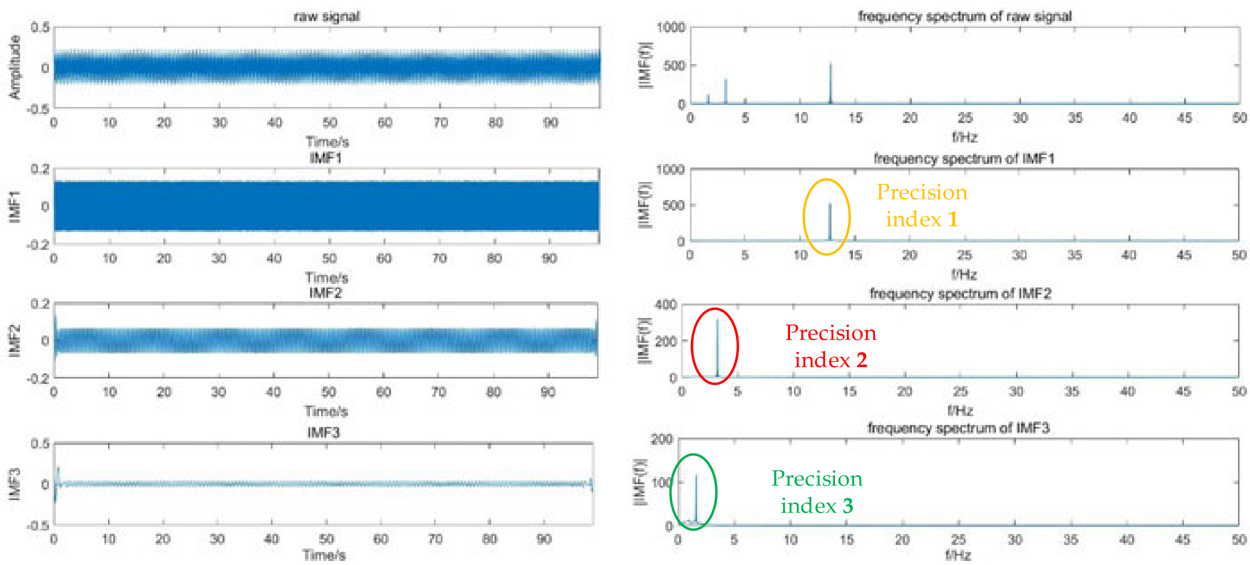

FIGURE 2. **A certain running signal and the three modes decomposed by EMD.**

In which, $R_X(\tau)$ is the autocorrelation function of the original signal $x(t)$. The distribution of the operating signal on the frequency is obtained by *PSD* analysis, which represents the distribution of current processing task load at different frequencies. The power spectrum of task load can be estimated by using the power spectrum density obtained from multiple samples. Since the power spectrum is a relation curve between the power spectrum density and the frequency value, the complex load can be divided into several simple loads through the *PSD* analysis. And the square of the amplitude A_0^2 and its corresponding frequency ω can be obtained. G is assumed to be the power spectrum density of a simple load. So, the power spectrum of complex task loads is calculated to be $G(\omega)$.

B. CALCULATION OF ENERGY SPECTRUM

The amplitude spectrum of complex loads is obtained by analogy with the calculation method of vibration energy under simple load.

$$[A(\omega)]^2 = [\beta(\omega)]^2 \cdot G(\omega) \tag{13}$$

When the sensitive frequency ω_n corresponding to the precision index n and the power spectrum $G(\omega)$ of the complex task load are known, the energy spectrum $E(\omega)$ resulting in the degradation of the precision index n can be obtained as follows:

$$\begin{aligned} E(\omega) &= \frac{1}{4} mG(\omega) \cdot [\beta(\omega)]^2 \left(\omega^2 + \omega_n^2\right) \\ &= \frac{1}{4} mG(\omega) \cdot \frac{\left(\omega^2/\omega_n^2 + 1\right)\omega_n^2}{\left(1 - \omega^2/\omega_n^2\right)^2 + \left(2\zeta\omega/\omega_n\right)^2} \end{aligned} \tag{14}$$

An example of the time domain waveform $x(t)$, power spectrum $G(\omega)$ and energy spectrum $E(\omega)$ under the complex loads are shown in Figure 3. The power spectrum $G(\omega)$ reflects the frequency distribution of the complex load amplitude. Based on the power spectrum, the calculation of energy spectrum $E(\omega)$ takes into account the sensitive frequency of precision index n. It can be seen from the figure that the vibration energy causing the equipment precision degradation is more concentrated near the sensitive frequency 5KHz due to the influence of the load frequency. At the same time, the vibration energy is not strictly subject to the variation law of simple load with frequency in Figure 1 due to the influence of load amplitude. Therefore, the vibration energy reflects the comprehensive effect of the amplitude and frequency on the degradation of the equipment precision.

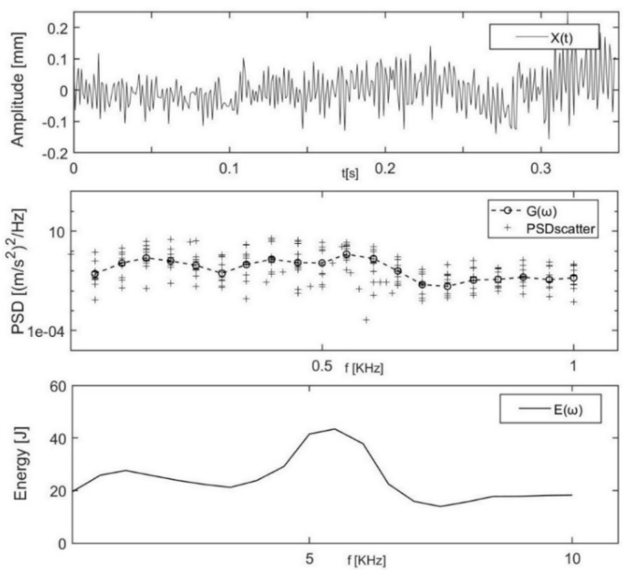

FIGURE 3. **Time domain waveform, power spectrum and energy spectrum under the complex loads.**

IV. EXPERIMENTAL SETUP AND DATA ACQUISITION

A. F-E-T SURFACE BASED ON FATIGUE LIFE CURVE

As the equipment is working for a long time, the equipment may be out of precision due to damage accumulation. According to the cumulative damage rule, damage will occur inside the equipment under each load. From the perspective of frequency domain, it is considered that with the accumulation of load energy at each frequency, damage will also occur inside the equipment. The equipment precision is out of tolerance when the load energy at any frequency accumulates to a certain value. Therefore, the precision degradation under single frequency is similar to the fatigue problem under stress.

The fatigue life curve is a very important tool in the fatigue analysis of materials. The curve takes the number of cycles N when the material reaches failure as the abscissa and the maximum stress σ on the specimen as the ordinate. Stress includes bending stress, tensile stress and compressive stress. Since stress and strain begin with the letter S in English, these three curves are also collectively referred to as S-N curves. In the stage of high cyclic fatigue, the power series equation can be used to describe the relationship between cyclic times and fatigue stress [24]:

$$\sigma^m N = C \tag{15}$$

In which, σ is the stress level; N is the number of cycles, that is, the fatigue life; m and C are constants related to the material. It can be seen that the number of cycles of the material is a finite constant in the region of finite life. The greater the stress, the smaller the fatigue life. If the logarithm is taken from both sides of the above equation, the following equation can be obtained:

$$\lg \sigma = (lgC - \lg N)/m \tag{16}$$

In log-log coordinates, the S-N curve is a straight line with a slope of $-1/m$ [25].

Based on the characteristics of S-N curve of fatigue life, the functional relationship among load frequency F, vibration energy E and precision retention time T is used to deduce the F-E-T surface and the E-T curve at each frequency.

B. CALCULATION OF THE PRECISION RETENTION TIME

Since the energy of complex load exists in a continuous frequency range, the functional relationship among load frequency F, load energy E and precision retention time T will form a surface in the three-dimensional space. The F-E-T surface is used to estimate the precision retention time of the equipment under complex loads. The F-E-T surface refers to a series of E-T curves corresponding to different frequencies.

When F is constant, an E-T curve is formed by taking the load energy E as the independent variable. According to the nominal stress method, the relationship between the load stress σ and load times N under constant amplitude loads satisfies the following [24].

$$\sigma^m N = \sigma_{-1}^m N_0 = C \tag{17}$$

Since $\sigma \propto A$, let $\sigma = cA$ (c is a constant). The vibration energy in unit time of simple load can be expressed as:

$$E_C = \int_{t=0}^{t=2\pi/\omega} Edt = \frac{\pi}{2\omega} mA^2(\omega^2 + \omega_n^2) \tag{18}$$

From the above equation, $E_C = c_E \sigma^2$ (c_E is a constant) can be obtained. In addition, $N \propto T$. Therefore, (16) can be converted into (19):

$$E_C^{m/2} T = C' \tag{19}$$

In which, C' is a constant, considered to be the cumulative limit of the energy that the equipment can withstand. It is determined by the type of precision index. m is a constant. It is the same as m in the nominal stress method.

When considering a precision index n, it is considered that the load energy and precision retention time at each frequency obey the E-T curve derived above. When the total energy of the equipment at any frequency accumulates to C', the equipment precision is out of tolerance. The precision retention time corresponding to the load energy E_i at frequency ω_i is:

$$\lg T_i = -\frac{m}{2} \lg E_i + \lg C' \tag{20}$$

The equipment precision is out of tolerance when the accumulated energy at any frequency exceeds the threshold. Then the precision retention time T considering the precision index n is:

$$T = \min\{T_i\} \tag{21}$$

The prediction method of the precision retention time based on F-E-T surface is described by the above two formulas. The F-E-T surface can be fitted by using the precision retention time data and running signal data of the same type of equipment under the historical task. According to the fitting result, the value of parameter m and C' can be obtained. When the above parameters are known, the operation information of the equipment under a certain task can be collected, and the precision retention time under the current task can be calculated. The framework for the PRT prediction model is shown in Figure 13.

V. METHOD VALIDATION AND APPLICATION

A. CUTTING TEST AND DATA COLLECTION

In order to verify the availability and effectiveness of the proposed method, the operation information is obtained by cutting test. The prediction model of PRT under different working conditions is established. A 5-axis CNC machine tool DMG CTX gamma 395 2000TC was used for the test. The tool was carbide turning tool. In the experiments, the vibration signals in three directions (X, Y and Z) during cutting process were collected by a PCB 356A32 triaxial acceleration sensor. The outer diameter of the workpiece after cutting is measured by caliper. Based on the machining requirements, when the diameter deviation of the outer circle exceeds 10% of the specified diameter, the precision of the machine tool is out of tolerance. In this case, 10% of the diameter is equal to 0.16mm. The acquisition and installation of cutting vibration and experimental environment are shown in Figure 4.

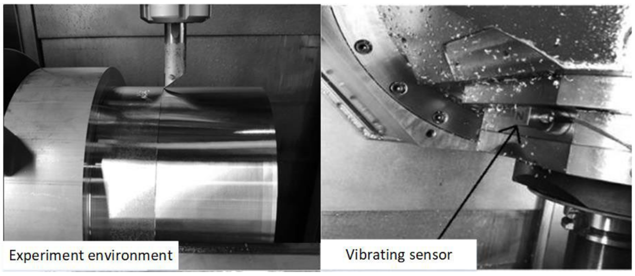

FIGURE 4. The experimental environment.

In this test, the processing task is designed based on the actual processing condition of a solid cylindrical workpiece. A total of six different tasks are included. Variables include feed and spindle speed. Task Numbers are *a, b, c, d, e* and *f*, as shown in Table 1. During the test, the cutting tools were cut in six task modes. In each task mode, the same lathe tool was used to continuously cut the surface of the workpiece. The outer diameter of the workpiece and vibration signals were collected in this process. The outer diameter was measured every two minutes for the task. When the diameter deviation of the outer circle reaches 0.16mm, the current processing task should be stopped and the next task should be carried out with a new cutter of the same type. This process is repeated until all six tasks are completed. The experimental data set contains six groups of cutting test data. Each group of data includes the vibration signals of X, Y and Z dimensions and the corresponding cutting time when the precision is out of tolerance. In this case, four groups of data were selected as the training set to establish the F-E-T surface and the other two groups were used as the test set to evaluate the effectiveness of the prediction method of PRT.

TABLE 1. Task parameters.

Task number	Spindle speed	Feed rate
a	400rpm	0.2mm/r
b	400rpm	0.5mm/r
c	800rpm	0.2mm/r
d	800rpm	0.5mm/r
e	1000rpm	0.2mm/r
f	1000rpm	0.5mm/r

B. VERIFICATION OF F-E-T SURFACE

EMD algorithm and correlation analysis were used to select the frequency sensitive to the diameter deviation of the outer circle. The Figure 5 shows the frequency domain analysis of the first IMF at different stages for Task c. (a) is the vibration in the x-direction at the initial stage. (b) is the vibration in the x-direction of the intermediate stage. (c) is the vibration in the x-direction in the later stage. It can be seen that the amplitude of three frequency bands has obvious changes.

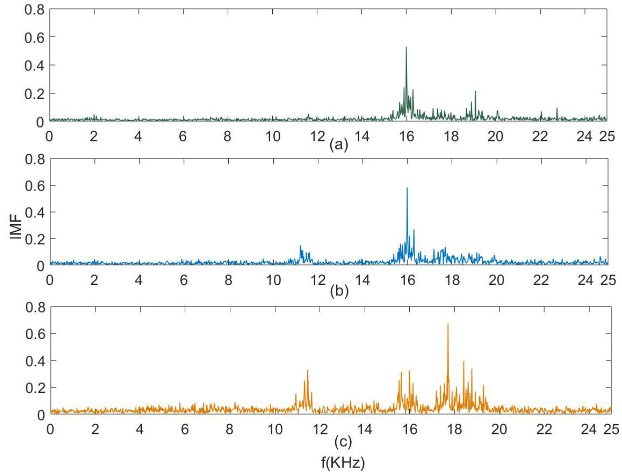

FIGURE 5. The frequency domain analysis at different stages for Task c.

According to the test design, three groups of frequency peak variables corresponding to three frequency bands and a group of variables with diameter deviation of outer circle can be obtained in the process of precision degradation. Based on (11), The correlation coefficients between the three groups of frequency peak variables and the diameter deviation variables of outer circle were calculated respectively. The results are shown in Table 2. According to the results, the frequency range of vibration signals sensitive to diameter deviation in this case is 11.2-11.4KHz. So, the frequency ω_n that is most sensitive to diameter deviation in this case is considered as 11.3KHz.

TABLE 2. Correlation coefficients for vibration with diameter deviation.

Frequency domain（KHz）	11.2~11.4	15.5~16.5	17~19
Correlation coefficient	0.8843	-0.4523	0.2278

Next, the frequency distribution of vibration signals under four kinds of tasks was obtained by PSD analysis. For each task, ten groups of vibration data were selected as samples. The mean points of PSD at each frequency were taken to obtain the power spectral lines of the four loads, as shown in Figure 6. The black dashed line in the Figure is the load power spectrum of the cutting task. (a) (b) (c) (d) is the task number that representing four cutting tasks. The energy spectrum of four kinds of task loads were calculated by (13) and (14), as shown in Figure 7.

The failure threshold of diameter deviation under current machining requirements is 0.16mm, so the cutting time corresponding to 0.16mm is selected as the PRT of the machine tool. According to test data, a three-dimensional

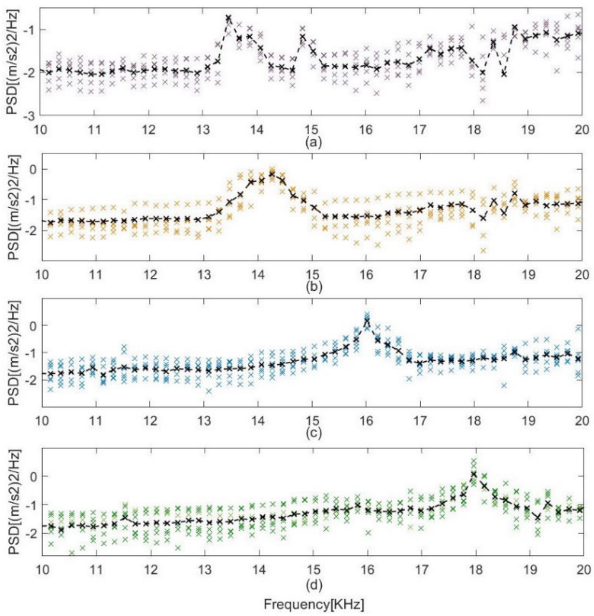

FIGURE 6. The load power spectrum of the cutting tasks.

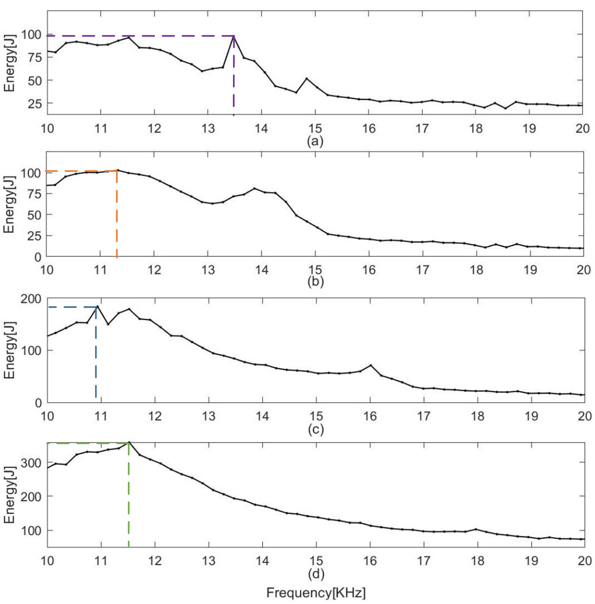

FIGURE 7. The energy spectrum of the cutting tasks.

surface (F-E-T diagram) reflecting the relationship among load frequency F, vibration energy E and precision retention time T can be obtained, as shown in Figure 8.

According to the analysis in part IV, the energy and PRT of each frequency obeys the same E-T curve. Therefore, the PRT under each task is determined by the maximum point of each energy spectrum line and the calculated results are shown in Table 3. It can be seen from the calculation results that the actual PRT of the machining tool decreases with the increase of vibration energy, which is consistent with the conclusion of qualitative analysis. The relationship between the maximum load energy E and precision retention time at any frequency ω_i is shown as Figure 9.

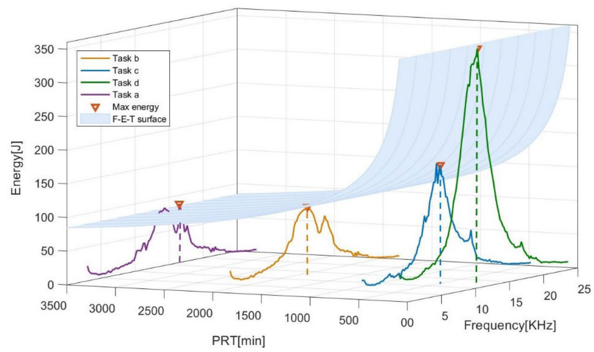

FIGURE 8. The relationship among load frequency, vibration energy and PRT.

TABLE 3. The calculated results of each task.

Task Number	a	b	c	d
Maximum load energy /J	94.7	105.1	179.8	352.4
Frequency /KHz	13.48	11.35	10.91	11.52
Actual PRT/min	3300	1820	468	88
Logarithmic PRT/lg(PRT)	3.53	3.21	2.67	1.94

The curve in Figure 9(a) is obtained by fitting the data. When the PRT reaches 10^7, the vibration energy tends to zero. It is consistent with the expected result of theoretical derivation. However, as the E-T curve is an exponential relation curve, the accuracy cannot be verified. So, the double logarithmic curve is drawn, as shown in Figure 9(b). It can be seen that the double logarithmic E-T curve is basically linear. The model fitting results are shown in Table 4. According to the fitting parameters, it is reasonable to use F-E-T curve to describe the relationship among load frequency, vibration energy and PRT.

TABLE 4. Linear fitting parameters and results.

Parameters	Value
m	-0.3732
n	3.259
RMSE	0.0386
R^2	0.9782

C. PREDICTION OF PRT AND METHOD VERIFICATION

In order to verify the feasibility of the PRT prediction method based on F-E-T surface, this paper uses the same training data to train the prediction model proposed by Wang *et al.* [17]. The relative errors of the two methods are calculated and compared.

According to the fitting results, the parameter $a = -0.3732$ and $b = 3.259$ in the double logarithmic E-T curve. So, the specific expression of the E-T curve is:

$$\lg(E_i) = 3.259 - 0.3732 \lg(T_i) \tag{22}$$

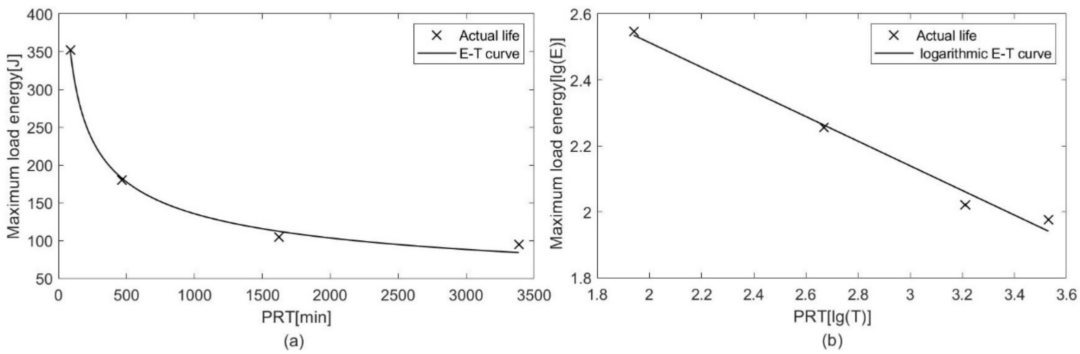

FIGURE 9. The relationship between the maximum load energy and PRT.

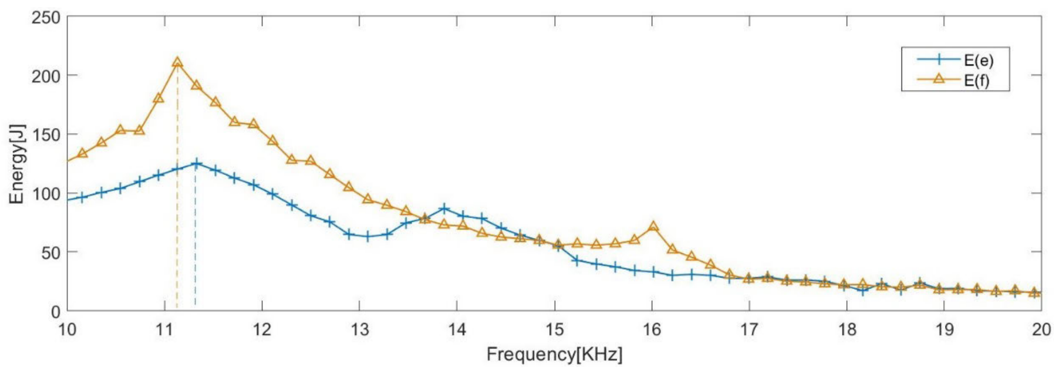

FIGURE 10. The energy spectrum of Task e and Task f.

From the above equation, it can be deduced that under a single frequency ω_i, the expression of precision retention time T_i changing with load energy E_i is (23).

$$\lg(T_i) = 8.7326 - 2.6795 \lg(E_i) \tag{23}$$

The energy spectrum of Task e and Task f are calculated by (13) and (14), as shown in Figure 10. According to the F-E-T surface parameters, the predicted PRT under Task e and Task f can be obtained. The predicted PRT value was compared with the actual value obtained from the experiment and the results are shown in Table 5.

TABLE 5. Comparison of predicted and actual PRT obtained by the method in this paper.

Task Number	Predicted PRT	Actual PRT	Relative error
e	1300	1422	8.58%
f	324	348	6.90%

The prediction model proposed by Wang can also be used to obtain the time prediction value and relative error when the diameter deviation of the outer circle reaches 0.16mm under Task e and Task f. The calculation results are shown in Table 6.

By analyzing the data in Figure 11 and Figure 12, it can be seen that the method based on F-E-T surface in this paper

TABLE 6. Comparison of predicted and actual PRT obtained by the method proposed by Wang.

Task Number	Predicted PRT	Actual PRT	Relative error
e	1620	1422	13.92%
f	412	348	15.39%

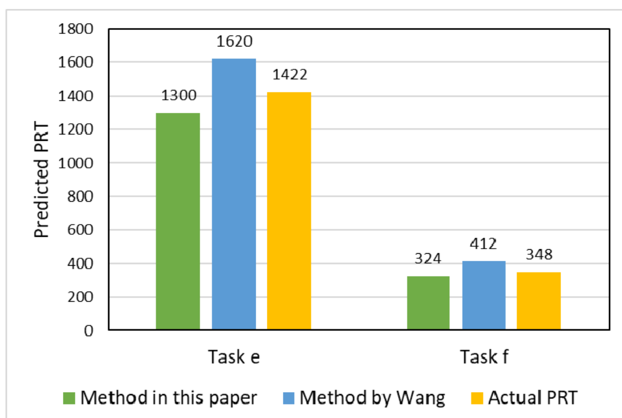

FIGURE 11. The comparison between the predicted PRT and the actual PRT.

has a great improvement in the accuracy of PRT prediction compared with the method proposed by Wang. The method proposed by Wang relies on the training data of the model.

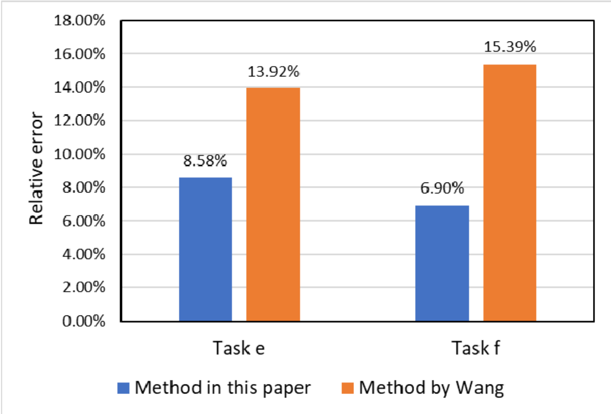

FIGURE 12. The comparison of relative error results.

```
//Function:PRT prediction model
use the sampling frequency(Fs) of the sensor as input
use the sampling points number(n) of the sensor as input
Initialize the power spectral density(G),
            the energy spectrum(E),
            the max energy(Emax),load frequency(ω),
            the sensitive frequency(ωn),
            the frequency peak(a),
            the correlation coefficient(ρ)
  for each task
  use the PRT and the value of precision index as input
    for each signal sample(xi)
      update the frequency peaks(aj) according to xi
      update the power spectral density(Gi)
          according to xi
      update load frequency(ω) according to Fs and n
      print the Gi and ω
    end
  update ρj according to aj and the value
         of precision index
  if ρn is the biggest in ρj, then
  update ωn according to ρn
  update G according to the mean of Gi
  update E according to G, ω and ωn
  update Emax according to E
  end
createfit m and n according to Emax and PRT
end
```

FIGURE 13. The framework for PRT prediction model.

Therefore, the prediction results of PRT under processing tasks without a large amount of data accumulation are not ideal. The prediction method based on F-E-T surface has an obvious effect on improving the prediction accuracy when the processing task changes, which indicates that the prediction method proposed in this paper can effectively solve the PRT prediction problem under flexible processing task.

VI. CONCLUSION

In this paper, a prediction method of the PRT based on operating vibration information of machining equipment was studied, which could quantify the task load by monitoring the sensor signals during operation. Firstly, according to the principle of mechanical dynamics, the calculation method of vibration energy with practical physical significance was proposed for the simple load at a single frequency. It was also proved that the vibration energy was a physical quantity which can reflect the combined action of load amplitude and frequency. Secondly, the complex loads were expressed by energy spectrum in frequency domain, and the calculation formula of load energy spectrum was derived. The *EMD* algorithm, correlation analysis and *PSD* analysis were used to process the operating information of the equipment. The result was taken into the energy spectrum formula to calculate the energy spectrum of the task load. Thirdly, according to the characteristics of *S-N* curve and the historical test data, the *F-E-T* surface reflecting the relationship among load frequency, vibration energy and precision retention time was obtained. This surface was used to predict the precision retention time of the equipment under a certain processing task. Finally, the dimensional precision degradation of workpiece during cutting is taken as an example to verify the feasibility of the method. The logarithmic *E-T* curve of vibration energy and precision retention time was basically linear, where the Root Mean Square Error (RMSE) was 0.0386, and the relative error of prediction results was controlled within 8.58%.

In the future, this method will be improved to solve the problem of equipment precision degradation under flexible machining tasks. For the machining equipment, the research of equipment precision degradation considering the change of task loads is more practical and this paper provides a methodology on the expression and calculation of complex loads from the dimension of frequency analysis. According to the expression of vibration energy spectrum, the effective parameters affecting the task load are vibration amplitude and vibration frequency. The larger the vibration amplitude, the greater the vibration energy under the task. The closer the vibration frequency is to the sensitive frequency of the precision index, the greater the vibration energy is. The degradation of precision index is accelerated by vibration energy. In engineering, the degradation of equipment precision can be delayed and the machining precision can be improved by controlling the load amplitude and keeping the load frequency far away from the sensitive frequency of the precision index.

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