Milling force coefficients-based tool wear monitoring for variable parameter milling

Tianhang Pan1 · Jun Zhang1 · Xing Zhang1 · Wanhua Zhao1 · Huijie Zhang1 · Bingheng Lu1

Received: 8 September 2021 / Accepted: 25 January 2022 / Published online: 18 March 2022
© The Author(s), under exclusive licence to Springer-Verlag London Ltd., part of Springer Nature 2022

Abstract
Tool wear is an important factor that affects the quality and machining accuracy of aeronautical structural parts in the milling process. It is essential to monitor the tool wear in titanium alloy machining. The traditional tool wear features such as root mean square (RMS), kurtosis, and wavelet packet energy spectrum are related to not only the tool wear status but also to the milling parameters, thus monitoring the tool wear status only under fixed milling parameters. This paper proposes a new method of online monitoring of tool wear using milling force coefficients. The instantaneous cutting force model is used to extract the milling force coefficients which are independent of milling parameters. The principal component analysis (PCA) algorithm is used to fuse the milling force coefficients. Furthermore, support vector machine (SVM) model is used to monitor tool wear states. Experiments with different machining parameters were conducted to verify the effectiveness of this method used for tool wear monitoring. The results show that compared to traditional features, the milling force coefficients are not dependent on the milling parameters, and using milling force coefficients can effectively monitor the transition point of cutters from normal wear to severe wear (tool failure).

Keywords Tool wear monitoring · Feature fusion · Milling force coefficients · c-SVM

1 Introduction

Due to the lack of manual intervention in an unattended machining system, the tool wear state cannot be judged in the milling process. [1, 2]. Therefore, tool wear monitoring plays an important role in ensuring the quality of the aeronautical structural parts and improving the processing efficiency [3, 4]. In order to maintain good performance of the cutters, components, and even the machine tools, changing the cutting tool frequently during the milling process must be done, which will affect the efficiency and machining cost [5]. On the other hand, if the severely worn tool is not changed immediately, the damage will be introduced to the part or even the machine tool. Therefore, it is essential to monitor tool wear during the machining process of the aeronautical structural parts.

Many direct and indirect methods have been developed to monitor tool wear. Visual and optical methods are the most direct. D’Addona et al. [6] stops machining after a fixed cutting time and uses a digital camera to photograph the tool wear area. Although this method can accurately judge the condition of tool wear, the measurement process needs to interrupt the machining process, which affects the machining efficiency. Elgargni et al. [7] uses infrared rays and cameras to track and locate the tool in the process of machining, and then judge the tool wear status (normal or damaged). However, because of the continuous contact between the tool and the workpiece and the harsh machining environment (cutting fluid and chip), this method cannot be applied during the actual machining process.

The indirect method compensates for the drawbacks of direct measurement, which is realized by sensor signals related to tool wear. The tool condition is estimated according to measurable signals, such as forces [8–11], acoustic emission (AE) [12–15], vibration [16–18], and motor current [19–21]. Farahnakian et al. [9] proposed a methodology to establish a relationship between cutting forces and tool flank wear during thermally enhanced turning of hardened steel AISI 4140. Kannatey-Asibu et al.
[13] successfully used the AE signal to monitor tool wear using the adaptive classifier learning model. Zhu et al. [22] points out that the AE signal is mostly used to determine tool breakage in the turning process, since the AE signal can reflect the impact characteristics when tool breakage occurs. However, since milling is intermittent, the continuous impact will affect the acoustic emission signal. Khajavi et al. [19] analyzed the influence on the motor content of feed rate, cutting depth, and other parameters on the motor current, and used the multilayer perceptron (MLP) neural network method to predict the tool wear in face milling. A series of experiments were carried out to verify the above method by Khajavi. However, Aslan and Altintas [23] points out that the milling force will affect the friction of the spindle system/feed system, and then affect the spindle/feed motor current. In order to avoid the single signal cannot accurately determine the tool state, multi-sensorial signals fusion method is used for tool state monitoring [24–33]. Caggiano [24] extracts the time/frequency domain features from the signal of AE, cutting forces, and acceleration then reduces the dimension of the features using the principal component analysis (PCA) method to monitor the tool wear in turning. Ghosh et al. [28] combined several machining zones signals, namely cutting forces, spindle vibration, spindle current, and sound to estimate the average flank wear of the main cutting edge. Although the method of multi-sensorial signals fusion makes up for the shortcoming of single signals, it needs to have a robust ability of generalization and non-linear fitting model such as the artificial intelligence model to feature fusion and tool wear monitoring. The artificial intelligence models achieved good results in these research projects, in the application of neural networks [19, 29, 30], support vector machines [31, 32], and Zhu and Liu [33]. However, the above referenced research focus on fixed milling parameters, and few scholars study the monitoring of tool wear under the condition of variable milling parameters.

The essential reason is that the traditional features are not only related to the tool wear but also sensitive to the milling parameters. Therefore, the traditional features are not feasible to monitor tool wear under variable milling parameters during the whole process. Once one of the milling parameters is changed, the artificial intelligence model needs to be re-trained using a large amount of training data to ensure model accuracy. In actual machining of the aeronautical structural parts, the milling parameters (feed rate, cutting width, etc.) will change frequently and the machining path is complex. Normally, samples are not enough to train the model. Therefore, it is essential to extract features independent of milling parameters and only related to tool status. Only Nouri et al. [34] extracted the radial and normal milling force coefficients to monitor the tool wear state using the statistical method.

In this paper, aiming at the disadvantage that the traditional feature is obviously affected by milling parameters, the milling force coefficients (including axial milling force coefficients) which are not sensitive to the milling parameters are extracted through the instantaneous milling force model. Then, the model of PCA is used to fuse the milling force coefficients, and the c-SVM model is used to establish the mapping relationship between the fused features and the actual state of the tool. Finally, experiments with different milling parameters are carried out to verify the proposed method for tool wear status monitoring. The results show that tool wear status can be monitored well during the process of machining without retraining the model under variable milling parameters.

### 2 Tool wear monitoring based on instantaneous milling force model

#### 2.1 The instantaneous milling force model in flank milling

According to the model of instantaneous rigid force [35], as shown in Fig. 1, the tangential, radial, and axial milling forces of the \( j \)th tooth on \( dz \) can be expressed as:

\[
\begin{align*}
\frac{\partial F_x}{\partial z} &= \left( K_{tc} \cdot h(\phi_j) + K_{te} \right) \cdot \frac{dz}{t} \\
\frac{\partial F_y}{\partial z} &= \left( K_{te} \cdot h(\phi_j) + K_{re} \right) \cdot \frac{dz}{t} \\
\frac{\partial F_z}{\partial z} &= \left( K_{ec} \cdot h(\phi_j) + K_{ea} \right) \cdot \frac{dz}{t}
\end{align*}
\]

(1)

where \( K_{tc}, K_{te}, K_{re}, K_{ec}, K_{ea} \) \((q = t, r, a)\) are the cutting and edge coefficients in the tangential, radial, and axial directions, respectively. \( h(\phi_j) \) is the chip thickness, given by

\[
h(\phi_j) = f_c \cdot \sin(\phi_j)
\]

(2)

where \( f_c \) is the feed per tooth, \( \phi_j = \omega \cdot t + (j-1) \phi_p \) is the angle of tooth engagement, \( \omega \) (rad/s) is the angular velocity of the spindle, and \( \phi_p = \pi / N \) is the inter tooth angle. \( N \) is the number of teeth on the cutting tool. By substituting Eq. (2) into Eq. (1), the instantaneous milling force in the coordinate of \( t, r, \) and \( a \) can be obtained by processing elemental forces of each layer along the \( z \)-axis of each tooth. Then the forces in the \( x, y, \) and \( z \) coordinate directions can be expressed as Eq. (3):

\[
\begin{bmatrix}
F_x(t) \\
F_y(t) \\
F_z(t)
\end{bmatrix} = \sum_{j=1}^{N} \int_{0}^{z} T \cdot \begin{bmatrix}
\frac{\partial F_x}{\partial z}(t) \\
\frac{\partial F_y}{\partial z}(t) \\
\frac{\partial F_z}{\partial z}(t)
\end{bmatrix}
\]

(3)
where $T = \begin{bmatrix} -\cos \phi_{jl} & -\sin \phi_{jl} & 0 \\ \sin \phi_{jl} & -\cos \phi_{jl} & 0 \\ 0 & 0 & 1 \end{bmatrix}$ is the transformation matrix.

### 2.2 Identification of milling force coefficients

According to the fast calibration method [36], the milling force coefficients can be calculated quickly and accurately. Assuming that the measured average milling force is equal to the nominal value of milling force, then the milling force coefficients can be expressed as:

$$F_x = \frac{N_{at}}{8 \pi} \left[ K_{ic} (\cos 2\phi_{ex} - \cos 2\phi_{et}) - K_{ic} (2\phi_{ex} - 2\phi_{et} - (\sin 2\phi_{ex} - \sin 2\phi_{et})) \right] +$$

$$\frac{N_{at}}{2 \pi} \left[ -K_{ic} (\sin 2\phi_{ex} - \sin 2\phi_{et}) + K_{ic} (\cos \phi_{ex} - \cos \phi_{et}) \right]$$

$$F_y = \frac{N_{at}}{8 \pi} \left[ K_{ic} (\cos 2\phi_{ex} - \cos 2\phi_{et}) + K_{ic} (2\phi_{ex} - 2\phi_{et} - (\sin 2\phi_{ex} - \sin 2\phi_{et})) \right] -$$

$$\frac{N_{at}}{2 \pi} \left[ K_{ic} (\sin 2\phi_{ex} - \sin 2\phi_{et}) + K_{ic} (\cos \phi_{ex} - \cos \phi_{et}) \right]$$

$$F_z = \frac{N_{at}}{2 \pi} \left[ K_{ic} (\phi_{ex} - \phi_{et}) - K_{ic} f_z (\cos \phi_{ex} - \cos \phi_{et}) \right]$$

where $F_x$, $F_y$, and $F_z$ are the average forces over a tooth period, $\phi_{et}$ is the axial cutting width, and $\phi_{et}$, $\phi_{ex}$ are the tooth angle of entrance and exit, respectively. When the machining type is down milling, $\phi_{et} = \pi - \arccos(1 - a_x / R)$, and $\phi_{ex} = \pi$, where $a_x$ is the radial cutting width and $R$ is the tool radius. The matrices of the average forces and force coefficients can be shown in Eq. (5):

$$\begin{bmatrix} F_{x1} \\ F_{y1} \\ F_{z1} \\ F_{x2} \\ F_{y2} \\ F_{z2} \\ \vdots \end{bmatrix} = \begin{bmatrix} A_{1x1} & A_{2x1} & A_{3x1} & A_{4x1} & 0 & 0 & 0 \\ A_{1y1} & A_{2y1} & A_{3y1} & A_{4y1} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & A_{5x1} & A_{6x1} & 0 \\ 0 & 0 & 0 & 0 & A_{5y1} & A_{6y1} & 0 \\ 0 & 0 & 0 & 0 & A_{5z1} & A_{6z1} & 0 \end{bmatrix} \begin{bmatrix} K_{ic} \\ K_{ic} \\ K_{ic} \\ K_{ic} \\ K_{ic} \\ K_{ic} \end{bmatrix}$$

Matrix $[A]$ is related to milling parameters, and its elements can be expressed as:

$$\begin{bmatrix} A_{ij} \end{bmatrix} = \begin{bmatrix} A_{1x1} & A_{2x1} & A_{3x1} & A_{4x1} & 0 & 0 & 0 \\ A_{1y1} & A_{2y1} & A_{3y1} & A_{4y1} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & A_{5x1} & A_{6x1} & 0 \\ 0 & 0 & 0 & 0 & A_{5y1} & A_{6y1} & 0 \\ 0 & 0 & 0 & 0 & A_{5z1} & A_{6z1} & 0 \end{bmatrix}$$

$$\begin{bmatrix} K_{ic} \\ K_{ic} \\ K_{ic} \\ K_{ic} \\ K_{ic} \\ K_{ic} \end{bmatrix}$$
Finally, least square estimation can be used in Eq. (5) to calculate the cutting force coefficients, as shown in Eq. (7):

$$\begin{align*}
A_{1i} &= \frac{N_{0,i}}{N_{0}} (\cos 2\phi_{ex} - \cos 2\phi_{st}) \\
A_{2i} &= \frac{N_{0,i}}{N_{0}} (\sin \phi_{st} - \sin \phi_{ex}) \\
A_{3i} &= \frac{1}{2\pi} (2\phi_{st} - 2\phi_{ex} + (\sin 2\phi_{ex} - \sin 2\phi_{st})) \\
A_{4i} &= \frac{N_{0,i}}{N_{0}} (\cos \phi_{ex} - \cos \phi_{st}) \\
A_{5i} &= \frac{1}{2\pi} (2\phi_{ex} - 2\phi_{st} - (\sin 2\phi_{ex} - \sin 2\phi_{st})) \\
A_{6i} &= \frac{N_{0,i}}{N_{0}} (\cos \phi_{ex} - \cos \phi_{st}) \\
A_{7i} &= \frac{N_{0,i}}{2\pi} (\cos \phi_{ex} - \phi_{st})
\end{align*}$$

(6)

$$\mathbf{K} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{F}$$

(7)

3 Verification of milling force coefficients by experiment

3.1 Experimental setup

A series of tests were conducted on a three-axis milling machine to verify the milling force coefficients during monitoring. The instantaneous milling forces were measured by a dynamometer (model: Kistler 9265B), as shown in Fig. 2a. The sampling frequency was set to 2 kHz. Titanium alloy (model: Ti-6Al-4 V) was chosen as the workpiece with dimensions of 180 mm \times 140 mm \times 90 mm, and two flutes cemented carbide cutter (the insert model: APMT1604, PVD coating; the tool holder model: HSK-A63-IMB) with a diameter of 50 mm was used, as shown in Fig. 1b. And material properties of the tool and workpiece are listed in Table 1.

A stereo microscope (model: RZSP-200C) with an accuracy of 0.01 mm was used to measure the area of wear on the tool flank (value VB) after a certain milling time, as shown in Fig. 2b. The experiment was stopped when one of the wear areas exceeded the preset value.

Table 1 Material properties of tool and workpiece

|                       | Workpiece                        | Tool insert                |
|-----------------------|----------------------------------|----------------------------|
| Composition           | 88.1% Ti, 0.3% Fe, 0.1% C, 0.05% N, 0.015% H, 0.20% O, 6.75% Al, 4.5% V | Cemented carbide (YG 813)  |
| Density (g/cm³)       | 4.51                             | 14.5                       |
| Thermal conductivity  | 7.96                             | 110                        |
| Specific heat (J/g/k) | 0.612                            | 0.95                       |
| Hardness (HRC)        | 30                               | 72                         |

Fig. 2 Experiment setup and tool wear measurement. a Experiment system. b Tool wear measurement

(a) Experiment system

(b) Tool wear measurement
the cutting edges’ maximum values of VB reached 0.5 mm, according to the ISO 8688–2 [37].

In the procedure of milling parameter setting, the parameter of $a_e$ and $f_z$ should be selected as small as possible to ensure the tool flank wear. Therefore, the change range of $f_z$ and $a_e$ parameters are 0.02 ~ 0.15 and 1 ~ 5 (not slotting), respectively. According to actual milling conditions and speed up the tool wear rate, the spindle speed sets 600 ~ 1500, and the parameters $a_p$ is setting 2 ~ 3 (convenient to measurement). Finally, the milling parameters used in the tests are listed in Table 2, and down milling was adopted without fluid in X direction. A total of 10 tests were designed, the first seven tests with fixed parameters, and the last three tests with variable milling parameters, as shown in Fig. 3.

When tool wear occurs, the contact between the flank face and the machined surface changes from one-dimensional (straight line) to two-dimensional (curved surface), especially in the machining of hard materials [38], which leads to the increase of milling forces. However, the tool wear area on the flank is typically irregular, as shown in Fig. 4. The value of VB was measured four times, and the mean value was calculated as follows:

$$VB = \frac{\sum_{i=1}^{N} VB_i}{N} \quad (N = 4) \quad (8)$$

where $VB_i$ is the measured value at equal intervals, as shown in Fig. 2b, and the wear areas on the tool flank is expressed as:

$$WearArea = VB \cdot a_p \quad (9)$$

Tool wear progression is illustrated in Fig. 5 according to the calculation in Eq. (9). The tool flank wear behaves differently in each milling test. The reason for this may be related to the varying milling parameters applied and random behavior of tool wear. It can be seen from Fig. 4 that in severe wear, the geometry of the tool changes, and there is slight chipping.

The ISO 8688–2 has defined the failure criteria for tool wear. However, in actual machining, the cutter transitions to the stage of severe wear before it reaches the failure criteria. In general, the tool needs to be replaced when it reaches the stage of severe wear, in order to prevent damage to the parts. Therefore, tool wear is divided into two states: normal wear (the initial wear is defined as the normal wear state) and severe wear (Fig. 5). The inflection point between the two states identifies the point of tool failure, at which point the tool needs to be replaced.

### 3.2 Calculation of milling force coefficients

The coefficients of the cutting force and the edge force can be obtained from Eqs. (5) to (7) by milling twice. Therefore, the sliding window method is used to calculate the coefficients [34]. Both the cutting force coefficients and edge force coefficients can reflect the tool wear, and are the best indexes for monitoring tool wear.

Figures 6, 7, 8 and 9 show the variable trends of the milling force coefficients with milling time. It seems that the change of cutting force coefficients ($Ktc$, $Krc$, $Kac$) changes stability, with only an upward trend in the state of severe wear. The cutting force coefficient is only related to the geometric dimensions of the tool. With progressive

---

![Image](image-url)
tool wear, the shape of the tool changes (edge, fillet, etc.), leading to variation of the cutting force coefficients. On the contrary, the edge force coefficients \((K_{te}, K_{re}, K_{ae})\) are related to tool wear, and their variations are caused by tool wear, which is not affected by milling parameters. The validity of six coefficients reflecting tool wear state is different. In addition, random factors in the milling process (vibration, chip entrapment, and so on), will affect the value of the coefficient. Moreover, the sensitivity of the coefficients in different directions is also different. Therefore, it is necessary to fuse the six coefficients to reflect the state of tool wear. And the fused features are not sensitive to the milling parameters and have a strong correlation with tool wear.

4 Tool wear monitoring using milling force coefficients

4.1 Tool wear feature fusion via PCA method

The number of features should be as large as possible in order to accurately describe the tool wear state. However, previous research has found that not all extracted features are useful [31]. Reducing features uncritically may cause the loss of a lot of information, resulting in wrong results because of the certain correlation among those features. Therefore, it is necessary to transform the original features into uncorrelated ones, and then fewer features can be used to represent the information.
The PCA algorithm maps features from dimensions $n$ to $k$ ($k < n$) by finding a set of orthonormal bases, which achieve the purpose of fusion. In order to find the orthogonal basis $\mathbf{u} = \{u_1, u_2, \ldots, u_k\}$, the variance of the fused sample features can be expressed as:

$$\frac{1}{m} \sum_{i=1}^{m} (\mathbf{x}^{(i)\top} \mathbf{u})^2 = \frac{1}{m} \sum_{i=1}^{m} \mathbf{u}^\top \mathbf{x}^{(i)} \mathbf{x}^{(i)\top} \mathbf{u}$$  (10)

where $m$ is the number of samples and $\mathbf{x}$ is the matrix of sample features, whose dimension is $n$. Denote...
\[
\sum_{i=1}^{m} \left( x^{(i)} \right)^2 = \lambda_i \sum_{i=1}^{m} x^{(i)} x^{(j)} \quad \text{as } \Lambda. \text{ Equation (10) can be rewritten as:}
\]

\[
\lambda = u^T \Lambda u
\]  

(11)

where \( \lambda \) is the eigenvalue of \( \Lambda \), and \( u \) is the eigenvector. Therefore, the best orthogonal basis is the eigenvector corresponding to the maximum eigenvalue. Eigenvalue decomposition of matrix \( \Lambda \) and the eigenvectors corresponding to the first \( k \) eigenvalues were selected. Therefore, the fused features can be expressed as:

\[
Y_{mok} = x_{mon} \cdot u_{ok}
\]  

(12)

Fig. 7 Variable trend of milling force coefficient with milling time in test 5

Fig. 8 Variable trend of milling force coefficient with milling time in test 8
The specific process is shown in Fig. 10. And the milling force coefficients are obtained from milling forces used through Eqs. (4) to (7).

In order to eliminate the influence of dimension, the 0-means method is used to normalize the milling force coefficients. The normalized results were used as input in the PCA algorithm to obtain the fused feature vector. The weight proportion of eigenvalue was set as > 95%. The fused features are shown in Fig. 11. The PCA method integrates six-dimensional tool wear features into two dimensions, the results of which can distinguish tool states distinctly. According to the performance of the fused features and the

![Fig. 9](image1.png) Variable trend of milling force coefficient with milling time in test 10

![Fig. 10](image2.png) Schematic diagram of features extraction and fusion of milling force coefficients
actual application requirements, the tool wear can be monitored by the SVM algorithm.

4.2 The monitoring of tool wear state via c-SVM method

Taking the fused feature of test 1 as an example, as shown in Fig. 12, a hyperplane is found in the fused feature sample space to separate different tool states, which can be shown as:

\[ y = \mathbf{w}^T \mathbf{x} + b = 0 \]  \hspace{1cm} (13)

where \( \mathbf{w} \) is the normal vector determining the direction of the hyperplane, and \( b \) is the displacement term expressing the distance between the hyperplane and the origin. The nearest training sample points to the hyperplane are called support vectors. The sum of the distances between the two heterogeneous support vectors and the hyperplane is called the margin, expressed as \( \gamma \). Therefore, the core of using a support vector machine to monitor the tool wear state is to find the optimal hyperplane; that is, to satisfy the parameters \( \mathbf{w} \) and \( b \) constrained in Eq. (13) to maximize the value of \( \gamma \).

Suppose the training data and its label are \( \{ \mathbf{x}(i), y(i) \} \) \( i = 1, 2, 3, \ldots, m \), \( y(i) \in \{0, 2\} \). The c-SVM of the L1 regular soft boundary can be expressed as:

\[
\begin{align*}
\min_{\mathbf{w}, b} & \frac{1}{2} \| \mathbf{w} \|^2 + C \sum_{i} \xi_i \\
\text{s.t.} & \quad y(i)(\mathbf{w}^T \mathbf{x}(i) + b) \geq 1 - \xi_i, \xi_i \geq 0
\end{align*}
\]  \hspace{1cm} (14)

Fig. 11 The fused features using PCA

Fig. 12 The diagram of tool wear monitoring using c-SVM
where $C$ is the regularization parameter and $\xi$ is the relaxation factor. According to the optimization theory [31], the dual problem is shown as follows:

$$\min \frac{1}{2} \sum_{j=1}^{m} \sum_{i=1}^{m} a_i a_j Q_{ij} - \sum_{i} a_i \quad \text{s.t.} \quad \sum_{i} y^{(i)} a_i = 0, \quad 0 \leq a_i \leq C$$ (15)

where $a_i$ is a Lagrange polynomial. $Q_{ij} = y^{(i)} y^{(j)} K(x^{(i)}, x^{(j)})$. $K$ is a kernel function. The quadratic programming (QP) problem in Eq. (15) is generally solved by sequential minimal optimization (SMO). The optimal solutions are $\{a_i^*, b^*\}$ where $i = 1, 2, 3...m$.

For a new sample $x^{(c)}$, the discriminant function is given by:

$$f(x^{(c)}) = \omega^T x^{(c)} + b^* = \sum_{j=1}^{m} a_j^* y^{(j)} K(x^{(c)}, x^{(j)}) + b^*$$

if $f(x^{(c)}) \geq 0$, then $y^{(c)} = 1$; if $f(x^{(c)}) < 0$, then $y^{(c)} = -1$ (16)

Therefore, ten groups of data set allocations are shown in Table 3 (277 samples in total), nine of which are used as a training set and one as a testing set in turn (cross-validation). The input of the c-SVM model is the fused features of milling force coefficients, and the output is the tool state (normal wear is 0, severe wear is 2). The model parameters $C = 10$, and scale = 1 (Gaussian kernel coefficient) are set. The modeled results are compared with the measured results, as shown in Fig. 13.

Figure 13 shows that the milling force coefficient can be used to monitor tool wear status, especially for variable milling parameters. The reason is that the milling force coefficient eliminates the influence of milling parameters and relates to the tool state directly. Besides, the alternating stress of the tool changes greatly with variable milling parameters, thus the tool wear ratio is fast. However, the error in test 5 is bigger because the milling force coefficient shows that the tool has transited the severe stage at 40 min or earlier as shown in Fig. 7. And Fig. 5 shows that the actual measured value of the wear area transitions to the severe stage at 45 min. The reason for this is that the vibration in the milling process has a great influence on the milling force, and the milling force coefficients cannot reflect the tool wear state well.

### 4.3 The comparison with traditional tool wear features

In general, the traditional tool wear features are divided into three types: time domain, frequency domain, and time–frequency domain. According to the literature [8, 28], RMS, kurtosis, and the wavelet packets energy spectrum can be extracted from the time and time–frequency domain respectively. Since the milling force can be resolved into three directions of $x$, $y$, and $z$, there are 30 features.

According to the method described in Sect. 4.1, the extracted features can be fused into three dimensions. Then, the fused features form the input of the c-SVM model in Sect. 4.2 (the model parameters are unchanged), and the results are shown in Fig. 14.

The general evaluation index is expressed as:

$$\text{accuracy} = \frac{T}{T + F}$$ (17)

where $T$ is the number of correctly monitoring samples, and $F$ is the number of incorrectly monitoring samples. Assuming that the results are all normal wear, the accuracy is 74% which is not suitable. Using a confusion matrix can solve the problem of data imbalance [39]. Table 3 lists a comparison of monitoring accuracy between traditional features and milling force coefficients. The larger the true positive rate (TPR) and the smaller the false positive rate (FPR), the more reasonable is the feature. For the convenience of comparison, the indicators can be expressed as follows:

$$\text{Index} = \frac{\text{TPR}}{\text{FPR}}$$ (18)

According to Eq. (18), the indexes are 2.15 and 2.75 by using traditional features and milling force coefficients, respectively. The results show that the accuracy of tool wear monitoring using milling force coefficients can be improved by nearly 30% compared with the existing traditional features.

In addition, Table 4 shows that under the fixed milling parameters, the monitoring accuracy of traditional features is higher than that of milling force coefficients. Because the traditional feature represents the tool wear from different dimensions (time domain, frequency domain, time–frequency domain); thus, the monitoring accuracy is higher. However, there are many differences in monitoring accuracy under variable parameters. Due to the traditional features are difficult to distinguish whether the forces change is caused by tool wear or the variable of milling parameters. As shown in Fig. 15, taking RMS as an example, the trend of the RMS data follows the milling forces, and cannot reflect the trend of tool wear (Fig. 15d–f) due to the influence of milling parameters. However, the milling force coefficients are not affected by milling parameters (Fig. 15g–i), which reflect the wear trend of the tool. Therefore, the milling force coefficient can be used to monitor the tool wear under variable milling parameters. In addition, as shown in Fig. 14, the traditional features are frequently misjudged under variable milling parameters, and cannot be used during the actual machining process.

| Tool states     | Number of samples | Labels |
|-----------------|-------------------|--------|
| Normal wear     | 205               | 0      |
| Severe wear     | 72                | 2      |

- **Table 3** Tool wear state classification

---

&copy; Springer
Fig. 13  The detection results of tool wear state
Fig. 14  The detection results of tool wear state using traditional features

| Test | Force coefficients | Traditional features |
|------|--------------------|----------------------|
|      | TPR | FPR  | TPR | FPR  |
| 1    | 1   | 0.4  | 1   | 0.2  |
| 2    | 1   | 0.4  | 1   | 0.4  |
| 3    | 1   | 0.5  | 1   | 0.17 |
| 4    | 1   | 0.67 | 1   | 0.56 |
| 5    | 1   | 0.69 | 1   | 0.63 |
| 6    | 1   | 0.29 | 1   | 0.29 |
| 7    | 0.97| 0.29 | 1   | 0   |
| 8    | 1   | 0.67 | 0.73| 0.67 |
| 9    | 1   | 0.67 | 0.67| 0.67 |
| 10   | 1   | 0.67 | 0.75| 0.67 |
| Average | 0.997 | 0.362 | 0.915 | 0.426 |

Table 4  Comparison of the accuracy between the proposed features and the general features (%)
A tool wear monitoring method based on feature extraction and fusion from milling forces is proposed. The transition point from normal wear to severe wear (tool failure) is used to judge whether the tool is invalid. A considerable number of milling experiments were conducted using a cemented carbide blade and a titanium alloy (TC4) workpiece under different milling parameters. The conclusions are as follows:

1. Compared with the traditional features present when using fixed milling parameters, the milling force coefficients calculated based on the instantaneous milling force model can well reflect the trend of tool wear under variable milling parameters.
2. Due to the differing influences of tool wear on cutting force coefficients and edge force coefficients, the feature fused by PCA can accurately reflect the tool wear state with fewer features.

3. The c-SVM algorithm was selected as the tool wear monitoring model, and the fused features of milling force coefficients were used as the input. The results show that the accuracy of tool wear monitoring can be improved by 30% compared with the traditional features used for tool wear monitoring, which has significant advantages in tool wear monitoring when using variable milling parameters.

The tool wear monitoring with variable milling parameters was investigated with implementation of an individual tool-workpiece (carbide-Ti6Al4V) system. More tests are needed using different tool types and workpiece materials to verify whether the performance of the proposed method is affected by them and provide more training data for the c-SVM model, leading to verify the versatility of the proposed method.

**Author contribution** Tianhang Pan: methodology, data curation, experiment, validation, formal analysis, writing—original draft, review and
ed; Jun Zhang: supervision, writing—review and editing; Xing Zhang: methodology, formal analysis, writing—review and editing; Wanhua Zhao: methodology, supervision, data curation, formal analysis; Huijie Zhang: experiment; Bingheng Lu: project administration.

Funding This work was financially supported by the National Key R&D Program of China (No. 2018YFB1701901) for Jun Zhang, the Key-Area R&D Program of Guangdong Province (No. 2020B090927002) for Huijie Zhang, the National Key R&D Program of China (No. 2018YFB1701901), the Major Science and Technology Project of Shaanxi Province (No. 2019dzx01-01-02), and the China Postdoctoral Science Foundation (No. BX20180253, 219,945) for Xing Zhang.

Availability of data and materials All data generated or analyzed during this study are included in this article.

Declarations

Consent to publish The authors consent that the work entitled as “Milling force coefficients-based tool wear monitoring for variable parameters milling” for possible publication in International Journal of Advanced Manufacturing Technology. The authors claim that the research in this paper is the authors’ original work and has not been published nor has it been submitted simultaneously elsewhere.

Conflict of interest The authors declare no competing interests.

References

1. Duro JA, Padget JA, Bowen CR, Kim HA, Nassehi A (2016) Multi-sensor data fusion framework for cnc machining monitoring. Mech Syst Signal Process 66–67:505–520. https://doi.org/10.1016/j.ymssp.2015.04.019
2. Tobon-Mejia DA, Medjaher K, Zerhouni N (2012) CNC machine tool’s wear diagnostic and prognostic by using dynamic Bayesian networks. Mech Syst Signal Process 28:4–167–182. https://doi.org/10.1016/j.ymssp.2011.10.018
3. Elhami S, Razfar MR, Farahnakian M (2016) Experimental study of surface roughness and tool flank wear during hybrid milling. Mater Manuf Process 31:933–940. https://doi.org/10.1080/10426914.2015.1048474
4. Mohanraj T, Shankar S, Rajasekaran S, Sakhivel NR, Pramanik A (2020) Tool condition monitoring techniques in milling process—a review. J Market Res 9(1):1032–1042. https://doi.org/10.1016/j.jmrt.2019.10.031
5. Yong H, Liang SY (2004) Modeling of CBN tool flank wear progression in finish hard turning. J Manuf Sci Eng 126:98–106. https://doi.org/10.1115/1.1644543
6. D’Addona AMM, Ulah AMMS, Matarazzo D (2017) Tool-wear prediction and pattern-recognition using artificial neural network and DNA-based computing. J Intell Manuf 28:1285–1301. https://doi.org/10.1007/s10845-015-1158-0
7. Elgarou A, Al-Habbaeh A, Lotfi A (2015) Cutting tool tracking and recognition based on infrared and visual imaging systems using principal component analysis (PCA) and discrete wavelet transform (DWT) combined with neural networks. Int J Adv Manuf Technol 77:1965–1978. https://doi.org/10.1007/s00170-014-6576-y
8. Amzi AI (2015) Monitoring of tool wear using measured machining forces and neuro-fuzzy modeling approaches during machining of GFRP composites. Adv Eng Softw 82:53–64. https://doi.org/10.1016/j.advengsoft.2014.12.010
9. Farahnakian M, Elhami S, Daneshpajooh H, Razfar MR (2017) Mechanistic modeling of cutting forces and tool flank wear in the thermally enhanced turning of hardened steel. Int J Adv Manuf Technol 88:2969–2983. https://doi.org/10.1007/s00170-016-9004-7
10. Huang SN, Tan KK, Wong YS, Silva C, Goh HL, Tan W (2007) Tool wear detection and fault diagnosis based on cutting force monitoring. Int J Mach Tools Manuf 47:444–451. https://doi.org/10.1016/j.ijmachtools.2006.06.011
11. Anicic O, Jovic S, Stanoejive N, Marsenic M, Pejovic B, Nedic B (2018) Estimation of tool wear according to cutting forces during machining procedure. Sens Rev 38(2):176–180. https://doi.org/10.1016/SR-07-2017-0147
12. Lee DE, Hwang I, Valente CMO, Oliveira JFG, Dornfeld DA (2006) Precision manufacturing process monitoring with acoustic emission. Int J Mach Tools Manuf 46:176–188. https://doi.org/10.1016/j.ijmachtools.2005.04.001
13. Kannatey-Asibu E, Yum J, Kim TH (2017) Monitoring tool wear using classifier fusion. Mech Syst Signal Process 85:651–661. https://doi.org/10.1016/j.ymssp.2016.08.035
14. Bhuiyan MSH, Choudhury IA, Dahari M, Nukan Y, Dawal SZ (2016) Application of acoustic emission sensor to investigate the frequency of tool wear and plastic deformation in tool condition monitoring. Measurement 92:208–217. https://doi.org/10.1016/j.measurement.2016.06.006
15. Pechenin V, Khaimovich A, Kondratiev A, Bolotov M (2017) Method of controlling cutting tool wear based on signal analysis of acoustic emission for milling. Procedia Eng 176:246–252. https://doi.org/10.1016/j.proeng.2017.02.294
16. Brili N, Ficko M, Klannik S (2021) Automatic identification of tool wear based on thermography and a convolutional neural network during the turning process. Sensors 21:1917. https://doi.org/10.3390/s21051917
17. Wang GF, Yang YW, Zhang YC, Xie QL (2014) Vibration sensor based tool condition monitoring using y support vector machine and locality preserving projection. Sens Actuators A 209:24–32. https://doi.org/10.1016/j.sna.2014.01.004
18. Ratava J, Lohtander M, Vairis J (2017) Tool condition monitoring in interrupted cutting with acceleration sensors. Robot Comput Integr Manuf 47:70–75. https://doi.org/10.1016/j.rcim.2016.11.008
19. Khajavi MN, Nasernia E, Rostaghi M (2016) Milling tool wear diagnosis by feed motor current signal using an artificial neural network. J Mech Sci Technol 30(11):4869–4875. https://doi.org/10.1007/s12206-016-1005-9
20. Koike R, Ohnishi K, Aoyama T (2016) A sensorless approach for tool fracture detection in milling by integrating multi-axial servo information. CIRP Ann Manuf Technol 65:385–388. https://doi.org/10.1016/j.cirp.2016.04.101
21. Silva LRRD, Franca PHP, Andrade CLF, Silva RBD, Guesser WL, Machado AR (2021) Monitoring tool wear and surface roughness in the face milling process of high-strength compacted graphite cast irons. J Braz Soc Mech Sci Eng 43:180. https://doi.org/10.1007/s40430-021-02897-7
22. Zhu KP, Mei T, Ye DS (2016) Online condition monitoring in micro milling: a force waveform shape analysis approach. IEEE Trans Ind Electron 62(6):3806–3813. https://doi.org/10.1109/TIE.2015.2392713
23. Aslan D, Altintas Y (2018) Prediction of Cutting Forces in Five-Axis Milling Using Feed Drive Current Measurements. IEEE/ASME Trans Mechatron 23(2):833–844. https://doi.org/10.1109/TMECH.2018.2804859
24. Caggiano A (2018) Tool wear prediction in Ti-6Al-4V machining through multiple sensor monitoring and PCA features pattern recognition. Sensors 18:823. https://doi.org/10.3390/s18030823
25. Kong DD, Chen YJ, Li N (2018) Gaussian process regression for tool wear prediction. Mech Syst Signal Process 104:556–574. https://doi.org/10.1016/j.ymssp.2017.11.021
26. Zhou YQ, Sun BT, Sun WF (2020) A tool condition monitoring method based on two-layer angle kernel extreme learning machine and binary differential evolution for milling. Measurement 166:180–186. https://doi.org/10.1016/j.measurement.2020.108186
27. Liu T, Zhu KP, Wang G (2020) Micro-milling tool wear monitoring under variable cutting parameters and runout using fast cutting force coefficient identification method. Int J Adv Manuf Technol 111:3175–3188. https://doi.org/10.1007/s00170-020-06272-z
28. Ghosh N, Ravi YB, Patra A, Mukhopadhyay S, Paul S, Mohanty AR, Chattopadhyay AB (2007) Estimation of tool wear during CNC milling using neural network-based sensor fusion. Mech Syst Signal Process 21:466–479. https://doi.org/10.1016/j.ymssp.2005.10.010
29. Xu XW, Tao ZR, Ming WW, An QL, Chen M (2020) Intelligent monitoring and diagnostics using a novel integrated model based on deep learning and multi-sensor feature fusion. Measurement 165:108086. https://doi.org/10.1016/j.measurement.2020.108086
30. Yao YX, Li XL, Yuan ZJ (1999) Tool wear detection with fuzzy classification and wavelet fuzzy neural network. Int J Mach Tools Manuf 39(10):1525–1538. https://doi.org/10.1016/S0890-6955(99)00018-8
31. Xu GD, Zhou HC, Chen JH (2018) CNC internal data based incremental cost-sensitive support vector machine method for tool breakage monitoring in end milling. Eng Appl Artif Intell 74:90–103. https://doi.org/10.1016/j.engappai.2018.05.007
32. Wang JJ, Xie JY, Zhao R, Zhang LB, Duan LX (2016) Multi-sensory fusion based virtual tool wear sensing for ubiquitous manufacturing. Robot Comput Integr Manuf 45(C):47–58. https://doi.org/10.1016/j.rcim.2016.05.010
33. Zhu KP, Liu TS (2018) On-line tool wear monitoring via hidden semi-Markov model with dependent durations. IEEE Trans Industr Inf 14–1:69–78. https://doi.org/10.1109/TII.2017.2723943
34. Nouri M, Fussell BK, Zimiti BL, Linder E (2015) Real-time tool wear monitoring in milling using a cutting condition independent method. Int J Mach Tools Manuf 89:1–13. https://doi.org/10.1016/j.ijmachtools.2014.10.011
35. Engin S, Altintas Y (2001) Mechanics and dynamics of general milling cutters. Part I: helical end mills. Int J Mach Tools Manuf 41:2195–2212. https://doi.org/10.1016/S0890-6955(01)00045-1
36. Budak E, Altintas Y, Armarego ELJ (1996) Prediction of milling force coefficients from orthogonal cutting data. J Manuf Sci Eng 118:216–224. https://doi.org/10.1115/1.2831014
37. ISO 8688–2 (1989) Tool life testing in milling - part 2: end milling. International Standards Institution, Switzerland
38. Farahnakian M, Keshavarz ME, Elhami S, Razfar MR (2016) Effect of cutting edge modification on the tool flank wear in ultrasonically assisted turning of hardened steel. Proc Inst Mech Eng Part B J Eng Manuf 233:1–12. https://doi.org/10.1177/0954405416640416
39. Sun YM, Wong AKC, Kamel MS (2016) Classification of imbalanced data: a review. Int J Pattern Recognit 23:687–719. https://doi.org/10.1142/s0218001409007326

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.