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Cutting tool operational reliability prediction based on acoustic emission and logistic regression model

Hongkun Li · Yinhu Wang · Pengshi Zhao · Xiaowen Zhang · Peilin Zhou

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Abstract Working status of cutting tools (CTs) is crucial to the products' precision. If broken down, it may lead to waste product. Condition monitoring and life prediction are beneficial to the manufacturing process. In this research, Logistic regression models (LRMs) and acoustic emission (AE) signal are used to evaluate reliability. Based on different conditions estimation, CTs are investigated to determine the best maintenance time. Based on experimental data analysis, AE and cutting force signals have better linear relationship with CT wearing process. They can be used to demonstrate CT degradation process. Frequency band energy is determined as characteristic vector for AE signal using wavelet packet decomposition. Two reliability estimation models are constructed based on cutting force and AE signals. One uses both signals, while the other uses only AE signal. The reliability degree can be estimated using the two models, independently. AE feature extraction and LRM can effectively estimate CT conditions. As it is difficult to monitor cutting force in a practical working condition, it is an effective method for CT reliability analysis by the combination of AE and LRM method. Experimental investigation is used to verify the effectiveness of this method.

Keywords Cutting tool · Acoustic emission · Logistic regression model · Wavelet analysis · Reliability

H. Li (✉) · Y. Wang · P. Zhao · X. Zhang
School of Mechanical Engineering, Dalian University of Technology, Dalian 116024, Liaoning, People's Republic of China
e-mail: lihk@dlut.edu.cn

P. Zhou
Department of Naval Architecture, Ocean and Marine Engineering, University of Strathclyde, Glasgow G4 0LZ, UK

Introduction

Equipment performance degradation assessment and remaining useful life (RUL) prediction are of importance in condition-based maintenance to lower cost, improve reliability, and reduce maintenance cost. Thus, it becomes an important research area for machine fault diagnosis and prognostic analysis (Heng et al. 2009; Jardine et al. 2006). Cutting tools (CTs) are an important equipment during machining (Kious et al. 2010), which has close relationship with precision of products. Its reliability influences the total manufacturing effectiveness and stability of machine tools. CTs have been broadly applied on manufacturing area, such as impeller production shown as Fig. 1, diesel engine cylinder head production, and so on. In the most circumstance, degradation is the main failure for CT. It will lead to the waste product if CT is failure for blade production. As well, CT condition is closely related to machine's efficiency and productivity. Therefore, CT condition reliability analysis is important. As well, how to predict a CT's RUL is also beneficial as it is helpful for predictive maintenance.

As an important concern during production, reliability analysis has been investigated by many researchers (Ding et al. 2009). Traditional reliability estimation method is based on the statistic analysis from huge amount of experiments (Zio 2009). Among them, statistic distribution models have been used in this area, such as normal distribution and Weibull distribution. This kind of method depends on plentiful historical data from related equipments. It has good performance if the monitored data are sufficient in their amount for analysis. Small samples are not suitable to reliability analysis for now. As well, the defect of above models are also typical as they are less of monitored data and not suitable to single CT reliability estimation. Therefore, further investigation should be carried on for small samples

Fig. 1 Milling impeller in five-axis machining center

analysis. The key information of CT prediction can be determined from monitored data. Logistic regression model (LRM) is a nonlinear statistic method. It was initially applied on population estimation and prediction. It also applied on risk analysis for medicine (Bender and Kuss 2010), bank (Martin 1977), and so on. In recent years, researchers apply LRM on machine reliability estimation and life prediction (Yan et al. 2004; Yan and Lee 2005; Caesarendra et al. 2010). Yan Yan et al. (2004); Yan and Lee (2005) constructed degradation model based on characteristic vector. As well, the probability distribution is constructed by using LRM. Yan et al. Yan et al. (2004) combined the LRM and ARMA models for machine performance assessment and estimate RUL estimation. Yan et al. Yan and Lee (2005) also presented a prognostic method for on-line performance degradation assessment and root cause classification using multiple logistic regressions. Caesarendra et al. Caesarendra et al. (2010) combined the LRM and relevance vector machine for machine performance degradation assessment and failure time prediction based on simulation and experimental data. Chen et al. Chen et al. (2011b) constructed CT LRM by vibration characteristic vector. This method can also be used on machine tools failure estimation and reliability analysis. CT history data are used to constructed LRM in this paper. It is also suitable to CT reliability analysis. In this research, a new method for CT operational condition classification estimation is developed by combining LRM and acoustic emission (AE) signal analysis. Wavelet packet feature extraction for AE signal is used to determine the related parameter for reliability analysis as well as LRM is used for estimation model construction. A CT's working or operational condition estimation is carried out to verify the effectiveness of this method. The results show that this method can benefit to the CT operational condition estimation. This paper is structured as follows. "Theory and method" section introduces theory of this method. "Experiment" section presents CT failure experiment. "Reliability evaluation" section provides the data analysis by using this method. Concluding remarks are given in "Conclusion" section.

Theory and method

Characteristic parameters

Condition monitoring is of vital importance in order to estimate the tool wear.Cutting force is used on condition estimation (Huang et al. 2007; Sharma and Sharma 2007; Jemielniak and Kwiatkowski 1998) as it is directly related to wearing process. Some researchers pay more attention on vibration signal to estimate CT conditions (D. E. Dimla S, 2002; Alonso and Salgado 2008). Our research aims to retrieve sufficient monitoring information of CT wear condition. It benefits cost reduction, implementation feasibility, and so on. The precision of wearing capacity obtained through directly measuring CT is high but affects the production. It is also not easy to implement the on-the-fly measurement of wearing capacity of CT in the actual production. Therefore, the research on indirect measuring method is necessary, and the performance degradation of CT wear is analyzed by measuring its relationship for milling force, vibration signal, AE signal, etc. To determine the best information for CT condition analysis, investigation is conducted to obtain the related parameters for condition analysis. Milling experimental data (Mill Data Set 2007) come from BEST laboratory at the University of California, Berkeley. In the cutting process, we record data like CT wearing capacity V_B, motor current, AE signal, and vibration signal. The motor speed is: 826r/min. The milling experiment refers to three variables, i.e. cutting depth, feed rate, and cutting materials in eight different working conditions. Correlation analysis is investigated to observe whether there is some kind of interdependence relationship between any two phenomena so as to explore the direction and degree of correlation with the phenomenon of dependency relationship, if any. Statistical method is used to study the correlation between random variables. The calculation formula for correlation coefficient of two variables, i.e., x and y, is shown as Eq. (1).

$$\rho(x, y) = \frac{\Sigma(x-\overline{x})(y-\overline{y})}{\sqrt{\Sigma(x-\overline{x})^2}\sqrt{\Sigma(y-\overline{y})^2}} \tag{1}$$

Larger $\rho(x, y)$ implies closer correlation between x and y. Table 1 provides cutting parameters under four working conditions. Through separately calculating the correlation coefficient for effective values of AE signal, effective value of vibration signal and wearing capacity under different working conditions, the results are shown in Tables 2 and 3. It can be concluded that the characteristics of AE signal have better relationship with the average wearing capacity no matter the testing position is on the workbench or principle axis. It

Table 1 Cutting parameters under different working conditions

Conditions	Cutting depth (mm)	Feed speed (mm/r)	Material
1	1.5	0.25	Cast iron
2	1.5	0.5	J45 stainless steel
3	0.75	0.5	Cast iron
4	0.75	0.25	J45 stainless steel

Table 2 Correlation coefficients for AE with tool wear

Conditions	RMS of workbench	RMS of principal axis
1	0.9385	0.9030
2	0.8739	0.8919
3	0.7105	0.7688
4	0.8591	0.9393

Table 3 Correlation coefficients for vibration with tool wear

Conditions	RMS of workbench	RMS of principal axis
1	−0.5685	−0.7779
2	−0.8815	−0.0923
3	−0.8210	−0.7759
4	−0.8370	0.8363

is also in a positive correlation with the average correlation coefficient of 0.8606 according to Table 2. It is much better compared with vibration signal as there is any clear relationship to CT wearing. Vibration signal has low frequency compared with AE signal. Because the wearing condition for the cutting tool is with high frequency, AE can effectively show the wearing characteristics and is more convenient for condition monitoring. The positive and negative correlations between vibration characteristics and wearing capacity are different as the developing trend is on the contrary. However, the numerical difference is larger. Based on the results, it can be proposed that, as for the method to monitor the performance degradation of CT in the milling process, the effect of AE signal is better than that of vibration signal. Moreover, the consistent and high correlation shows the stability of AE signal monitoring method. Thus, AE signal is used as an indicator to evaluate the reliability of CT.

Wavelet packet energy

Nowadays, wavelet transformation has been intensively investigated and applied on signal processing, especially on vibration signal feature extraction (Peng and Chu 2004; Liu 2005; Zhu et al. 2009). It can effectively filter noise and preserve signal feature. Different frequency bands can be determined for low frequency by different scales. Further analysis can be used for the decomposed signals. But it doesn't preserve high resolution for high frequency signal analysis. Wavelet packet is developed from wavelet, which has good performance on both high and low frequency analysis. By setting finite signal scale-space U_0^0, it can be decomposed into multi-space through wavelet transformation by binary system. Its iterative process can be expressed by Eq. (2),

$$U_{j+1}^k = U_j^{2k} \oplus U_k^{2k+1},\ j \in Z, k \in Z^+ \tag{2}$$

where, $j\,(j \geq 0)$ is the level for decomposition, $\oplus$ is the orthogonal decomposition, Z denotes the domain of integers, and Z^+ denotes the domain of positive integers. U_{j+1}^k ,U_j^{2k}, and U_k^{2k+1} are three parameters corresponding to $\psi_n(t)$, $\psi_{2n}(t)$, and $\psi_{2n+1}(t)$. $\psi_n(t)$ is expressed by Eqs. (3) and (4).

$$\psi_{2n}(t) = \sqrt{2}\sum_{k\in Z} h(k)\psi_n(2t-k) \tag{3}$$

$$\psi_{2n+1}(t) = \sqrt{2}\sum_{k\in Z} g(k)\psi_n(2t-k) \tag{4}$$

When $n = 0$, $\psi_0(t)$ and $\psi_1(t)$ correspond to mother wavelet functions. In the meanwhile, $h(k)$ and $g(k)$ correspond to quadrature mirror filters associated with the scaling function and the mother wavelet function $\phi(t)$, respectively. With sub-signal at U_j^{n-1}, the nth subspace of jth level can be reconstructed by a linear combination of wavelet packet function $\psi_k^{j,n}(t)$ reconstructed shown as Eq. (5),

$$s_j^n(t) = \sum_{k\in Z} D_k^{j,n}\psi_k^{j,n}(t) k \in Z \tag{5}$$

where, $D_k^{j,n}$ is wavelet packet coefficient and can be determined by Eq. (6).

$$D_k^{j,n} = \int_{-\infty}^{+\infty} f(t)\psi_k^{j,n}(t)dt \tag{6}$$

The frequency band of energy sub-signal $s_j^n(t)$ can be calculated.

$$E_n = \sum_k |D_k^{j,n}|^2 \tag{7}$$

The normalization energy is shown as Eq. (8).

$$E = E_n \Big/ \sum_n E_n \tag{8}$$

Logistic regressive model (LRM)

Neural networks have been used on reliability analysis for CT (Xiaoyu and Wen 2008; Venkatesh and Mengchu 1997; Sukhomay and Heyns 2009). Fuzzy clustering is also further investigated on condition estimation (Wang and Wlofhard

1996). Compared with neural networks, LRM is more convenient for analysis. It is a nonlinear regressive mode and usually used on two-variables condition and to find the best suitable fitting model to describe two-characteristic relationships (Peng et al. 2002). Chen provides more introduction about this method (Chen et al. 2011a). It is useful for this method to be applied on practical CT analysis. Given that the feature vector of tool degradation is $X(t) = [x_1(t), x_2(t), \ldots x_n(t)]$ as an independent variable, each element of $X(t)$ represents a characteristic index of tool degradation. It corresponds to a covariance for input vector and can be the characteristic vectors determined by feature extraction. In an LRM, the output dependence variable is the probability of event. Tool conditions $y_1, y_2, \ldots y_n$ are valued at binary classified variables i.e.,0 or 1, the subscript represents testing time, and y represents a dependence variable of the LRM. Therefore, the output is a discrete time series. The reliability estimation model can be written as Eq. (9).

$$R(t) = P(y_t = 1|X(t)) = \frac{exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}{1 + exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)} \tag{9}$$

where, $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots \beta_n)$ is the model parameter vector and $\beta_0 > 0$ The output $R(t)$ is the degree of reliability for machine reliability with time variable t. When a machine works in a normal condition, the result will be 1 for Eq. (9). The occurrence ratio can be defined as Eq. (10).

$$Odds(P) = \frac{P(y_t = 1|X(t))}{1 - P(y_t = 1|X(t))} = exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n) \tag{10}$$

$\log it(y)$ is the log transform for occur ratio $Odds(P)$. It can be determined by Eq. (11).

$$\log it(y) = \ln \frac{P(y_t = 1|X(t))}{1 - P(y_t = 1|X(t))} = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n = \boldsymbol{\beta} X_t \tag{11}$$

The estimated value of the parameters $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots \beta_n)$ can be estimated by the maximum likelihood estimation (MLE) function, and the numerical calculation is required in its solving process. Therefore, LRM can be constructed for reliability analysis.

$$\ln[L(\beta)] = \sum_t y_t(\beta X(t)) - \ln[1 + exp(\beta X(t))] \tag{12}$$

The model coefficients $\beta_0, \beta_1, \ldots, and \beta_m$ reflect the changes of advantage ratio. $\beta_i > 0$, the occurrence ratio increases with the increase of independent variables i.e., characteristic index, and vice versa. $\beta_i = 0$ means that independent variables have no effect in this model, same as 0. Based on the parameter estimation, the reliability can be obtained by Eq. (13). At the same time, the 0.95 confidence interval

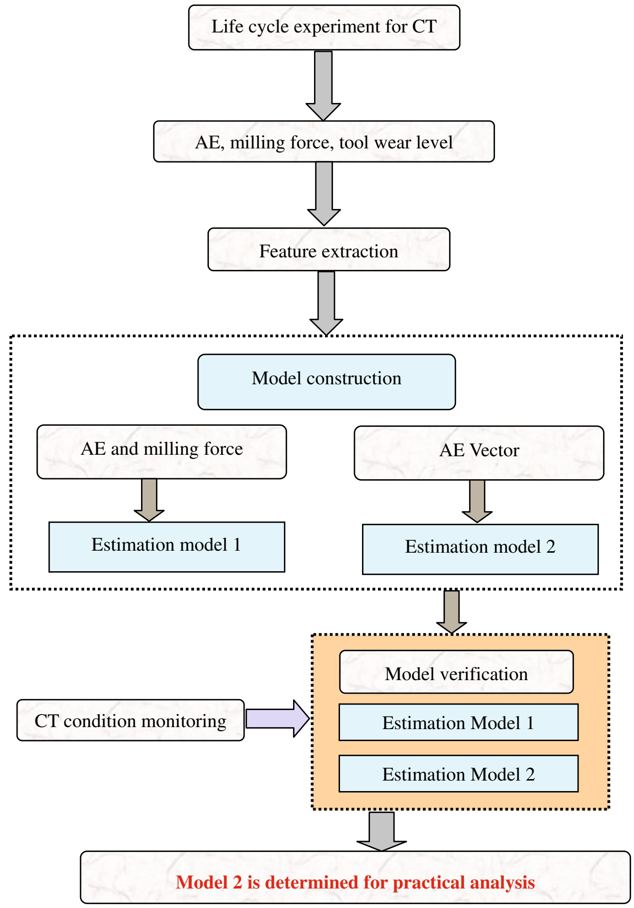

Fig. 2 Flow chart of CT reliability evaluation

can also be calculated as Eq. (14). $var(\widehat{\beta} X(t))$ is the variance of model parameters. Therefore, it can be further used for operational reliability analysis (Zhu et al. 2009).

$$R(t) = P(y_t = 1|X(t)) = \frac{exp(\widehat{\beta} X(t))}{1 + exp(\widehat{\beta} X(t))} \tag{13}$$

$$\left[\frac{exp(\widehat{\beta} X(t) - 1.96\sqrt{var(\widehat{\beta} X(t))})}{1 + exp(\widehat{\beta} X(t) - 1.96\sqrt{var(\widehat{\beta} X(t))})}, \frac{exp(\widehat{\beta} X(t) + 1.96\sqrt{var(\widehat{\beta} X(t))})}{1 + exp(\widehat{\beta} X(t) + 1.96\sqrt{var(\widehat{\beta} X(t))})}\right] \tag{14}$$

Flow chart for implementation method

In this paper, the AE characteristics and the LRM are applied to the reliability evaluation of CT, and its method process is shown in Fig. 2. There are mainly two parts,i.e., modeling and model verification. The first step is a CT experiment, where the milling parameters are selected to make a tool life-cycle test. AE and milling force signals are collected in the milling process to evaluate the wearing capacity of CT. The second step is feature extraction and modeling, i.e., AE and milling force signals are analyzed based on feature extraction. Wavelet packet energy of cutting force and AE signals with different frequency bands are selected as the input variables for regression model. Combined with CT condition, the model parameters can be estimated and Model 1 can be constructed. After correlation analysis, it is concluded that cutting force and AE characteristics have larger correlation, and the wavelet packet energy of AE signals with different frequency bands are selected as the input variables to establish Model 2. In the end, model test and contrast are executed. An example for CT analysis is investigated in this research to verify the effectiveness of the method.

Experiment

Milling test

The milling experiment has been made on Dongyu Machine and Tool CMV-850A machining center. The materials are FV520B. APOLL550 portable industrial personal computer and PAC AEwin data acquisition software are used for the data acquisition of AE signals. The dynamometer is YDX 97-type three-dimensional milling force test platform from the School of Mechanical Engineering, Dalian University of Technology. The acquisition and installation of cutting forces are shown in Fig. 3. Schematic diagram for the experiment is shown in Fig. 4. In the experiment, tool life-cycle experiments are made for 4 milling cutters by inspecting the wearing capacity of CT. When the wearing capacity of flank surface $V_B > 0.6mm$, it is deemed as tool failure. In order to reduce the influence of other factors on the AE signals, the same cutting parameters are selected in the experiments of four CTs. Rotating speed is 1000r/min, cutting depth is 0.4 mm, and feed rate is 400 mm/min. Figure 5 provides different milling cutters among which one is in normal condition while the other is in failure condition.

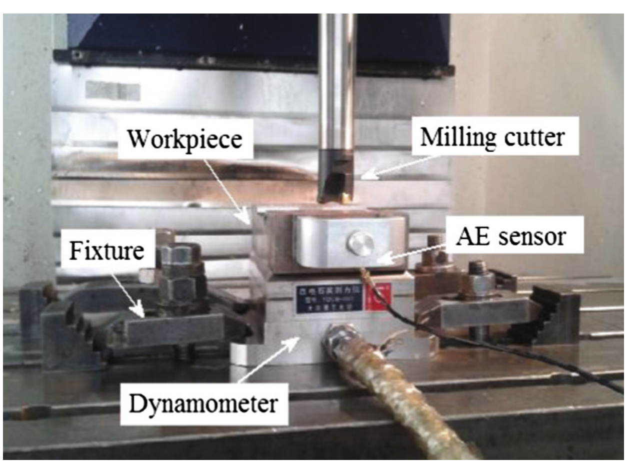

Fig. 3 The installation of dynamometer

Figures 6 and 7 show time and frequency domain analysis for cutting force under different working conditions. Figure 6 is the cutting force for normal condition and Fig. 7 is cutting force in the failure condition. It is obvious that cutting force increases with wearing stage as the CT is not sharp. It will increase force for cutting process. At the same time, its high frequency band energy also increases with wearing stage because the wearing process will lead to disperse of energy distribution. Energy will move to high frequency as for the wearing condition. Therefore, it can be used as an effective parameter for CT condition analysis. Figures 8 and 9 show time and frequency domain analysis for the AE signals. Figure 8 shows time-domain signal and frequency spectrum of AE signals at the initial stage of tool cutting, where a CT is in a good condition. Figure 9 shows a CT is seriously worn. During wearing condition, milling force increases if CT is not sharp. It leads to much energy increment during milling process. Therefore, AE energy will also increase with the wearing condition. It can also be seen from the frequency spectrum that the energy is widely distributed at the early stage of tool cutting with less amplitude, while the energy concentrates in low-frequency band at the late stage with more amplitude.

Reliability evaluation

Feature extraction

Regardless of the emergency, tool wearing should be a degradation process, similar to the wear process of most of mechanical parts, and is an irreversible process. The actual degradation process of CT should be a monotonous process, difficult to be obtained in the actual production. The CT degradation process can be observed only through indirect methods. According to the method in "Characteristic parameters" section, AE signals are processed. Due to high frequency of AE signal, the decomposition layer is selected as 6, so that the original signal is decomposed into 64 frequency bands. The normalized wavelet energy spectrum of 64 frequency bands is extracted. Figure 10 shows the contrast of normalized wavelet energy spectrum of the first 20 frequency bands in the severe wear at the initial stage and late stage of a milling test. It can be seen that the numerical values are very small and have obvious change after frequency band 13. Frequency bands 1 and 2 have larger energy, no matter at the initial stage of wear or at the stage of severe wear condition. Frequency band 2 is always the one having the maximum energy. In addition, it can be seen that frequency band 7 has higher energy spectrum value than those of other frequency bands with lower energy at the initial stage of wear and tear.

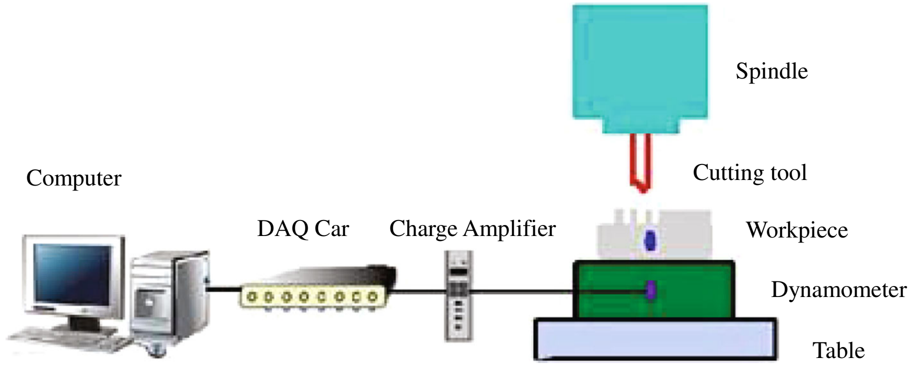

Fig. 4 Schematic diagram for the experiment

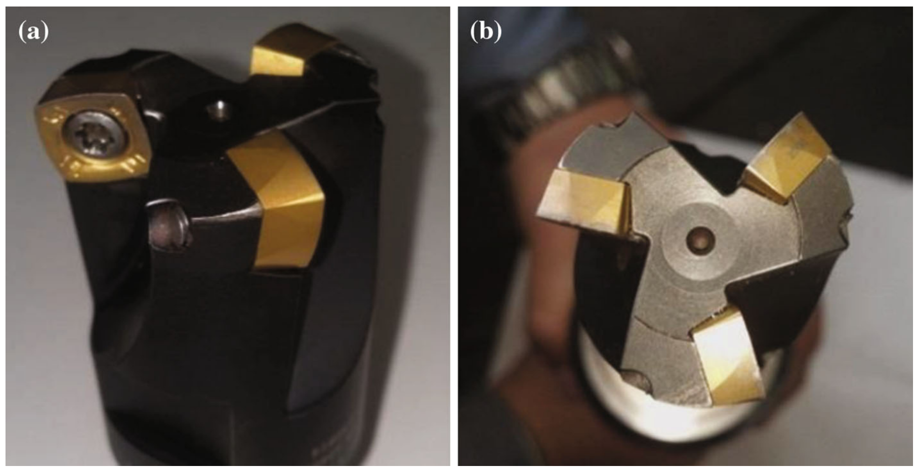

Fig. 5 CT in different conditions **a** normal condition and **b** failure condition

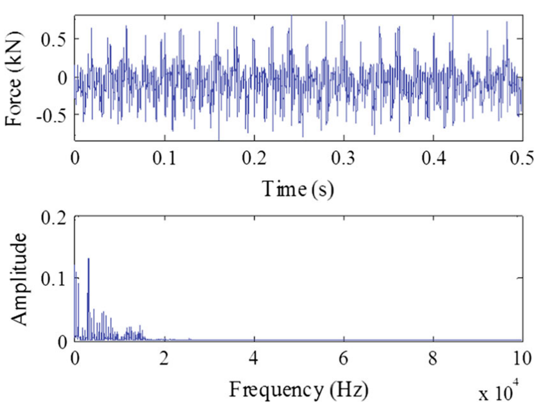

Fig. 6 Time and frequency spectrum of the milling force signal under normal condition

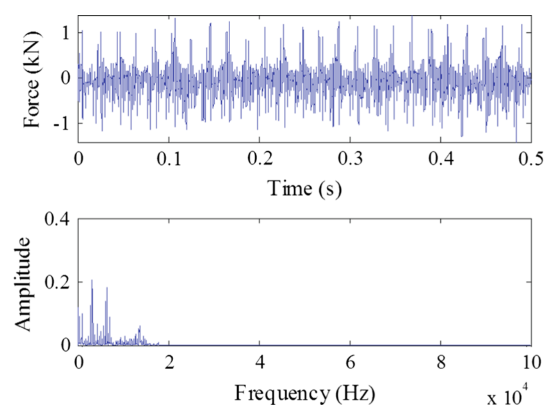

Fig. 7 Time and frequency spectrum of the milling force signal under failure condition

Figure 10 is a trend chart for energy change of wavelet packet of frequency bands 2 and 7 of AE signal in the cutting process.

A cutting force test is one of the frequently used methods to monitor tool condition in the milling process. With the increase of tool wear, the cutting edge is passive and inevitably leads to the change of cutting force. As there are many reasons affecting the milling process, the milling force is not stable especially with wearing condition increment. But both of them have a larger correlation. In many components of cutting force, the influence of tool wear on the radial force is obvious. Figure 11 is a time-dependent trend chart for average value of radial cutting force of CT. Anyhow, the cutting force increases with the CT wear despite some fluctuation. It is mainly related to some factors such as material properties, built-up edge and measurement error cumulated in the cutting process. But the influence on the overall up trend of cutting force is small shown in Fig. 12.

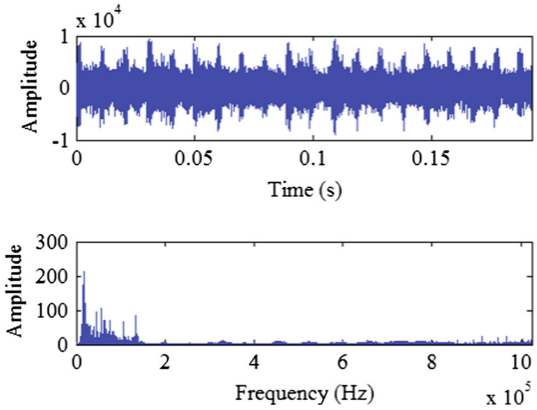

Fig. 8 Time domain and frequency spectrum of the AE signal under normal condition

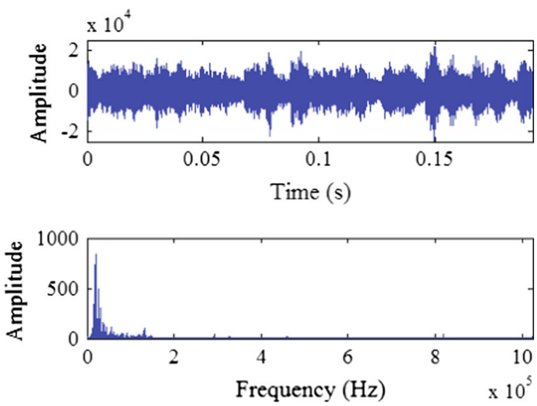

Fig. 9 Time domain and frequency spectrum of the AE signal under failure condition

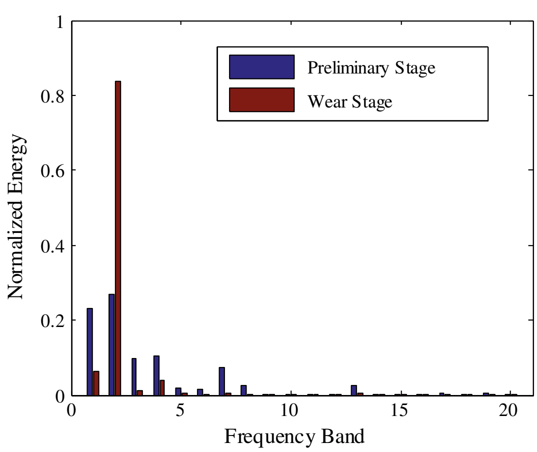

Fig. 10 Wavelet energy in different frequency band for preliminary and wear stage

Correlation coefficients of cutting force and normalized wavelet packet energy of frequency bands 2 and 7 are calculated independently. $\rho(F, E_2) = 0.900$, $\rho(F, E_2) = -0.895$, and the energy and cutting force of frequency band

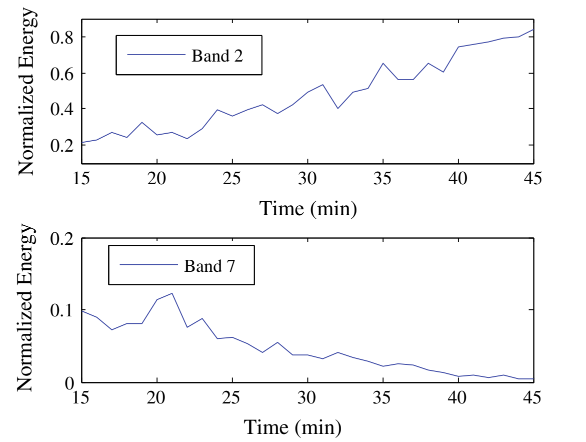

Fig. 11 Trend of wavelet power spectrum in the 2nd and 7th frequency bands

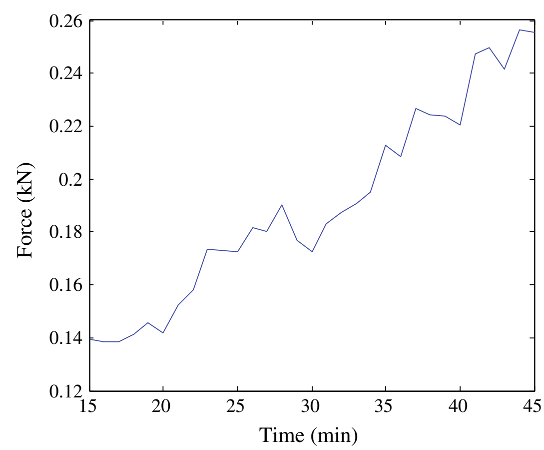

Fig. 12 Trend of cutting force

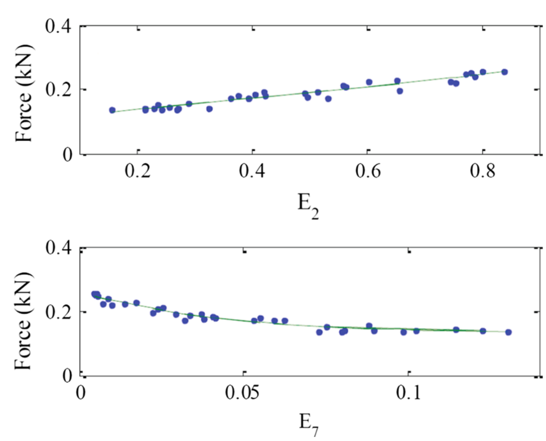

Fig. 13 Cutting force relationship with different AE signal frequency bands

2 are in the positive linear correlation, and frequency band 7 is in the negative linear correlation. Frequency band 7 has higher correlation based on the comparison shown in Fig. 13.

Table 4 Coefficient estimates of logistic regression model

Parameters	Model 1	Model 2
β_0	36.74	11.30
β_1	−160.0	−18.17
β_2	−4.49	76.70
β_3	91.46	–

Reliability estimation

The characteristic indie sequence extracted from test data of Nos. 1 to 3 CT are used for modeling. No. 4 CT is used for testing the validity of the model. Three characteristic indexes, i.e., cutting force, normalized wavelet packet energy of frequency bands 2 and 7 constitute input variables of the LRM, namely, $A_1 = x_1, x_2, x_3 = F, E_2, E_7$. It is also expressed as Model 1. From the previous section it can be known that cutting force F is highly correlated with E_2,E_7 of AE characteristics. It also means that input variables of Model 1 have information redundancy. Therefore, cutting force F is removed from feature vectors. In the end, input variables corresponding to the new model are: $A_2 = x_1, x_2 = E_2, E_7$, expressed as Model 2. The CT condition in the cutting process ($y = 1$ means that CT is in the normal condition) and the corresponding characteristic index sequence are input into SAS software respectively to estimate the parameters of Models 1 and 2. The coefficients of the CT LRM are shown in Table 4. In the output results of SAS, the overall inspection shows that these two models have a similar statistical significance, their values are less than 0.001. The results for an information criterion, standard criterion, and $-2 \ln L$ are basically equal for Models 1 and 2, namely, 619.2, 629.7 and 613.2 respectively. In addition, Score statistics of Model 1 is 215.95, better than 204.22 that of Model 2. Therefore, the goodness-of-fit of Model 1 is better than Model 2. The estimated reliability model is also shown as Eqs. 15 and 16, respectively.

$$\log it(y)_1 = 36.74 - 160.0F - 4.49E_2 + 91.46E_7 \quad (15)$$

$$\log it(y)_2 = 11.30 - 18.17E_2 + 76.70E_7 \quad (16)$$

After model parameters $\beta_0, \beta_1, \ldots \beta_m$ are obtained, the characteristic indices of No. 4 CT at different time are substituted into Eqs. 15 and 16, to calculate the change of reliability in the tool cutting process. Figure 14 shows the results of reliability evaluation and confidence index (CI) can be obtained based on the two models. In an LRM, 0-1 variables are used as explained variables, so that the threshold value of reliability failure is 0.50 (Chen et al. 2011b). The failure time of Model 1 is estimated to be 39.3 min, and that of Model 2 is estimated to be 39 min. The tool failure (wearing capacity of blade flank surface is more than 0.6 mm) time is tested to be 40.5 min as this experiment belongs to the one

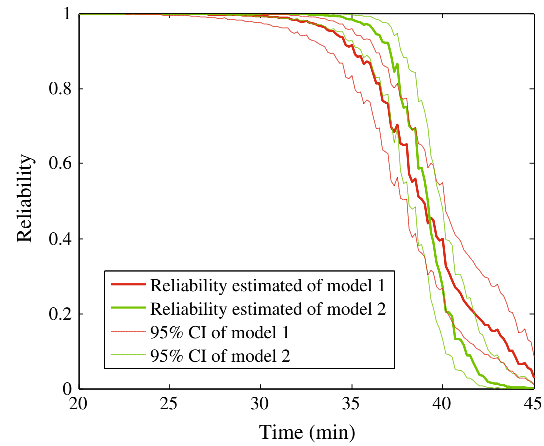

Fig. 14 Evaluation curve of CT reliability

of accelerating destruction. The errors of above two models are 0.0296 and 0.037, respectively. From the results, the estimated results of two models are relatively accurate. As well, the accuracy of Model 1 is better than Model 2. But there is a little difference between Models 2 and 1, showing that two methods to monitor tool wear, namely, cutting force, and AE signal are effective. Based on the above analysis, cutting force is better for condition monitoring and reliability estimation.

At present, the cutting force measurement is only used in the experimental study. But it is hard to be applied to the actual production for CT condition monitoring. During cutting and processing, restricted by acquisition hardware, installation, environmental conditions, it is difficult to obtain accurate cutting force, and is harder to popularize the use of dynamometer in the large-scale automated production. The method for reliability evaluation of CT based on AE signal is better. There is a close relationship with AE signal for cutting force though it is not as good as cutting force. But it is convenient to monitor. Therefore, Model 2 can be selected for practical application investigation in the future. A system is also investigated based on this method for CT condition monitoring and reliability analysis to ensure the quality of product.

Conclusion

This paper studies the condition monitoring based on the milling process and the method for operation reliability evaluation. The AE characteristics have a larger correlation with tool wear. AE signal has great correlation with wavelet packet energy and cutting force in some frequency bands. A more accurate results can be obtained through using cutting force and AE characteristics in the CT reliability evaluation. The method to combine AE characteristics with the LRM can also be used for accurate CT reliability evaluation. Under the condition that the actual cutting force is difficulty to obtain, the CT reliability evaluation model based on AE is more practical.

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References

Alonso, F. J., & Salgado, D. R. (2008). Analysis of the structure of vibration signals for tool wear detection. *Mechanical Systems and Signal Processing*, *22*(3), 735–748. doi:10.1016/j.ymssp.2007.09.012.

Bender, R., & Kuss, O. (2010). Methods to calculate relative risks, risk differences, and numbers needed to treat from logistic regression. *Journal of Clinical Epidemiology*, *63*(1), 7–8.

Caesarendra, W., Widodo, A., & Yang, B.-S. (2010). Application of relevance vector machine and logistic regression for machine degradation assessment. *Mechanical Systems and Signal Processing*, *24*(4), 1161–1171. doi:10.1016/j.ymssp.2009.10.011.

Chen, B., Chen, X., & Li, B. (2011a). Reliability estimation for cutting tools based on logistic regression model using vibration signals. *Mechanical Systems and Signal Processing*, *25*(7), 2516–2537.

Chen, B. J., Chen, X. F., & Li, B. (2011b). Reliability estimation for cutting tool based on logistic regression model. *Chinese Journal of Mechanical Engineering*, *47*(18), 158–164.

Dimla S, D. E. (2002). The correlation of vibration signal features to cutting tool wear in a metal turning operation. *The International Journal of Advanced Manufacturing Technology*, *19*(10), 705–713.

Ding, F., He, Z. J., & Zi, Y. Y. (2009). Reliability assessment based on equipment condition vibration feature using proportional hazard model. *Chinese Journal of Mechanical Engineering*, *45*(13), 89–94.

Heng, A., Zhang, S., Tan, A. C., & Mathew, J. (2009). Rotating machinery prognostics: State of the art, challenges and opportunities. *Mechanical Systems and Signal Processing*, *23*(3), 724–739.

Huang, S. N., Tan, K. K., Wong, Y. S., de Silva, C. W., Goh, H. L., & Tan, W. W. (2007). Tool wear detection and fault diagnosis based on cutting force monitoring. *International Journal of Machine Tools and Manufacture*, *47*(3–4), 444–451. doi:10.1016/j.ijmachtools.2006.06.011.

Jardine, A. K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, *20*(7), 1483–1510.

Jemielniak, K., & Kwiatkowski, L. (1998). Diagnosis of tool wear based on cutting forces and acoustic emission measures as inputs to a neural network. *Journal of Intelligent Manufacturing*, *9*(5), 447–455.

Kious, M., Ouahabi, A., Boudraa, M., Serra, R., & Cheknane, A. (2010). Detection process approach of tool wear in high speed milling. *Measurement*, *43*(10), 1439–1446.

Liu, B. (2005). Selection of wavelet packet basis for rotating machinery fault diagnosis. *Journal of Sound and Vibration*, *284*(3–5), 567–582. doi:10.1016/j.jsv.2004.06.047.

Martin, D. (1977). Early warning of bank failure: A logit regression approach. *Journal of Banking and Finance*, *1*(3), 249–276.

Mill Data Set. (2007). *BEST lab*. UC Berkeley.

Peng, C. Y. J., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. *Journal of Educational Research*, *96*(1), 3–14.

Peng, Z. K., & Chu, F. L. (2004). Application of the wavelet transform in machine condition monitoring and fault diagnostics: A review with bibliography. *Mechanical Systems and Signal Processing*, *18*(2), 199–221. doi:10.1016/s0888-3270(03)00075-x.

Sharma, V. S., & Sharma, S. (2007). Cutting tool wear estimation for turning. *Journal of Intelligent Manufacturing*, *19*(1), 99–108.

Sukhomay, P., & Heyns, P. (2009). Tool wear monitoring and selection of optimum cutting conditions with progressive tool wear effect and input uncertainties. *Journal of Intelligent Manufacturing*, *22*(4), 491–504.

Venkatesh, K., & Mengchu, Z. (1997). Design of artificial neural networks for tool wear monitoring. *Journal of Intelligent Manufacturing*, *8*(3), 215–226.

Wang, Z., & Wlofhard, L. (1996). Feature-filtered fuzzy clustering for condition monitoring of tool wear. *Journal of Intelligent Manufacturing*, *7*(1), 13–22.

Xiaoyu, W., & wen, W. (2008). Design of neural network-based estimator for tool wear modeling in hard turning. *Journal of Intelligent Manufacturing*, *19*(4), 383–396.

Yan, J., Ko, M., & Lee, J. (2004). A prognostic algorithm for machine performance assessment and its application. *Production Planning and Control*, *15*(8), 796–801. doi:10.1080/09537280412331309208.

Yan, J., & Lee, J. (2005). Degradation assessment and fault modes classification using logistic regression. *Journal of Manufacturing Science and Engineering*, *127*(4), 912–914.

Zhu, K., Wong, Y. S., & Hong, G. S. (2009). Wavelet analysis of sensor signals for tool condition monitoring: A review and some new results. *International Journal of Machine Tools and Manufacture*, *49*(7–8), 537–553. doi:10.1016/j.ijmachtools.2009.02.003.

Zio, E. (2009). Reliability engineering, old problems and new challenges. *Reliability Engineering and System Safety*, *94*(2), 125–141. doi:10.1016/j.ress.2008.06.002.