Degradation Information-Based Instantaneous Reliability Prediction of Cutting Tool

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In order to predict the reliability of cutting tools, whose failure is mainly caused by degradation, a forecasting method based on degradation information is proposed, which includes: extraction of degradation indicesÿcomputation of instantaneous reliabilityÿestablishment and application of the neural network prediction model. The key issue of prediction accuracy is the computation of instantaneous reliability. A novel approach incorporated Bayes theorem and Kaplan-Meier (KM) estimator principle is employed to calculate the instantaneous reliability. As validated by the time-varying wear data of the toolsÿthe trained network is available of predicting the failure time accurately judging by the criterion of reliability. The results show the feasibility and effectiveness to predict reliability based on degradation information.

Key words: Degradation Information, Cutting Tool, Reliability Prediction, Instantaneous Reliability.

CNC (computerized numerical control) machine are the major equipments and play very important roles in modern manufacturing systems. The breakdown of one machine may result in the halt of the whole production and bring about tremendous financial losses. Since that, great attention of manufacturer has been paid on machine reliability improvement to reduce unexpected downtime and raise product quality. As an important part of CNC machine, cutting tools' reliability influences the total manufacturing effectiveness and stability of equipment. With an accurate estimation of tool lifetime, worn tools can be changed in time to avoid the production of waste and reduce tools costs noticeably.

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Traditional approaches to reliability analysis of physical and other electro-mechanical products are predominantly based on life time of large samples (O'Connor *et al*, 2005). Such analyses have been extensively studied and many articles have been published in various journals (Zio, 2005). With very few exceptions, all these analyses are aimed at estimating a population characteristic(s) of a system, subsystem or component. But for single and a small sample device(s), such statistic data have little meaning. People are particularly interested in life margin and current reliability of items used in their systems. In the event, degradation measures often provide more information about device performance and precision during operation (Wu *et al*, 2000) (Gorjian *et al*, 2009). It is helpful to determine the product time dynamic characteristics and reflect the relationship between failure and performance degradation. Lu and Meeker introduced a general nonlinear mixed-effects model and developed a Monte Carlo simulation procedure to calculate an estimate of the distribution function of the time-to-failure (Lu *et al*, 1997). Chinnam *et al* collected and analyzed thrust-force and torque signals generated by drilling operation to predict on-line reliability of the drill-bit (Chinnam *et al*, 2007). However, the above listed methods require a specific mechanistic knowledge and make more assumptions about degradation index paths and their probability density function (PDF).

In this paper, an instantaneous reliability prediction approach for NC (numerical control) lathe cutting tools is proposed based on degradation information. A Back-Propagation neural network (BPNN) is used as the prediction tool. The input of BPNN is the degradation index vector, which indicates the equipment performance and has an evident changing trend and clearly defined failure threshold. The output of BPNN is the instantaneous reliability corresponding different feature values at different running time. The key issue of accurate prediction is how to calculate the instantaneous reliability. The frequently used method is to calculate the interval integral of feature parameters' Probability density function (PDF) between the observed value and the threshold. But the method embraces two problems: one is the selection of the failure PDF; the other is the number requirement of samples size. Inappropriate hypothesis of the failure PDF and too small sample may result in large estimated error. In the present paper, a different algorithm of instantaneous reliability is developed, where the Bayes method is combined with Kaplan–Meier (KM) estimator. The proportional association relationships of the degradation features are taken as instantaneous reliability. The proposed method is validated by the accurate reliability prediction to the practical in-used cutting tools.

Reliability prediction model based on BPNN

Artificial neural network (ANN) is a type of non-linear dynamic network system built upon the structure simulating the nerve cell of human being's cerebra. It has strong ability of distributed parallel processing, associated memory, self-organization, self-learning and non-linear mapping. BPNN is a forward multi-layer network and widely applied in different fields, such as intelligent control, fuzzy recognition, adaptive filtering, signals processing and fault diagnosis (Yi *et al*., 2007). Being trained by using back propagation algorithm, BPNN can automatically establish the relationships between the data and the law can be used to predict unknown information.

The prediction model used in this paper is a three-layer BPNN and its structure is shown in Figure 1. The number of input nerve cell is d+1 and the number of output nerve cell h. The input of BPNN is a feature vector $\mathbf{X}=[x(t)\ \ x(t-\Delta t)\ \ \cdots\ \ x(t-d\Delta t)]^T$ of equipment degradation composed of the current observed value and its previous d measurements. The output of BPNN is the predicting reliability of successive h time intervals, expressed as

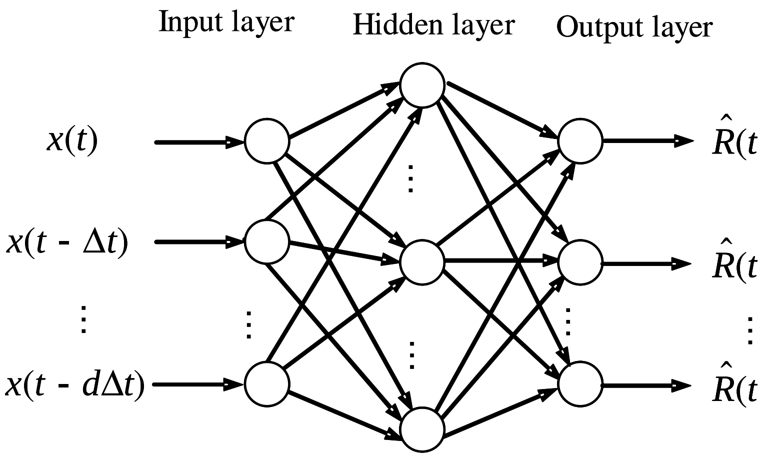

Fig. 1. The model structure of reliability prediction based on BPNN

$\hat{\mathbf{R}} = [\hat{R}(t+\Delta t) \quad \hat{R}(t+2\Delta t) \quad \cdots \quad \hat{R}(t+k\Delta t)]^T$.

Instantaneous reliability algorithm

In traditional reliability theory, reliability is defined as the probability that a product can complete the specified function under specified condition and time. It can be calculated as

$$R(t) = P(T > t) = \int_t^{+\infty} p(u)du \qquad ...(1)$$

where T is the life of the product, t is the specified time and p is the life PDF. Traditional reliability estimation method depends on the product life data. But for cutting tools, whose failure reason is degradation and failure sample size is small and sparse. Thus performance degradation information is introduced into reliability assessment (Chen *et al.*, 2005) (Gebraeel *et al.*, 2008). When degradation path hits a specified failure threshold, the Pseudo-life of the equipment is decided. A life PDF such as Exponential, Weibull, and Log-Normal is subsequently used to model the Pseudo-life data and applied to evaluate the reliability. But what these methods estimated is still population reliability. Some experts proposed the concept of instantaneous reliability and defined as the interval integral of degradation indices' PDF between the observed value and the threshold (Heng *et al.*, 2009). Suppose $U = \{x_1(t) \quad x_2(t) \quad \cdots \quad x_m(t)\}$ is the set composed of the degradation indices of m products at time *t*, whose PDF is $f(x|t)$ and failure threshold is X_{th}.

The population reliability can be expressed as

$$R(t) = P(T > t) = P(X(t) < X_{th}) = \int_0^{X_{th}} f(x|t)dx \quad ...(2)$$

If the degradation index of product i at time $t + k\Delta t$ is $x_i(t + k\Delta t)$. The instantaneous reliability is shown as

$$R_i(t+k\Delta t) = \prod_{j=1}^{k} \frac{P(x_i(t+j\Delta t) \le X(t+j\Delta t) < X_{th} \mid P(x_i(t+(j-1)\Delta t) \le X(t+(j-1)\Delta t) < X_{th})}{P(x_i(t+j\Delta t) \le X(t+j\Delta t) \mid P(x_i(t+(j-1)\Delta t) \le X(t+(j-1)\Delta t))} = \prod_{j=1}^{k} \frac{\int_{x_i(t+j\Delta t)}^{X_{th}} f(x|t+j\Delta t)dx}{\int_{x_i(t+j\Delta t)}^{\infty} f(x|t+j\Delta t)dx}$$

(3)where $\int_{x_i(t+j\Delta t)}^{X_{th}} f(x|t+j\Delta t)dx$ is the integral of the PDF between the observed degradation index $x_i(t + k\Delta t)$ and the thresholdof item at time; and is the interval integral of the PDF over all possible values equal to or higher than the observed degradation index of item at time . In Equation (3), the even product shows the thought of Bayes conditional probability. It means that if the product is reliable at time, it must be reliable at . According to Equation (3), it is known that the PDF of should be estimated appropriately. In addition, when the equipment is close to failure, the reduced sample size may cause a large estimated error. The KM estimator is a kind of non-parametric estimation method (Kaplan *et al.*, 1958). It does not depend on the choices of failure PDF and time intervals. If the samples consisted of degradation indices and corresponding equipment state (normality or failure) were acquired, the Equation (3) can be changed as

$$R_i(t + k\Delta t) = \prod_{j=1}^{k} \frac{\int_{x_{i,t+j\Delta t}}^{X_{th}} f(x|t + j\Delta t)dx}{\int_{x_{i,t+j\Delta t}}^{\infty} f(x|t + j\Delta t)dx} = \prod_{j=1}^{k} \frac{d_{i,t+j\Delta t}}{n_{i,t+j\Delta t}} \qquad ...(4)$$

where is the sample size whose degradation index values are equal to or higher than and lower than threshold at time . is the sample size, whose degradation index values are equal to or higher than at time. In order to avoid too conservative estimation to reliability, the failure sample size before is not added in.

Reliability prediction of cutting tool

Experiment

Tool failure and lifetime is judged by its wear measurement described in several standards (ISO3685, ISO8688, and ANSI/ASME B94.55M) (Sick, 2002). These standards provide wear threshold values at several points of the worn region which is acquired by its direct measurement. Refer to ISO3685, flank wear of tool is selected as degradation index and the failure threshold is selected as in this paper. An NC lathe is employed for the interrupted cutting of steel bars fixed to the work holder. The cutting tool used in this test is a diamond carbide tool and the experiment conditions are shown in Table 1. Tool wear was measured by a micro-optical system with a CCD camera, an adjustable circular-ring-mode LED light and a built-micrometer. The maximum resolution is . At the same time, for purpose of further research, the vibration signals, the acoustic emission (AE) signals and the workpiece surface roughness data were measured respectively (Dimla *et al.*, 2000). The installation of micro-optical system, accelerometer and AE sensor are shown in Figure 2.

Reliability prediction of cutting tool

From the beginning to the middle of

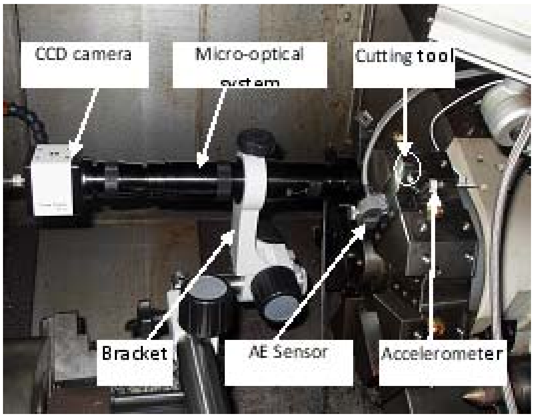

Fig. 2. The installation of micro-optical system accelerometer and AE sensor

cutting process, tool wear increases slowly and have little influence to the machining quality of the workpiece. But at the end of the process, wear increases significantly faster and influence the machining quality notably (Abouelatta *et al*., 2001). So the wear data collected in the experiment mainly focus in the range of . There are 12 time-varying tools wear data were measured and shown in Figure 3. The dashed line denotes as failure threshold . The tool wear data were introduced into Equation (4) to calculate the instantaneous reliability corresponding to different wear values at different time, as shown in Figure 4.

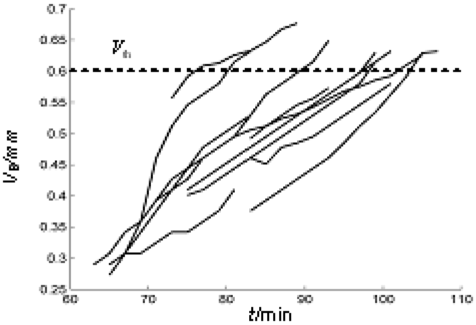

Fig. 3. Time-varying wear data of the tools

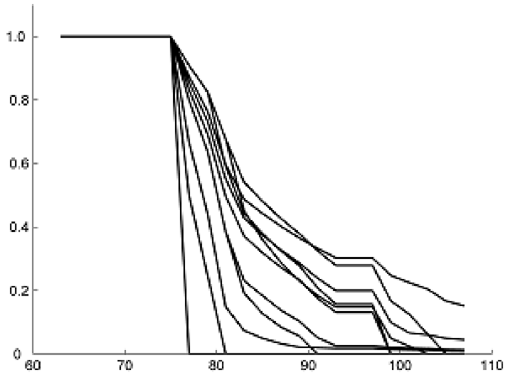

Fig. 4. Instantaneous reliability of the tools

Table 1. Experimental conditions

Lathe	Type: Horizontal
Cutting Tool	Model:FTC-20 Spindle Speed: 45 ~ 4500rpm Rated Powe :11kw Type: Diamond Carbide Tool Model: CNMG120408-HM Material:42CrMo4
Workpiece Material	45# Steel Bars

Table 2. The MSEs with different training parameters

Algorithm	Function	Number of hidden layer nerve cell		
		9	12	15
Gradient descent	Traingd	0.0456	0.0951	0.0349
Bfgs quasi-newton	Trainbfg	0.0093	0.0075	0.0062
Fletcher-powell Conjugate gradient	Traincgf	0.0072	0.0065	0.0073
Elastic bp	Trainrp	0.0091	0.0096	0.0093
Levenberg-marquardt	Trainlm	0.0331	0.0025	0.0037

Table 3. The reliability prediction results based on tool wear time-varing data

Time t(min)	87	89	91	93	95	97	99	101
Wear VB(mm)	0.49	0.51	0.53	0.55	0.56	0.58	0.61	0.63
In next 1 interval	0.768	0.695	0.635	0.608	0.542	0.351	0.208	0.025
In next 2 interval	0.703	0.613	0.677	0.593	0.348	0.220	0.066	0.001
In next 3 interval	0.615	0.556	0.696	0.474	0.186	0.074	0.009	0
In next 4 interval	0.622	0.539	0.429	0.267	0.061	0.016	0.001	0
In next 5 interval	0.575	0.368	0.264	0.106	0.009	0.001	0	0

Once the degradation indices and the corresponding instantaneous reliability have been identified, the BPNN can be set up and trained to realize the prediction function. The wear data of first 11 tools have been taken as training samples. The input feature vector X contains the wear values at the current time and 6 previous time steps. The training target vector consists of the estimated reliability in the 5 successive intervals. It means that the number of input nerve cell is 7 and the number of output nerve cell is 7. When training epoch is 1000, the mean square errors (MSE) between output of BPNN and target vectors with different training parameters are listed in Table 2. It can be observed that when the training algorithm is Levenberg-Marquardt method and the number of hidden layer nerve cell is 12, the MSE is the smallest. So the algorithm and the number are selected as the training parameters.

The wear data of tool 10 is taken as detecting sample to validate the prediction function of the trained BPNN. The prediction results are shown in Table 3. The real failure time of the tool is 99 min and the corresponding wear is $0.61mm$.

According to the failure threshold $V_{th} = 0.6mm$, when tool is running to 86min, the BPNN first predicts the failure will happen in the successive 5 time interval, viz. $t = 99\,\text{min}$. It is consistent with the real failure time. With the increase of machining time, the trained BPNN all predicts the real failure time accurately when the tool is running to 91min, 93min, 95min and 97min, respectively.

CONCLUSIONS

This paper presents a reliability prediction approach integrated on degradation information and neural network. Degradation measures can provide more information about device performance and precision. It is helpful to determinate the product time-varying characteristics and reflect the relationship between failure and performance degradation. The proposed instantaneous reliability algorithm is simple and efficient. It does not need make more assumption about the PDF of degradation index. A case study shows that the proposed approach is available of forecasting the reliability and failure time accurately. The positive results shown in this research have clearly demonstrated the potential of this approach in performance and reliability prediction.

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