Milling Tool Wear Estimation Based on Regression Analysis and Fuzzy Logic Model Using Cutting Power Signals

Chuangwen Xu , Ting Xu, Jianming Dou

***Abstract*— In a modern machining system, tool wear monitoring systems are needed to get higher quality production. In precision machining processes especially surface quality of the manufactured part can be related to tool wear. This increases industrial interest for in-process tool wear monitoring systems. For modern unmanned manufacturing process, an integrated system composed of sensors, signal processing interface and intelligent decision making model are required. In this study, regression analysis and fuzzy logic method use the relationship between flank wear and the resultant cutting power to estimate tool wear. A series of experiments were conducted to determine the relationship between flank wear and cutting power as well as cutting parameters. Speed, feed, depth of cutting and cutting power were used as input parameters and flank wear width and tool state were output parameters. The network model of tool wear is established, so the inherent relation of tool wear and cutting power was reflected indirectly. It is used to cutting parameters to adjust the network part parameters in real-time so that the model has dynamic, real-time and fuzziness. In variable cutting conditions, the result indicated that the tool wear are more sensitive to cutting feed power. Because the processing situation and other factors are of different sensitivity to the model of spindle power and feed power , the further applied the tool wear method, to eliminate the false deduction and the false alarm lied in the single signal , the proposed fusion pattern is better than the single factor cutting power recognition of tool wear in full detection recognition effect. According to the proposed method, the static and dynamic power components could provide the effective means to detect milling tool wear estimation for varying cutting conditions in milling operation.**

***Index Terms*— End-milling, Cutting power, Regression analysis, Wear model, Wear estimation**

I. Introduction

Metal-cutting tool wear directly affects the precision, efficiency and cost-effective of machining, so the on-line monitoring tool wear is becoming more and more people's attention, and becomes an important research topic of flexible manufacturing system (FMS). In the past 20 years there had been great achievement on the research of monitoring tool breakage, especially, on the occurrence, development and evolvement of the tool breakage, and some significant conclusions were also drawn. But the tool wear monitoring is being researched at present. Some methods are applied to the special aspect; others are in the testing phase[1-5]. Compared with other machining, the milling tool wear mechanism is more complicated and the accurate model of the milling tool wear can not set up at all because there are many factors that affect the milling tool wear and these factors are influenced each other. Because the wear is in the complex cutting process, the data processed for collecting the wear state are very huge, and the wear signal mixed with the noise is very difficult to be separated. In addition, in milling process, the tool wear is affected by the various parameters, so that the cutting test and data are uncertain and unrepeatable. There are two techniques for tool wear sensing: direct and indirect. The direct technique includes measuring the actual wear, using radioactive analyses of the chip. Generally direct measurements are avoided because of difficulty of online measurements. For indirect methods of tool wear monitoring, the following steps are followed: use of single or multiple sensors [6] to capture process information; use of signal processing methods to extract features from the sensor information; use of decision-making strategy to utilize extracted featured for prediction of tool failure. Indirect technique includes the measuring of cutting forces, torque, vibration, acoustic emission (stress wave energy), sound, temperature variation of the cutting tool, power or current consumption of spindle or feed motors and roughness of the machined surface [7-14]. No matter what kind of sensor is adopted, a successful monitoring system must try to find tool wear features which are not only relevant to the development of tool wear are but also independent of changes in cutting conditions. The strategies for wear feature extraction in developed monitoring systems may be summarized in two categories based on the techniques for signal processing and analysis. The non-parameter method uses time-domain features (e.g., mean value, variance, correlation and change rate) and frequency-domain features (e.g., power spectrum and inverse spectrum). A pattern recognition method is used to identify tool wear based on various features. However, since the process of feature extraction does not consider the cutting conditions, monitoring systems based on the nonparametric method are less reliable in FMS than parametric method. The parametric method uses an empirical model to describe the quantitative relationship between cutting state signals (e.g., force, power, acoustic emission, vibrations and temperature), cutting conditions and tool wear. The parametric method includes two stages. In stage one; an empirical model is developed by regression analysis of experimental data [15-17]. In stage two, tool wear is estimated in real-time by using the empirical model and measurements of the cutting state signal and conditions. The

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advantage of the parametric method is that cutting conditions are used as a model input so that wear estimation is independent of variation in cutting condition. However, since there are stochastic variations in workpiece materials, machine vibrations and temperature as well as different types of tool wear (such as crater wear, flank wear, tool point wear, etc.). In actual machining, the empirical model still has large errors in the estimated tool wear or mistakes in recognition [18].

The work presented here is evolutionary in that it follows and expands on the work done in intelligent tool condition monitoring as noted above. However, the contribution of the present work is that the resulting framework, at least in principle, offers a robust representation of the process in the event of changes in the machining environment. Optimization objective of many earlier model based on fuzzy logic for tool wear monitoring and prediction works is mean square error between actual output and model output. It also shows that it is possible to reduce mean square error of the forecast tool wear and actual tool wear to obtain the best prediction model by adjusting the parameters properly. However, we can get a better model result by setting up a more optimized goal. For example, with the prediction accuracy as the maximum objective function, the best prediction model is obtained by adjusting the parameters, then out of sample extension is also considered and combined with fault detection algorithm, which can reduce computation task obviously and improve real time capability of the algorithm.

The organization of the paper is as follows. We first state the problem in a rather succinct manner. Next we discuss the methodology used to develop the established model of tool wear in two steps: We will first discuss the cutting power model based the regression analysis that is used to correlate the rather set of data obtained from machining tests. We will subsequently discuss the manner in which this network based model is used to adaptively construct a fuzzy logic based tool wear monitoring algorithm, which as mentioned above offers the relative transparency that the network based model lacks. We will next discuss the another data set is used to evaluate the network model and finally conclude the paper with an assessment of the proposed approach and some suggestions concerning future work in this area.

II. NETWORK MODEL OF TOOL WEAR

2.1 Regression Model

In the milling process, the cutting power P has close relations with the cutting speed v, the feed speed f, the cutting depth a_p and tool wear VB. At the same time, the cutting power changes with the different conditions such as the workpiece material, the tool material and so on. According to the metal cutting theory, the spindle cutting power P_s and the feed power P_f are defined as follows

$$P_s \propto a_1 v^{a_2} f^{a_3} a_p^{a_4} \qquad (1) \qquad P_f \propto b_1 v^{b_2} f^{b_3} a_p^{b_4} \qquad (2)$$

Where a_1 and b_1 are the coefficient decided by the cutting tool geometry dimension and performance of the material. a_2, a_3, a_4 and b_2, b_3, b_4 are the cutting-parameter exponent.

As Equation.(1) and Equation.(2) shows, cutting tool is used when the certain cutting condition and tool wear state, a corresponding power value can be output. For the convenience of calculation, which applies logarithm to the evaluation, the result is as follows

$$\ln P_s \propto \ln a_1 + a_2 \ln v + a_3 \ln f + a_4 \ln a_p \qquad (3)$$

$$\ln P_f \propto \ln b_1 + b_2 \ln v + b_3 \ln f + b_4 \ln a_p \qquad (4)$$

In the actual milling process, the cutting power is constantly changing, it is difficult for us to accurately model the power. For this purpose, the fuzzy classification is introduced to describe its change. Supposed there are l fuzzy rules, that is, l values are output according to regression model, correspondingly, there are l sets different equations as follows

If $S=\ln P_s$, then

$$S_i \propto a_{i1} + a_{i2} \ln v + a_{i3} \ln f + a_{i4} \ln a_p \qquad (i=1,2,\cdots,l) \qquad (5)$$

If $F=\ln P_f$, then

$$F_i \propto b_{i1} + b_{i2} \ln v + b_{i3} \ln f + b_{i4} \ln a_p \qquad (i=1,2,\cdots,l) \qquad (6)$$

These coefficients in Equation.(5) and Equation.(6) are obtained from linear regression of experiment data. We first discuss coefficients in Equation.(5). The sample size is divided l according to the rank of the cutting tool wear. Supposed sample size is confirmed as n, sample size of class i is equal to n_i ($i \le l$), Equation.(5) can be as follows

$$\begin{bmatrix} S_1 \\ S_2 \\ S_3 \\ \vdots \\ S_l \end{bmatrix}_{l\times1} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ \vdots & \vdots & \vdots & \vdots \\ a_{l1} & a_{l2} & a_{l3} & a_{l4} \end{bmatrix}_{l\times4} \begin{bmatrix} 1 \\ \ln v \\ \ln f \\ \ln a_p \end{bmatrix}_{4\times1} \qquad (7)$$

Where l sets coefficients matrix is fitted by the least square method, that is

$$\begin{bmatrix} \alpha_{i1} \\ \alpha_{i2} \\ \alpha_{i3} \\ \alpha_{i4} \end{bmatrix} = \left(\boldsymbol{X}_i^{\mathrm{T}} \boldsymbol{X}_i\right)^{-1} \boldsymbol{X}_i^{\mathrm{T}} Y_i$$

$$\boldsymbol{X}_i = \begin{bmatrix} 1 & \ln v_{i1} & \ln f_{i1} & \ln a_{p_{i1}} \\ 1 & \ln v_{i2} & \ln f_{i2} & \ln a_{p_{i2}} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \ln v_{in} & \ln f_{in} & \ln a_{p_{in}} \end{bmatrix} \quad \boldsymbol{Y}_i = \begin{bmatrix} S_{i1} \\ S_{i2} \\ S_{i3} \\ \vdots \\ S_{in} \end{bmatrix} = \begin{bmatrix} \ln P_{i1} \\ \ln P_{i2} \\ \ln P_{i3} \\ \vdots \\ \ln P_{in} \end{bmatrix}_{n\times1}$$

2.2 The Fuzzy Classification

The cutting tool wear is generally divided into three stages, that is, initial wear stage, normal wear stage and acute wear stage, each of which is the feature of overlapping and fuzziness. According to the wear three stages , the tool wear states are separated as 8 groups or A,B,C,D,E,F,G and H, each of which is corresponding to a certain spindle cutting power. In the light of different tool wear range and Equation.(5) ,the functional relation between the wear value and the spindle cutting power and the cutting parameters is as follows

$S_1 = \ln P_1 = a_{11} + a_{12} \ln v + a_{13} \ln f + a_{14} \ln a_p$

VB<0.1mm

$S_2 = \ln P_2 = a_{21} + a_{22} \ln v + a_{23} \ln f + a_{24} \ln a_p$

0.05mm<VB<0.15mm

$S_3 = \ln P_3 = a_{31} + a_{32} \ln v + a_{33} \ln f + a_{34} \ln a_p$

0.10mm<VB<0.20mm

$S_4 = \ln P_4 = a_{41} + a_{42} \ln v + a_{43} \ln f + a_{44} \ln a_p$

0.15mm<VB<0.25mm

$S_5 = \ln P_5 = a_{51} + a_{52} \ln v + a_{53} \ln f + a_{54} \ln a_p$

0.20mm<VB<0.30mm

$S_6 = \ln P_6 = a_{61} + a_{62} \ln v + a_{63} \ln f + a_{64} \ln a_p$

0.25mm<VB<0.35mm

$S_7 = \ln P_7 = a_{71} + a_{72} \ln v + a_{73} \ln f + a_{74} \ln a_p$

0.30mm<VB<0.40mm

$S_8 = \ln P_8 = a_{81} + a_{82} \ln v + a_{83} \ln f + a_{84} \ln a_p$

0.35mm<VB

2.3 The Membership Grade Function

The function of the membership grade on wear state is set up according to fuzzy classification of the tool wear, as Fig.(1) shows.

2.4 The Network Model on Tool Wear

After the coefficient matrix of Equation.(7) being obtained through regressive analysis of the experimental data, if the spindle cutting speed v, feed speed f and the cutting depth a_p is known, $S_1 \sim S_8$ is calculated directly through Equation.(5), then $P_1 \sim P_8$ is calculated by using inverse operation. In monitoring tool wear, $P_1 \sim P_8$ is taken as the center of the fuzzy clustering in Figure.1. Compared the actual cutting power value with clustering center, the current tool wear membership grade can be determined, thus tool wear can be identified accurately. The membership grade is calculated as follows

$$\mu = 1 - \left| \frac{P - P_{j-1}}{P_j - P_{j-1}} \right| \qquad (8)$$

Where P is the actual value, P_j and P_{j-1} is the estimation value. The net model to recognize the tool wear is shown in Fig.(2). For the coefficient determination of feed power in Equation.(6), methods can be taken with same determination of spindle power coefficient, here are not repeated.

III. EXPERIMENTAL STUDY

3.1 Experimental Design

The objective of the design of experiments is to provide an efficient means of experimentation and analysis of results. The experiments are carried out on a CNC machining center of XKA714 using the strategy described above. The milling experimental condition is shown in Table 1. The cutting parameters are in Table. 2. Cutting experiment is used in Taguchi based orthogonal array experimental design, respectively, according to the first, second and third group of cutting parameters in Table 2. Taguchi's orthogonal array structure offers robust experimental design with decreased experiment number. Taguchi method involves analysis between the factors, their interactions and responses. The method is widely used in engineering applications. Taguchi's orthogonal array structure was used for experimental design, as reduced number of experiments can be acceptable for industry. A standard Taguchi orthogonal array was chosen for the most controlled factors such as, cutting speed, feed speed and cutting depth . Take the turn from little to more to cut according to the tool wear rank. In different wear stage(0.05mm,0.1mm,0.15mm,0.2mm,0.25mm,0.3mm,0.35 mm,0.4mm), the power value is collected about every set different cutting conditions separately and every value is the average of 640 sets data. Milling tool wear monitoring system is set up as Fig.(3)

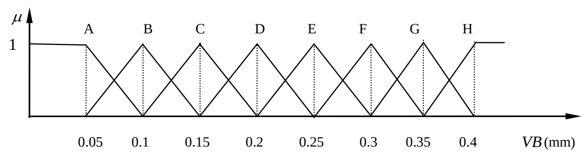


Fig.(1). The Function of the Membership Grade on Wear State

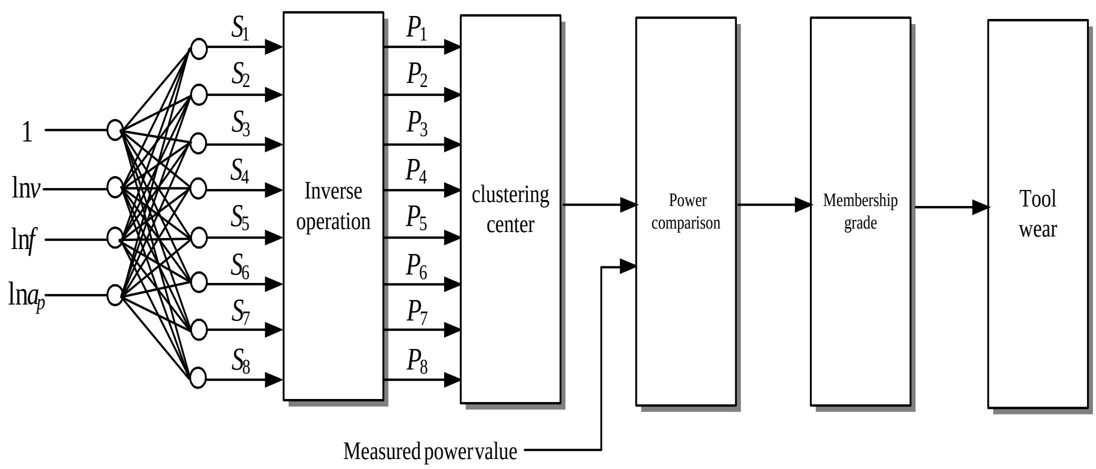


Fig.(2).The Net Model of Tool Wear

Table 1.Cutting Experiment Condition

Cutting tool	Material	High-speed steel
	Type	End milling cutter
	Diameter(mm)	14 to 20
Equipment	XKA714	
Milling method	Climb milling	
Workspace material	Thermal refining 45 steel	
Cutting speed/(m/min)	8.792 to 21.98	
Feed speed/(mm/min)	20 to 35	
Cutting depth/mm	2 to 5	
Cutting fluid	Motor-oil	

Table 2.Cutting Parameters

Group number	Cutting parameters
1	v=8.792, 13.19, 17.584, 21.98; f=20,25,30,35; a_p=2,3,4,5
2	v=9.671, 11.43, 15.38,17.584; f=20,25,30,35; a_p=2.5,3.5,4.5,5.5
3	v=11.43, 17.584,19.36, 21.98; f=20,25,30,35; a_p=2,3,4,5

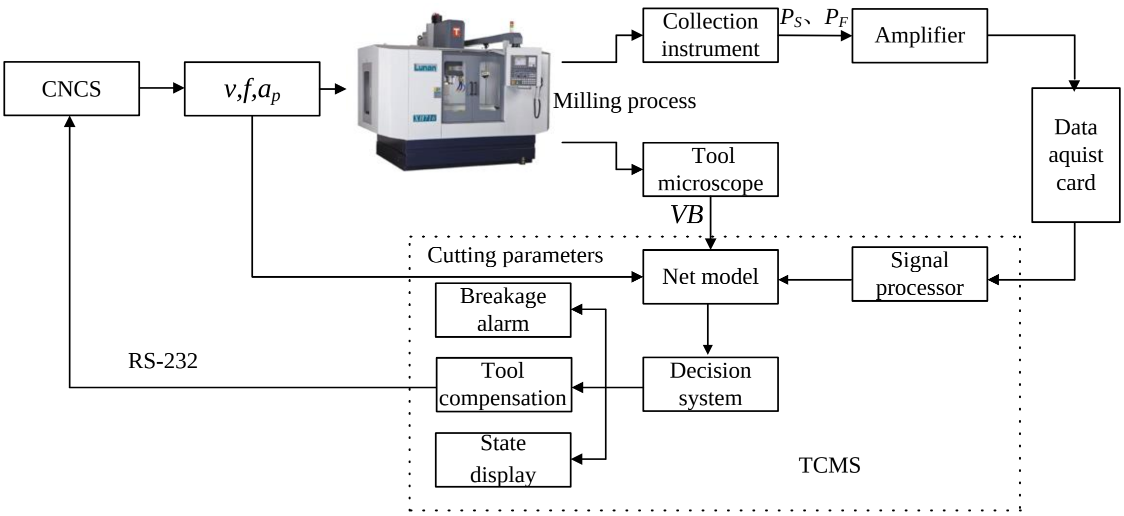


Fig.(3). The Monitoring System.

3.2 Data Acquisition

The first types of signals are spindle motor currents measured by hall current sensor AKH-0.66 control unit installed on machining center. The second types of signals are feed drive nominal currents measured by Heidenhain TNC 426 CA control unit installed on vertical machining center. Although the machine has got three controlled feed axis, only the measurements of working table feed drive nominal currents (Ix, and Iy) were enabled by control unit. After the electric current generated between working electrode and reference electrode is transformed, filtered and amplified, it is transfered to the converter of STC-2 for A/D conversion. The signals were sampled every 0.6 [ms]. The flank wear was measured on a tool maker's microscope. As it is shown in Fig.(4) and Fig.(5), every curve is obtained in the same combination cutting condition. The coefficient in Equation.(7) and the correlation coefficient R obtained through the regression analysis is shown in Table 3.

It is shown in the Table 3 by the correlation coefficient that the model reflects the relation between the cutting power and the cutting parameters.Based on determining the coefficient of above training sample, adopting the new measured data in the different cutting condition, whether the net model of the tool wear is suitable for the recognizing the tool wear on line can be testified. In each of the cutting conditions, measurement data is draw randomly. An example for 12 sample sets was given in Table 4.The measurement results of the spindle power and feed power model can be found in Table 5 and Table 6 . In order to analyze intuitively the examination effect to the spindle cutting power and feed cutting power as shown in Table 5 and Table 6, the examination effect is shown in Fig.(6)

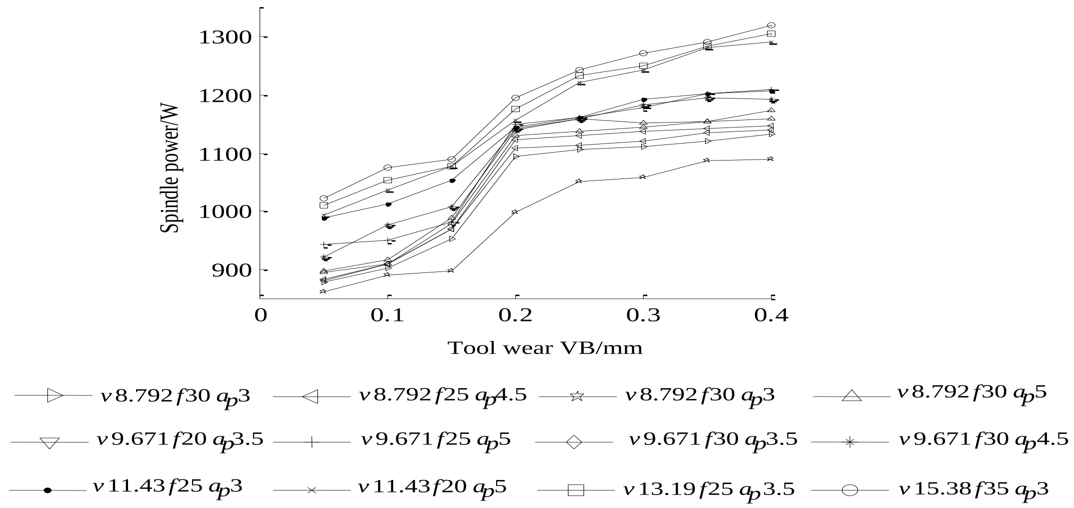


Fig.(4). The Training Sample of Spindle Power

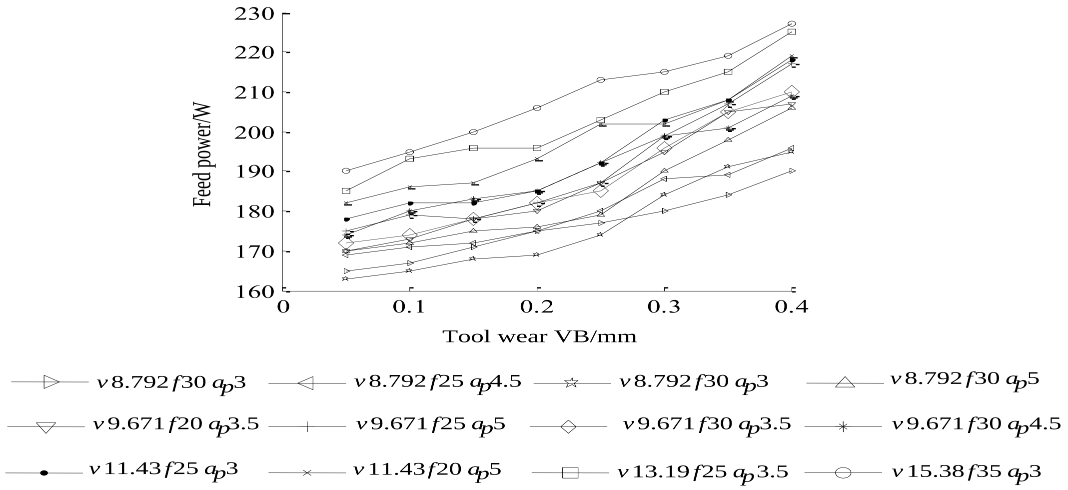


Fig.(5). The Training Sample of Feed Power

Table 3.The Model Coefficient and Correlated Coefficients

No	a_{i1}	a_{i2}	a_{i3}	a_{i4}	R^2	b_{i1}	b_{i2}	b_{i3}	b_{i4}	R^2
1	5.8310	0.1705	0.1602	0.0680	0.9593	4.4006	0.1462	0.1061	0.0626	0.9915
2	5.7739	0.1929	0.1815	0.0387	0.9550	4.2931	0.1688	0.1213	0.0850	0.9912
3	5.9394	0.1094	0.2071	0.0229	0.9727	4.3657	0.2061	0.0764	0.0910	0.9946
4	6.3406	0.0327	0.1651	0.0539	0.8482	4.3375	0.2120	0.0852	0.0924	0.9910
5	6.2498	0.1086	0.1481	0.0514	0.9547	4.2522	0.2212	0.1078	0.1086	0.9933
6	6.1584	0.1196	0.1688	0.0591	0.9721	4.3782	0.1165	0.1599	0.0891	0.9851
7	6.1456	0.1510	0.1543	0.0628	0.9668	4.4156	0.0738	0.1914	0.0745	0.9582
8	6.1073	0.1900	0.1387	0.0711	0.9720	4.3347	0.0751	0.2240	0.0785	0.9856

Table 4.An Example for 12 Sample Sets

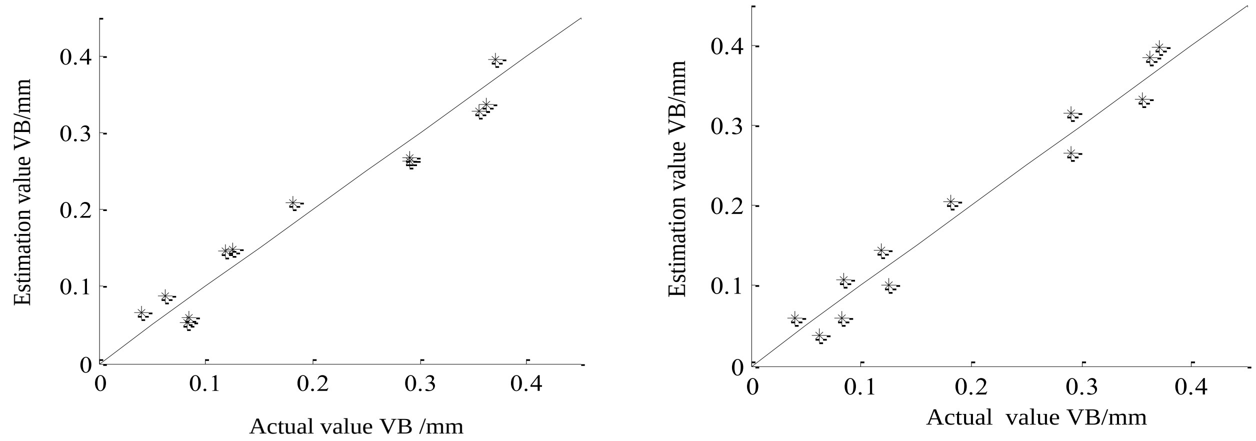
No	Cutting speed (m/min)	Feed speed (mm/min)	Cutting depth(mm)	Wear value (mm)	Spindle power(w)		Feed power（w）	
					Estimation value	Actual value	Estimation value	Actual value
1	8.792	20	2	0.04	836	830	161	155
2	8.792	25	3	0.182	1099	1042	177	176
3	13.19	30	4	0.085	1035	1010	192	190
4	13.19	35	5	0.125	1091	1083	203	202
5	17.584	20	4.5	0.355	1255	1256	203	204
6	17.584	30	3	0.362	1342	1352	222	217
7	17.584	30	4	0.118	1094	1090	202	204
8	21.98	25	3	0.062	1041	1052	193	195
9	21.98	35	3	0.291	1330	1320	223	224
10	21.98	30	5	0.290	1336	1325	227	230
11	8.792	35	5	0.370	1241	1250	216	222
12	8.792	30	4	0.082	962	956	181	179

Table 5. Measurement Results of Spindle Power Model

Number	Actual value/mm	Membership grade								Estimation value/mm	Absolute error
		$\mu_{0.05}$	$\mu_{0.1}$	$\mu_{0.15}$	$\mu_{0.2}$	$\mu_{0.25}$	$\mu_{0.3}$	$\mu_{0.35}$	$\mu_{0.4}$		
1	0.04	0.70	0.30	0	0	0	0	0	0	0.065	0.025
2	0.182	0	0	0	0.84	0.16	0	0	0	0.208	0.026
3	0.085	0.80	0.20	0	0	0	0	0	0	0.060	0.025
4	0.125	0	0.02	0.98	0	0	0	0	0	0.149	0.024
5	0.355	0	0	0	0	0	0.44	0.56	0	0.328	0027
6	0.362	0	0	0	0	0	0.28	0.72	0	0.336	0.026
7	0.118	0	0.08	0.92	0	0	0	0	0	0.146	0.028
8	0.062	0.26	0.74	0	0	0	0	0	0	0.087	0.025
9	0.291	0	0	0	0	0.74	0.26	0	0	0.263	0.028
10	0.290	0	0	0	0	0.66	0.34	0	0	0.267	0.023
11	0.370	0	0	0	0	0	0	0.10	0.90	0.395	0.025
12	0.082	0.92	0.08	0	0	0	0	0	0	0.054	0.028

Table 6.Measurement Results of Feed Power Model

Number	Actual value /mm	Membership grade								Estimation value /mm	Absolute error
		$\mu_{0.05}$	$\mu_{0.1}$	$\mu_{0.15}$	$\mu_{0.2}$	$\mu_{0.25}$	$\mu_{0.3}$	$\mu_{0.35}$	$\mu_{0.4}$		
1	0.04	0.80	0.20	0	0	0	0	0	0	0.06	0.02
2	0.182	0	0	0	0.90	0.10	0	0	0	0.205	0.023
3	0.085	0	0.86	0.14	0	0	0	0	0	0.107	0.022
4	0.125	0	0.98	0.02	0	0	0	0	0	0.101	0.024
5	0.355	0	0	0	0	0	0.34	0.66	0	0.333	0022
6	0.362	0	0	0	0	0	0	0.29	0.71	0.385	0.023
7	0.118	0	0.14	0.86	0	0	0	0	0	0.143	0.025
8	0.062	1	0	0	0	0	0	0	0	0.038	0.024
9	0.291	0	0	0	0	0.70	0.30	0	0	0.265	0.026
10	0.290	0	0	0	0	0	0.73	0.27	0	0.314	0.024
11	0.370	0	0	0	0	0	0	0.08	0.92	0.396	0.026
12	0.082	0.82	0.18	0	0	0	0	0	0	0.059	0.023



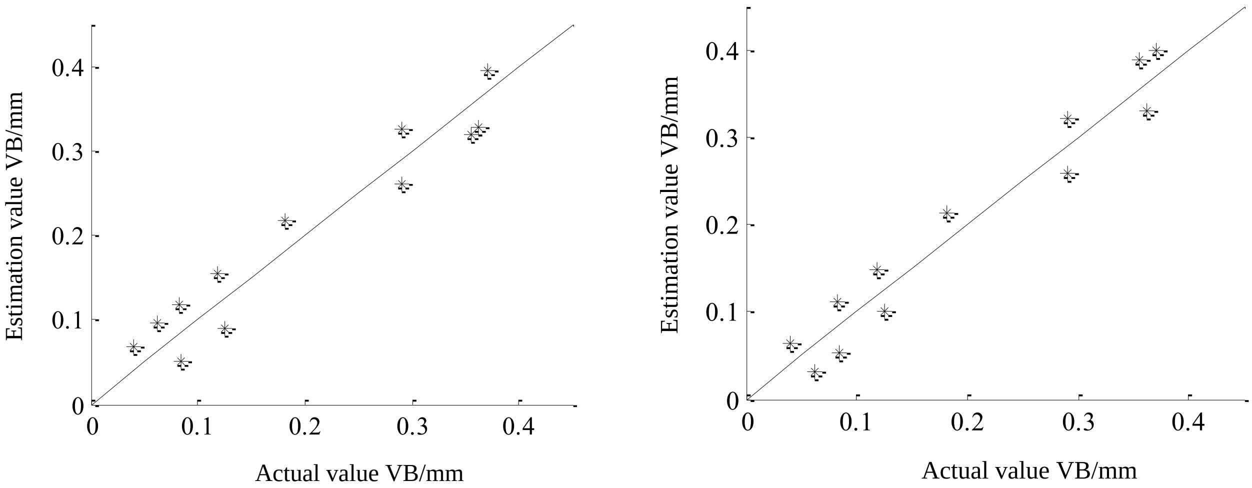
（a） Spindle power （b） Feed power

Fig.(6). Cutting Power Test Results for Group 1

The tool wear experiment found that the max absolute difference between the estimation wear value and the actual wear value about the spindle cutting power and feed cutting power is 0.028 mm and 0.025 mm respectively and the average error is equal to 0.026 mm and 0.023 mm respectively. Therefore, the factor that feed power affects the cutting tool wear is more than other factors. Namely, recognizing tool wear is much more effective on the basis of feed power. It is shown that the measurement error of cutting tools caused by greater tool wear is obvious as far as whole-process of monitoring tool wear. The reasons of these uncertainties may be that the cutting force is larger with tool wear increasing normally, the condition of contact between the tool and workpiece is worsened, these can cause tool edge bluntness, increase of friction , deformation stress and cutting temperature, leading to larger measurement error.

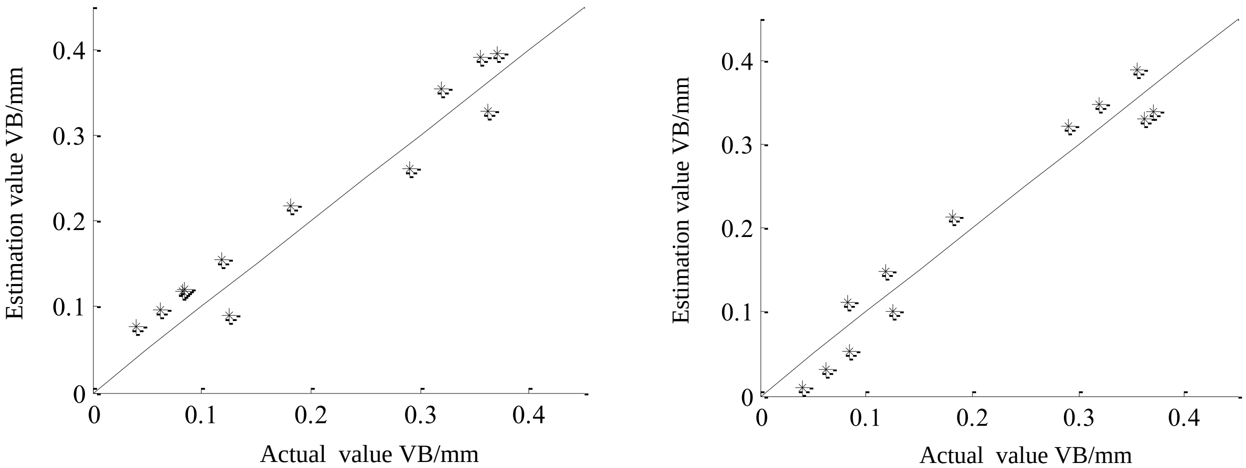
3.3 On-line Recognition Effect for Non-modeling Sample

In order to test whether the tool wear network model of cutting power model coefficient by modeling sample is suitable fo other online recognition of cutting conditions on tool wear, choose the second group, third groups of cutting parameters, the random measurement data of each cutting conditions is obtained. Fig.(7) and Fig.(8) is test results of second group and third groups of cutting parameters respectively.



（a）Spindle power （b）Feed power

Fig.(7). Cutting Power Test Results for Group 2



（a）Spindle power （b）Feed power

Fig.(8). Cutting Power Test Results for Group 3.

As far as second groups of cutting parameters, the tool wear experiment found that the max absolute difference between the estimation wear value and the actual wear value about the spindle cutting power and feed cutting power is 0.036 mm and 0.032 mm respectively and the average error is equal to 0.035 mm and 0.031 mm respectively. As far as third groups of cutting parameters, the max absolute difference between the estimation wear value and the measured wear value about the spindle cutting power and feed cutting power is 0.035 mm and 0.033 mm respectively and the average error is equal to 0.034 mm and 0.032 mm respectively. From test results of the first group of cutting parameters and other two groups, general trend of the max absolute difference and the average error have been increased significantly, feed cutting power tool wear recognition is superior to spindle power, which also shows that the two in the tool wear recognition put up some differences or sensitivity.

3.4 Fusion Pattern of The Cutting Tool Wear Recognition

For overcoming some disadvantages of measurement error by single factor analysis of power on-line recognition was used for fusion pattern . Fusion pattern in two power ways carry out combination.

$$\mu = k_1\mu_s + k_2\mu_f \qquad (9)$$

Where μ is comprehensive membership grade, μ_s and μ_f is membership grade of spindle power and feed power model respectively. Comprehensive membership grade with different properties can be made up according to k_1 、 k_2 different structure, for example, when structure is $\mu = 0.5(\mu_s + \mu_f)$, $\mu = 0.4\mu_s + 0.6\mu_f$, $\mu = 0.6\mu_s + 0.4\mu_f$. It is concluded that the monitoring wear error in which fusion pattern is used to $\mu = 0.4\mu_s + 0.6\mu_f$ is minimum, this is because that feed cutting power is more sensitive than the spindle cutting power in tool wear recognition. Table.7 is error comparison about measurement error in $\mu = 0.4\mu_s + 0.6\mu_f$ fusion pattern and before fusion in the previous three groups of cutting parameters.

IV. CONCLUSIONS

In this paper, using the regression analysis and fuzzy logic to establish the mathematical model between the milling cutting parameter and cutting power, and then tool wear model of spindle and feed power is presented. Theoretical analysis and experimental tests show that the cutting power is closely related to the tool wear. The main work and conclusions are as follows.

1) Establish the mathematical model between milling cutting parameter and power in cutting process, and applies it to the analysis and measurement of tool wear in milling.

2) The network model of tool wear of cutting power is established. It is used to cutting parameters to adjust the network part parameters in real-time so that the model has dynamic, real-time and fuzziness. In variable cutting conditions, the proposed fusion model is better than the single factor cutting power recognition of tool wear full detection recognition effect. At the same time, the results also reflect the spindle power and the feed power difference in sensitivity.

3) It is show that the cutting power model formed by the fixed model coefficient can be recognition large error and low precision in the cutting conditions change fast , its application can be limited.

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REFERENCES

[1] Xu, C.W.,Chen,H.L. (2009) “Condition Monitoring of Milling Tool Wear based on Fractal Dimension of Vibration Signals”, Strojniški vestnik - *Journal of Mechanical Engineering* , 55(1),p.15-25.

[2] Xu, C.W., Xu,T. (2011) “Study on Adaptive Model Parameter Estimation for Milling Tool Wear”, Strojniški vestnik - *Journal of Mechanical Engineering* , 57(7-8),p.568-578.

[3] Bülent, K., Cuneyt, O. (2011) “Force-torque based on-line tool wear estimation system for CNC milling of Inconel 718 using neural networks”, *Advances in Engineering Software - AES*, 42(3), p.76-84.

[4] Dražen, B., Luka, C.,and Sonja, J. (2012) “Modeling of the influence of cutting parameters on the surface roughness, tool wear and cutting force in face milling in off-Line process control”, *Strojniški vestnik - Journal of Mechanical Engineering*, 58(11),P.673-682.

[5] Ghani, J.A., Rizal, M., and Nuawi ,M.Z. (2011) “Monitoring online cutting tool wear using low-cost technique and user-friendly GUI”, *Wear*, 271(9-10),P.2619-2624.

[6] Franci, Č. and Uroš, Ž. (2011) “Real-Time Cutting Tool Condition Monitoring in Milling”, *Strojniški vestnik - Journal of Mechanical Engineering*, 2,P.1429-150.

[7] Oliveira, V.V., Beltrão,C.,and Pintaude, G. (2011) “Effect of tool geometry on the wear of cemented carbide coated with TiAlN during drilling of compacted graphite iron” , *Wear* , 271(9-10),P.2561-2569.

[8] Tobon-Mejia,D.A., Medjaher,K.,and Zerhouni, 3N. (2012) “CNC machine tool's wear diagnostic and prognostic by using dynamic Bayesian networks”,*Mechanical Systems and Signal Processing*, 28(4),P.167-182.

[9] Tony, B.and Ming, L. (2011) “Detection and diagnosis of bearing and cutting tool faults using hidden Markov models” ,*Mechanical Systems and Signal Processing*, 25(6),P.2102-2124.

[10] François, G., Didier, R.,and Jean-François, R . (2010) “Tool wear detection in milling—An original approach with a non-dedicated sensor” ,*Mechanical Systems and Signal Processing,* 24(6),P.1907-1920.

[11] Ibrahim, D., Khaled, A., and Firas, H. (2009) “On modeling of tool wear using sensor fusion and polymonial classifiers”,*Mechanical Systems and Signal Processing* , 23(5),P.1719-1729.

[12] Bovic, K., Pierre,D.,and Xavier ,C. (2011) “Tool wear monitoring by machine learning techniques and singular spectrum analysis”,*Mechanical Systems and Signal Processing,* 25(1),P.400-415.

[13] Chia, L. Y., Ming-Chyuan, L.,and Jau-Liang, C. (2013) “Applying the self-organization feature map (SOM) algorithm to AE-based tool wear monitoring in micro-cutting” ,*Mechanical Systems and Signal Processing*, 34(1-2),P.353-366.

[14] Jun, H. Z., Chee, K. P., and Zhao-Wei, Z. (2011) “Tool wear monitoring using acoustic emissions by dominant-feature identification, ” I*nstrumentation and Measurement*, 60(2),P.547-559.

[15] Xu, C.W. and Chen, H.L. (2009) “Milling Tool Wear Forecast Based on the Partial Least-Squares Regression Analysis,” *Structural Engineering and Mechanics*，31（1）,P.57-74.

[16] Qun, R., Marek, B., and Luc, B. (2010) “TSK fuzzy modeling for tool wear condition in turning processes,”*Engineering Applications of Artificial Intelligence*, 24(2),P.260-265.

[17] Tomas, K. and Yean-Ren, H. (2010) “A cutter tool monitoring in machining process using Hilbert–Huang transform,”*Machine Tools and Manufacture* , 50(5),P.495-501.

[18] Wan,J., Zhao,F., and Wu,X. (1996) “Intelligent tool failure monitoring or machining processes,”*Tsinghua Science and Technology* , 1(2),P.172-175