TELKOMNIKA, Vol. 11, No. 9, September 2013, pp. 5176~5181
ISSN: 2302-4046

Study on the Cutting Prediction of Supercritical Material

Hongtao Chen*, Pan Fu, Xiaohui Li
Institute of Mechanical Engineering of Southwest Jiaotong University, Chengdu 610031, China
*Corresponding author, e-mail: scdycht@163.com

Abstract

The technology of the artificial neural network (ANN) was applied in the research of supercritical material cutting. Two-dimensional Gaussian surfaces of the three cutting elements and workpiece surface hardness had been established fitting through JMP software. Base on the orthogonal milling experiments, the rules of cutting forces variation were forecasted, as well as the effect to the hardness on workpiece surface. The cutting parameters selected according to the process were built, providing an important basis for the optimization of machining conditions. The prediction results were in good agreement with the experimental results.

Keywords*: artificial neural network (ANN), supercritical material, cutting, prediction*

1. Introduction

The main features of supercritical materials are high temperature resistance, creep resistance, fatigue resistance, high strength, corrosion resistance, anti-oxidation, and low coefficient of expansion. Such parts of the cutting process requirements are very strict, because of the special working conditions. The cutting force is a very important physical quantity which reflects the state of cutting process. It has a great influence on the workpiece quality, tool life, production efficiency, etc. There are many factors which affect the milling force, such as the workpiece material, tool material and geometry, cutting parameters and process system rigidity, so it is difficult to accurately calculate them in practice [1]. These parts, such as turbine blades and impeller, are mainly manufactured by the supercritical material, because they are worked in special working conditions of high temperature and high pressure. That is, the main parts of turbine have very strict requirements on materials and the machining process. At present, the impact on the cutting law of supercritical material is mainly based on qualitative factors. Thus in actual production, the choice of cutting parameters based primarily on experience, it is difficult to meet the needs of high quality, high efficient, and low-cost production [2, 3].

The artificial neural network (ANN) theory provides a powerful tool for the study of nonlinear systems. It has been successfully applied in many research areas, more and more attention in the application of mechanical engineering disciplines. In our study, three signals of the cutting force had been collected in the orthogonal milling experiments. The basis of this approach is to train and test the cutting force model. The inputs to the model consist of cutting velocity v_c , feed rate f_z , and depth of cut a_p, while the outputs are composed of thrust force F_x , radial force F_y , and main cutting force F_z [4-8].

JMP is a computer program for statistics developed by the JMP business unit of SAS Institute. It was created in the 1980s to take advantage of the graphical user interface introduced by the Macintosh. It has since been improved and made available for other operating systems. JMP is used in applications such as Six Sigma, quality control and engineering, design of experiments, and scientific research [9, 10].

By the analysis of the data based on ANN and JMP, the impacts of cutting parameters on milling force, hardness, and microstructure of workpiece surface have been discovered.

Received February 19, 2013; Revised June 6, 2013; Accepted June 19, 2013

2. Experimental Design

2.1. Test Cutting Conditions

The test cutting conditions are shown in Table 1.

Table 1. Test Cutting Conditions

Item	Cutting conditions
Machine tool	Machining center: BV750; Spindle speed range: 20 to 8000 rpm; Spindle motor power: 15Kw
Blank	Supercritical material: 1Cr11; 50 mm×70mm×40 mm
Cutting tool	Face milling cutter: ϕ 32mm; Insert designation: APKT 1604 PDTR KC725M; Cutting edge angle: 90°
Cooling condition	Water base cutting fluid
Cutting parameter	As shown in Table 2

2.2. Test Equipment and Installation

Kistler9257B Swiss Kistler Dynamometer provides dynamics and quasi-static measurement of three orthogonal force (F_x, F_y, and F_z) acting from any direction onto the tool. In order to capture the cutting force signal of milling process, first of all, a tool set that makes a good match with the dynamometer was designed. And then we fixed dynamometer with four screws on the tool set. Finally, milling two step surfaces and drilling four holes on each blank, we clamped the blank on the dynamometer with four screws, as shown in Figure 1.

Figure 1. Test Equipment and Installation

DEWE-3021 series PC instrument (portable data acquisition system) was used in our test. This system which has up to 16 x MDAQ input channels and single-channel sampling frequency of 100 KHz can collect sensor data in time.

Orthogonal milling experimental design is an effective fast and economical mathematical method for multi-factor experimental design [11]. In order to study the impact of cutting parameter's change on the milling force, and to obtain the best results using fewer tests, we applied orthogonal milling experimental design to arrange the test program.

According to the cutting rules and possible cutting parameters in CNC milling of supercritical material, the value of the cutting speed(v_c)、cutting depth(a_p) , and feed rate (f_z) was selected, as shown in Table 2.

Table 2. Cutting Parameters

v_c (m/min)	a_p (mm)	f_z (mm/z)
50	0.1	0.05
100	0.5	0.1
150	1	0.15
200	1.5	0.2
250	2	0.25

3. Measurement and Analysis

3.1. Cutting Force

In this study, three force signals of F_x, F_y, and F_z are detected. As an example of the first group of force signal being detected, Fig. 2 was three-axis signals of F_x, F_y, and F_z that was drawn at random time period. The abscissa means cutting times from 10.501s to 10.801s. The ordinate means voltage signal (unit: V) of three force channels, being force ratio 1V = 500N. As can be seen from the figure, x direction amplitude of the force signal which the mean value gets 0.318V is greater than the other two directions. It can be obtained by calculating that the F_x force is corresponding to 159N. Having been completed by orthogonal test, the force signals of each test are detected. The cutting force data that cutting depth equal 0.5 mm are shown in Table 3.

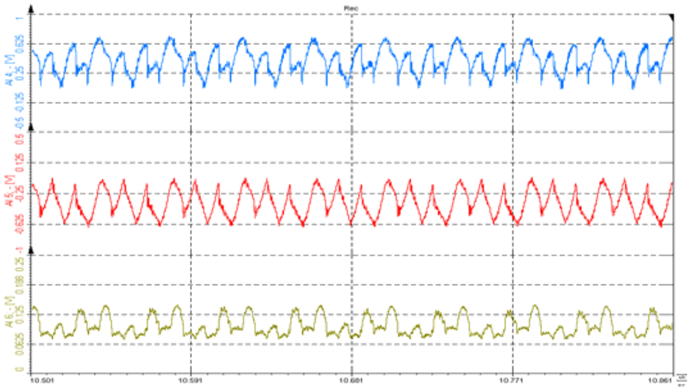


Figure 2. Three-axis Force Sgnals

Table 3. Orthogonal Milling Experiments ($a_p = 0.5mm$)

No.	Cutting parameter			Cutting force (N)					
	v_c(m/min)	*fz*(mm/z)	a_p(mm)	F_{XMAX}	F_{XAVE}	F_{YMAX}	F_{YAVE}	F_{ZMAX}	F_{ZAVE}
1	100	0.05	0.5	165	75	-171	-63	68	38
2	200	0.05	0.5	151	63	-165	-59	58	34
3	150	0.05	0.5	161	68	-164	-59	61	33
4	50	0.1	0.5	230	126	-200	-84	85	61
5	100	0.1	0.5	232	123	-205	-88	83	54
6	250	0.1	0.5	225	113	-225	-90	82	50
7	50	0.15	0.5	280	162	-227	-93	97	73
8	150	0.15	0.5	288	153	-245	-103	95	61
9	250	0.15	0.5	275	150	-229	-91	94	61
10	100	0.2	0.5	360	194	-290	-128	125	87.5
11	150	0.2	0.5	314	180	-239	-103	128	83
12	200	0.2	0.5	330	178	-300	-130	129	88.5
13	50	0.25	0.5	380	232	-306	-123	132	107
14	150	0.25	0.5	360	213	-265	-115	141	92.5
15	200	0.25	0.5	377	201	-319	-146	140	98

Note: 1）F_{XMAX}、F_{YMAX}、F_{ZMAX}: Maximum cutting force of x, y, z axis.
2）F_{XAVE}）、F_{YAVE}、F_{ZAVE}: Average cutting force of x, y, z axis.

Two-dimensional Gaussian surfaces of the cutting force and three cutting elements have been established fitting through artificial neural network in JMP software, as shown in Figure 3. Based on the analysis, we can easily get the following results.

The cutting depth in the cutting parameter has the greatest impact on milling force, followed by cutting feed. Cutting speed has little effect on milling force. In particular, note that Z-axis cutting force (F_z) is smaller in most cases. However, mutations of the cutting force value and direction occur in some specific combinations of cutting parameters. The process systems of test have produced resonance in these specific parameters. The formation of resonance is related to cutting conditions, rigidity of process system and other factors. We all know that the resonance is extremely detrimental to the cutting process. Therefore, the resonance region should be avoided in selecting cutting conditions [11].

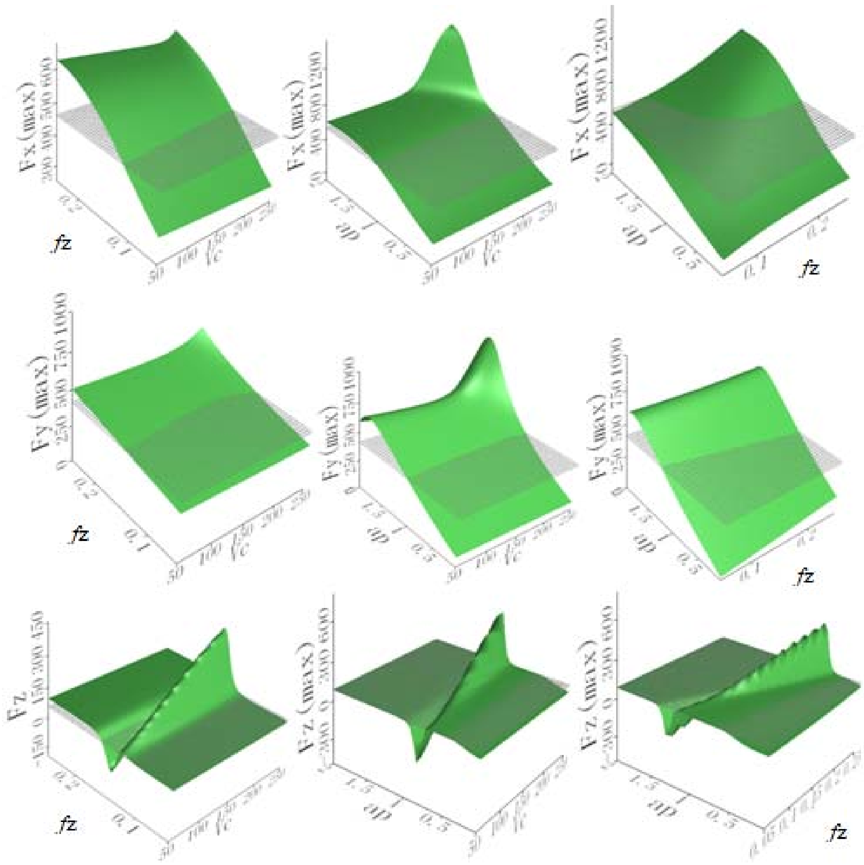


Figure 3. Relationship between Cutting Forces and Cutting Parameter

3.2. Workpiece Surface Hardness

In order to research the influence of cutting conditions on the surface of the physical and mechanical properties of supercritical material artifacts, the surface hardness was detected to each workpiece. Figure 4 is a three-dimensional contour surface chart of surface hardness and cutting parameters. We can see clearly from the Figure 4, the most significant impact on the surface hardness is the depth of cut. Especially in $a_p = 0.5$ mm is bounded, workpiece surface hardness has undergone significant changes in this region.

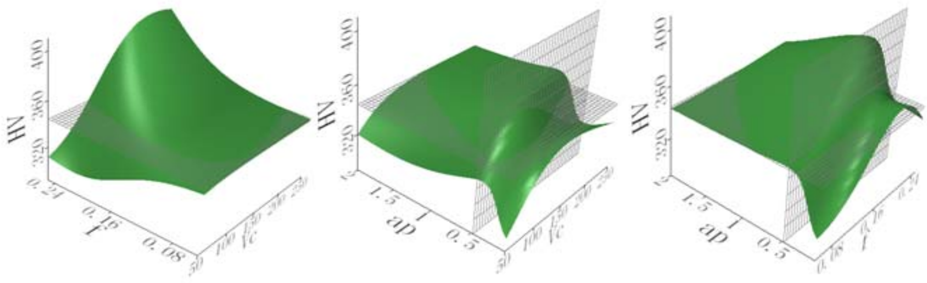
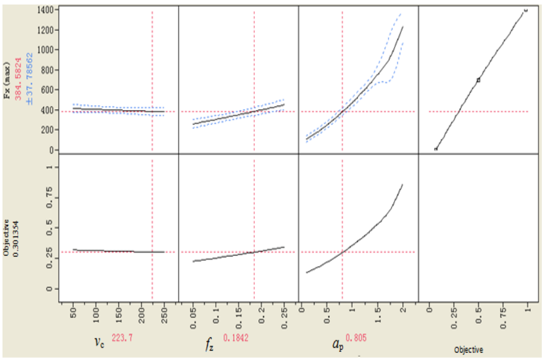


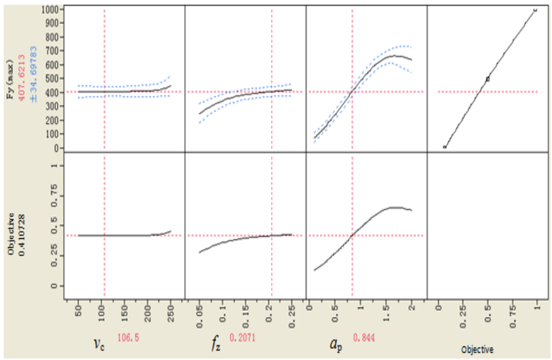
Figure 4. Relationship between Hardness and Cutting Parameter

4. Predictive Control

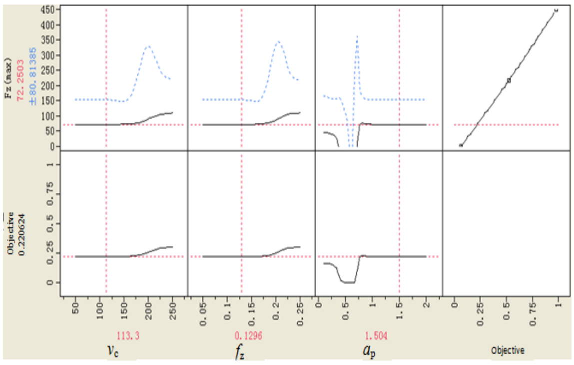
Predictive control to cutting forces in CNC milling process is ultimate goal of our test. By fitting the data after the factors portray, continuously adjustable to change the wishes of factors, the response curve will change accordingly and get ultimately the response that we expect [12]. The results of predictive control to F_x, F_y, and F_z in JMP software are as shown in Figure 5.



(a) Results of predictive control to F_x



(b) Results of predictive control to F_y



(c) Results of predictive control to F_z

Figure 5. Results of Predictive Control to Cutting Force

Similar to the above, we can get the results of predictive control to hardness of workpiece surface, as shown in Figure 6.

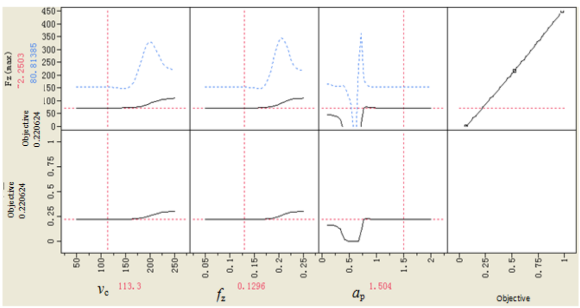


Figure 6. Results of Predictive Control to Hardness

Predicted by the above analysis, we can get continuous information of cutting forces in CNC milling process. The results show that the prediction results are in good agreement with the experimental results, as shown in Table 4. The deviation of the maximum milling force predicted in tests of No. 3 and No. 4 are bigger than other regions. The reason is that the cutting parameters of experimental selection are on resonance region of the machine tool. Experimental results show that deviation of the prediction results are within 10%.

Table 4. Prediction of Experimental Results

No.	Cutting parameter			Prediction valve (N)		Experimental valve (N)		Deviation(%)
	v_c ($m \cdot min^{-1}$)	a_p(mm)	f_z ($mm \cdot z^{-1}$)	F_{xmax}	F_{zmax}	F_{xmax}	F_{zmax}	
1	35	0.2	0.06	53	43	56	44	≤ 2.42
2	66	0.28	0.08	66	46	69	46	≤ 1.21
3	80	0.6	0.11	760	140	697	173	≤ 9.03
4	120	0.7	0.14	820	214	907	229	≤ 9.57
5	170	1.1	0.20	563	60	552	63	≤ 1.99
6	190	1.6	0.21	748	65	713	63	≤ 4.90
7	210	1.8	0.23	875	96	916	85	≤ 4.43

5. Conclusion

The change of the cutting conditions has great influence on the cutting force and the hardness of workpiece surface, and follows certain rules. By orthogonal test method, ANN and factor characterization technology are used predictive control to supercritical material CNC milling process. We can get a series of consecutive and predictable machining information from a limited test. Predictions of the cutting forces and hardness of workpiece surface can be a good fit with validation tests.This method can effectively predict the variation of supercritical material milling force at different cutting conditions. It can also be applicable to other predicted milling force in the absence of empirical formula of cutting force and testing conditions. Therefore, the method of our test has an important guiding significance to the optimization of cutting parameters.

Acknowledgment

This study is supported by the Fundamental Research Funds for the Central Universities, China (SWJTU12CX039).

References

[1] WS, Hao XS, Zhu XF Li. Prediction of cutting force for self-propelled rotary tool using artificial neural networks. *Journal of Materials Processing Technology*. 2006; 180, pp. 23-29.
[2] Yongjuan, Zhao, Yutian, Pan, Meixia, Huang. Numerical Simulation of Chip Formation in Metal Cutting Process. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(3): 486-492.
[3] XH Zheng, QX Yu, J Lin, M Lu, SQ Pang. Research on the cutting performance of carbon nitride cutting tools. *Journal of Materials Processing Technology.* 2002; 129: 157-160.
[4] M Hayat. Short Term Load Forecasting Using Artificial Neural Networks for the West of Iran. *Journal of Applied Sciences.* 2007; 7(22): 1582-1588.
[5] S Tamas. Cutting force modeling using artificial neural networks. *Journal of Materials Processing Technology.* 1999; 92-93: 344-349.
[6] Mardiyono Mardiyono, Reni Suryanita, Azlan Adnan. Intelligent Monitoring System on Prediction of Building Damage Index using Artificial Neural Network. *TELKOMNIKA Indonesian Journal of Electrical Engineering.* 2012; 10(1): 155-164.
[7] Guilin Yang. Forecast Surface Quality of Abrasive Water Jet Cutting Based On Neural Network. *Journal of Theoretical and Applied Information Technology*. 2013; 47(3): 1087-1091
[8] P Sibi, S Allwyn Jones. Analysis Of Different Activation Functions Using Back Propagation Neural Networks. *Journal of Theoretical and Applied Information Technology*. 2013; 47(3): 1344-1348.
[9] Lovell, David P. Review of JMP genomics.Pharmaceutical Statistics. 2011; 10 (4): 384–392 .
[10] BJ ones, J Sall. JMP statistical discovery software. *Wiley Interdisciplinary Reviews: Computational Statistics*. 2011; 3(3): 188–194.
[11] Hongtao Chen, Sui Huang, Pan Fu. Tool Wear Prediction Based on Fuzzy Cluster Analysis. *Lecture Notes in Electrical Engineering*. 2012; 67 LNEE: 739-749.
[12] SE Oraby, DR Hayhurst. Development of models for tool wear force relationship in metal cutting. *International journal of mechanical sciences*. 1991; 22(2): 125-138.