Prediction of Surface Roughness of Difficult-to-cut Material by HSM Based on RBF Neural Network

LI ZHANJIE, YAN BING, TIAN MEILI
School of Mechanical Engineering
Tianjin University of Technology and Education
Tianjin 300222
CHINA
http://www.tute.edu.cn

Abstract: Prediction of surface roughness has become an important trend of quality analysis. In this paper, RBF neural network is used to predict surface roughness. Compared with measured value and the result from regression analysis, the result of prediction using RBFneural network indicates its feasibility, which provides references for optimization of cutting parameters and development of cutting database.

Key-Words: difficult-to-cut material; HSM; neural network; roughness; prediction

1 Introduction

Austenitic stainless steel 1Cr18Ni9 is a typical difficult-to-cut material therefore the deep-going research on the high-speed milling (HSM) mechanism combined with machining practice is one of our urgent tasks, which is important to both basic and application research for the manufacturing. Surface roughness is an essential index in the quality measurement of cutting and manufacturing, which reflects the synthetic effect of the cutting parameters and systematic variables on the cutting process [1]. The construction of a model on accurate control and prediction of the surface roughness as well as the reduction in time and cost spent on the cutting experiments have become the shared concern of domestic and abroad scholars. In [2], hard machining reveals that the best range of cutting conditions to get good surface roughness should be the combination of high cutting speed, low feed rate and low depth of cut. Among them, the last factor plays a greater role. In [3,4], based on experience models, the major parameters that affect surface roughness in ball-end milling and high-speed turning are investigated. It has been proved theoretically and experimentally that the surface roughness will increase when the feed rate and radial depth of cut increase; the roughness will decrease as the cutting speed increases. In view of the immaturity in the current studies on the mechanisms of the surface roughness by HSM, cutting experiments remains the major way to analyze and approach the mechanism about how the cutting parameters affect the surface quality. The previous models have simplified the working situations to a large extent so that the integral study on the effect from factors such as cutting parameters and systematic variables becomes impossible. In those models, there exists great error in precision, i.e., the experiment result deviates from the calculated result greatly, sometimes as great as five times the value of the latter in extreme cases[5]. Major causes of the imprecision are the complexity and uncertainty during the cutting process. At present the major difference in analytical method lies in the methods of data processing. The most frequently exploited methods include regression analysis and range analysis, etc. With the development of computer techniques in both software and hardware, artificial neural network (ANN) has become one of the most powerful computer modelling techniques in the field of engineering[6–9].

2 RBF neural network and its realization

Based on statistical approach, ANN is a powerful tool for the identification of the relevant parameters and their interactions especially when the relationships are very complex and highly non-linear. Furthermore, as neural networks have the ability to learn from set of examples and generalize this knowledge to new situations, they are excellent for work requiring adaptive control systems. Neural network modelling is suitable for simulations of correlations which are hard to describe by physical methods. They have been applied very successfully in the field of metal-cutting modelling.

Many different neural networks have been established over the past 20 years. They include perceptrons, Hebbian, Kohonen, backpropagation and Hopfield networks. In the current work, radial basis function (RBF) neural network is used to predict surface roughness. With Gaussian activation functions, RBF network is a two layer fully interconnected neural network, which has some additional advantages such as rapid convergence and less error. In practice, the number of parameters in RBF network starts becoming unmanageably large only when the number of input features increases beyond about 14, which is not the case in our study. Details on the neural network modelling approach are given in [6-10]. In this paper, the input/output dataset of the model is illustrated schematically in Fig. 1[10].

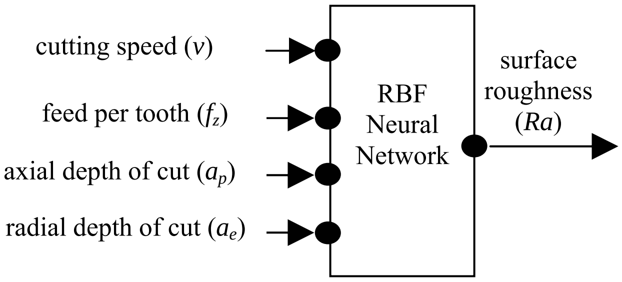

Fig.1. Schematic model of RBF neural network for prediction ofsurface roughness for austenitic stainless steel 1Cr18Ni9

3 Orthogonal experiment and data analysis

3.1 Experimental conditions

(1) Machine tool: Germany DMC75V linear DECKEL MAHO, 5-axis, maximal rotate speed:28000rpm.
(2) Tool: ϕ20mm,HDM-2020-130L, end mill carbide:Hitachi CY250ACMT100308R,2 blades.
(3) Material: Austenitic stainless steel 1Cr18Ni9(170×100×80mm^3)
(4) Surface roughness tester: Surftest500

3.2 Experimental scheme

The orthogonal experimentation is a powerful design of experimental method. It provides a simple, efficient, and systematic approach to optimising designs for performance, quality and cost. According to [11] and experience, the factors and levels are assigned as in Table 1 according to finishing condition for the said material when machingg at high cutting speed and a standard $L_9(3^4)$ orthogonal array is chosen as in Table 2 in which each row represents one trial[12]. However, the sequence in which these trails are carried out is randomized. Experimental results are shown in the last column of Table 2.

Table 1 Factors and levels used in the experiment

Factor	Level		
	0	1	2
n--rotate speed (rpm)	5000	7500	10000
f --feedrate (mm/min)	1500	1875	2000
a_p --axial depth of cut (mm)	0.1	0.2	0.3
a_e --radial depth of cut (mm)	1	2	3

Table 2 Experiment Design and Experimental Results

No.	*n* (rpm)	*f* (mm/min)	a_p (mm)	a_e (mm)	*Ra*(μm) (climb)
1	5000	1500	0.1	1	0.3075
2	5000	1875	0.2	2	0.36
3	5000	2000	0.3	3	0.4
4	7500	1500	0.2	3	0.4275
5	7500	1875	0.3	2	0.33
6	7500	2000	0.1	1	0.31
7	10000	1500	0.3	2	0.38
8	10000	1875	0.1	3	0.54
9	10000	2000	0.2	1	0.285

3.3 Data analysis

3.3.1 Multivariate Linear Regression Model

Prior to the use of the datasets, principal component analysis is performed to test the correlation between the input and output dataset. Result shows that each of the four selected cutting parameters (input dataset) accounts for more than 97%(R^2=0.973) variability of surface roughness (output dataset). Post processing of the surface roughness data analysis is performed using Microsoft Excel 2000^{TM} software. The result of regression analysis is as follow[13]:

$$Ra = 0.155785\, v^{0.1079} \cdot f_z^{-0.0239} \cdot a_p^{-0.1914} \cdot a_e^{0.4304} \quad (1)$$

3.3.2 Comparison of predictive results between ANN and regression

The data in Table 2 from No. 1 to 8 is taken as training samples to establish a network by newrbe function in MATLAB 7 Neural Network Toolbox, and No.9 as testing samples to verify the precision of the network[14]. Before training the network, the input/output datasets are normalised within the range of ±1. The normalised value (X_i) for each raw input/output dataset (*X*) was calculated as

$$X_i = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (2)$$

The predictive results using ANN and regression are listed in Table 3.

Table 3 Comparison of predictive results between ANN and regression`

No.	*Ra* μm				
	Measured value	Predicted value by ANN	Relative error *B%*	Predicted value by regression	Relative error *B%*
1	0.3075	0.3075	0	0.30282	-1.52
2	0.36	0.36	0	0.35547	-1.26
3	0.4	0.4	0	0.39103	-2.24
4	0.4275	0.4275	0	0.44886	5.00
5	0.33	0.33	0	0.34698	5.14
6	0.31	0.31	0	0.31727	2.35
7	0.38	0.38	0	0.36231	-4.66
8	0.54	0.54	0	0.52949	-1.95
9	0.285	0.285106	0.03715	0.28383	-0.41

In Table 3, relative error is defined as *B%* =[(Predicted value-Measured value)/ Measured value]×100%. As shown in Table 3,the precision of prediction using ANN is much better than that using least-squares regression.

3.3.3 Discussion on the influence of single factor on climb milling surface roughness

In consideration of the characteristics that RBF neural network has a strong self-adaptability and study function, shows the stronger nonlinear mapping ability than the regression analysis, can realize the mapping of complex inputs and outputs samples through the way of error control, and its error is very small in the range of test conditions, we fix the optimal levels of other factors, and do research on the influence of of single factor on climb milling surface roughness through RBF neural network, as shown in Fig. 2.

From Fig. 2 we can see that the roughness of climb milling increases with the increase of radial depth of cut (a_e), and the change is very notable. The lowest surface roughness can be got when a_e is about 1.3mm. This predition is in accordance with the result from the way of range analysis, that is to say, the lower value of surface roughness can be obtained when a_e is at the lower level, as shown in Fig. 3.

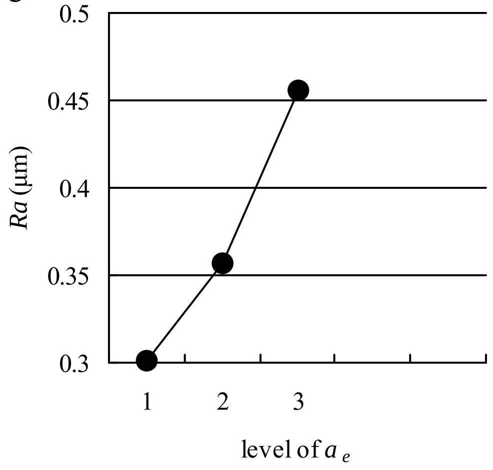

Fig. 3 Relation between a_e and *Ra*(climb milling) using range analysis

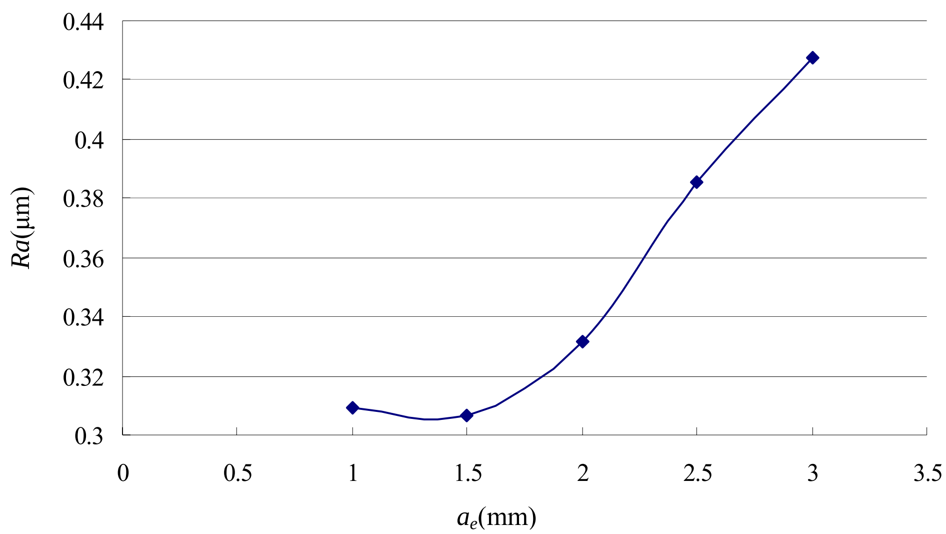

Fig. 2 Relation between a_e and *Ra*(climb milling) using ANN (v =7.85 m/s f_z =0.133 mm per tooth a_p =0.2mm)

With the rise of radial depth of cut, removed volume of material increases. So do the consumed power and cutting forces. The radial cutting force was the most sensitive to the tool wear[15]. Higher mechanical load would bring about higher cutter deflections thereby increasing the wear of the cutter due to the intermittent cutting effect against the workpiece material. Thus, the surface roughness of climb milling increases with the increase of radial depth of cut.

4 Conclusions

(1) RBF neural network has strong self-adaptability and study function, shows the stronger nonlinear mapping ability than the regression analysis, and allows any quantified cutting conditions as the inputs of network. Thus, many influencing factors on roughness can be added into the model. In order to improve the adaptability and veracity of the network, enough experiment samples should be provided.

(2)The regression model established by statistic regression between surface roughness and cutting parameters(v, f_z, a_p, a_e) is credible. From the forecasting effects of the testing data, its relative error is far less using RBF neural network than that using multivariate linear regression model, which has values of reference and application for the prediction of surface roughness.

(3) The model of prediction using RBF neural network helps to the study on cutting parameter optimation and cutting database.

(4) During the period of finish machining of stainless steel 1Cr18Ni9, the radial depth of cut (a_e) has great influence on the value of climb milling surface roughness.

References:

[1] WANG Suyu, ZHAO Jun, AI Xing, Theoretical Research of Surface Roughness for HSM [J].*Mechanical Engineer*,2004(10), pp.3-6.

[2] LIU Xianli, Research on cutting perfomace and manufacturing of PCBN Tool [D].Harbin:Harbin Institue of Technology,1999.

[3] Alauddin M. et al, Computer-aided analysis of a surface roughness model for end milling [J]. *Journal of Material Processing Technology*, 1995(55), pp.123-127.

[4] Lin W.S. et al, Modeling the surface roughness and cutting force for turning[J]. *Journal of Material Processing Technology*, 2001(108), pp.286-293.

[5]Van luttervelt C. A. et al, Present situation and future trends in modeling of machining operations [J]. *Annals of the CIRP*, Vol.47, No.2,1998, pp.587-626.

[6] Benardos P.G. , Vosniakos G.C. ,Prediction of surface roughness in CNC face milling using neural networks and Taugchi's design of experiments [J]. *Robotics and Computer Integrated Manufacturing*, 2002 (18), pp.343-354.

[7] Liu T.L., Chen W.Y., Anantharaman K.S., Intelligent detection of drill wear, *Mech. Syst. Signal Process*, Vol.12, No.6, 1998, pp.863-873.

[8] Dimla Sr. D.E., Lister P.M., On-line metal cutting tool condition monitoring: Tool-state classification using multi-layer perceptron neural networks, *Int. J. Mach. Tool Manuf*, Vol.40, 2000, pp.769-781.

[9] Dimla Sr. D.E., Application of perceptron neural networks to tool state classification in a metal-turning operation, *Eng. Appl. Artif.Intell*, Vol.12, 1999, pp. 471-477.

[10] Ezugwu E.O., Fadare D.A. et al, Modelling the correlation between cutting and process parameters in high-speed machining of Inconel 718 alloy using an artificial neural network *International Journal of Machine Tools & Manufacture*,Vol.45, 2005, pp.1375-1385.

[11] ZHOU Huaze, *Principle of Metal Cutting*, Shanghai Technology Press, 1993.

[12] YUAN Zhejun, *Experimentation of Metal Cutting*, China Machine Press, 1988.

[13] CHEN Kui, *Design and analysis of experiment*, Tsinghua University Press,1996.

[14] FEI Si Center of R&D of hi-tech Products, *Theoryof neural network and its realization using MATLAB7*, Electronic Industry Press, 2005.

[15] Toh C.K., Static and dynamic cutting force analysis when high speed rough milling hardened steel, *Materials & Design*, Vol. 25, 2004, pp.41-50.