中國機械工程學刊第四十一卷第五期第 615~622 頁(民國一百零九年)
Journal of the Chinese Society of Mechanical Engineers, Vol.41, No.5, pp 615~622 (2020)

Surface Roughness Prediction Based on Surface Temperature and Tool Vibration Using BP Neural Network on Turning Machine

Bin Wang*, Dan-Gui Wang**, Li-Ping Bi*** and Hui Wang*

Keywords：RVLR, Surface quality, Surface temperature, Tool vibration.

ABSTRACT

In machining process, the quality of surface finish is an important requirement for many turned workpieces. Thus the controlling of machining conditions is very important for improving surface quality. This paper proposes an in-process monitoring system of surface temperature and tool vibration and discusses on surface roughness prediction based on surface temperature and tool vibration. The authors incorporate a new training scheme to BP (back propagation) neural network, namely reinforced strategy of variable learning rate (RVLR), to predict surface roughness using cutting parameters and performance characteristics, surface temperature and tool vibration. Finally, the paper shows surface roughness prediction results. Compared with SD (steepest descent) update method and traditional strategy of variable learning rate (TVLR), the RVLR method required shorter processing time to converge to the global minimum of least mean squared error. SD update method lead neural network fall into local minimum, 26.18 m^2/min^2. With either the TVLR or the RVLR method, the network was able to avoid settling at the local minimum and reach the global minimum. However, their respective least mean square errors were 9.23 m^2/min^2 and 8.21 m^2/min^2 as the best-record. In addition, the new learning algorithm only required a quarter of the TVLR processing time to reach the “stable” region. This method would be helpful in selecting cutting parameters and controlling of surface temperature and tool vibration for the required surface quality.

Paper Received June, 2020. Revised July, 2020, Accepted September, 2020, Author for Correspondence: Bin Wang.

* *Lecturor, Five-year Higher Vocational* ***School****, Shandong University of Engineering and Vocational Technology, Jinan, China.*

** *PHD Student, School of Chemistry and Chemical Engineering, Huazhong University of Science and Technology, Wuhan, China.*

*** *Associate Professor, Five-year Higher Vocational School, Shandong University of Engineering and Vocational Technology, Jinan, China.*

INTRODUCTION

The quality of products has to be monitored in each production stage and immediate corrective actions have to be taken in case of deviation from desired trend. In machining process, surface roughness is one of the most important quality evaluation responses and a technical requirement for mechanical products in most cases. In actual practice, Surface roughness is harder to attain and track than physical dimensions is, because there are many factors which affect the surface roughness, i.e. tool variables, workpeice variables and cutting conditions. As the turning process involves large numbers of parameters, the process control becomes complex and it would be difficult to select the appropriate parameters for achieving the required quality. A considerable number of studies has studied the effects of the speed, feed rate, depth of cut and other factors on the surface roughness. Neural network models were utilized by Ozel and Karpat (2012) to predict surface roughness and tool flank wear for various different cutting conditions in turning process. Regression models were also developed, but the neural network models provided more accurate surface roughness and tool wear prediction than the regression models. Risbood et al. (2003) found that the neural network could predict surface roughness and dimensional deviation within a reasonable degree of accuracy if the cutting force and the acceleration of radial vibration of tool holder were taken as a feedback. The purpose of studying these factors in machining processes is to increase surface quality while decreasing cost and time of manufacture.

Various researchers have developed the surface roughness predictive models. Regression analysis and neural network-based models were compared to investigate surface roughness for various cutting conditions in turning by Nalbant et al. (2007). The trained neural network models showed better predictive surface roughness than various regression models. Chien and Yao (1997) developed a neural network model for predicting the cutting forces and surface roughness under some specified cutting conditions. Then the genetic algorithm was adopted to find the optimum cutting conditions to obtain the maximum metal removal rate (MMRR) based on the constraint of surface roughness. An artificial neural network was developed by Assadi et al. (2004) to acquire the skilled of machinists on-line in turning process, and the intelligent system has been proven to predict the appropriate cutting parameters after the training.

The cutting temperature and tool vibration are key factors which directly affects surface integrity according to the relative motion between the tool and workpiece. The combined effects of cutting parameters, including cutting speed, feed rate, depth of cut and cutting tool vibration on surface roughness were investigated while employing the analysis of variance (ANOVA) by Hessainia et al. (2013). ANOVA demonstrates that the feet rate and the cutting speed have the highest influence on the evolution of machined surface roughness. The quadratic model of RSM associated with response optimization technique and composite desirability was utilized to find optimum cutting parameters and tool vibration with respect to announced objectives which are the prediction of surface roughness. Abouelatta (2012) developed a mathematical model for the predicted roughness parameters, based on both cutting parameters and machine tool vibrations. The in-process monitoring of the cutting force and the cutting temperature is utilized by Tangjitsitcharoen (2013) to analyze the relation between the surface roughness and the cutting condition. Because no researcher previously used surface temperature and tool vibration as indicators of cutting performance, this research proposes an in-process monitoring system of surface temperature and tool vibration in order to improve surface roughness via the controlling of surface temperature and tool vibration during machining process. In this paper, the authors incorporate a new training scheme to BP neural network, namely reinforced strategy of variable learning rate (RVLR) to predict surface roughness based on cutting parameters and performance characteristics including surface temperature and tool vibration. Simulating with Ms Visual C++, a series of error curves of cutting parameters were required. The experimental results show the influence of surface temperature and tool vibration on surface roughness. Compared with TVLR, the RVLR algorithm also shows its advantages, faster convergence speed and greater accuracy.

EXPERIMENTAL CONDITIONS AND PROCEDURES

The workpiece material chosen for the test samples was medium carbon steel AISI 1020 (0.05 m diameter). Its chemical composition is shown as follows: C, 0.20; Si, 0.15; Mn, 0.72; P, 0.011; S, 0.023. CNMG 432 TT5100 insert with Sandvik tool holder PCLNR 2525M/12 universal turning machine tool was used in the experiments. Cutting tool wear is an important factor affecting surface quality. In order to avoid the affection of cutting tool, the new insert with some material was used at each experiment.

The machining tests were carried out on a lathe turning machine in dry condition. In general, changes in cutting speed, feed rate and depth of cut affect the signal generated during the turning process. Those parameters influence surface roughness by a large extent. Therefore, the effect of Cutting speed, feed rate and depth of cut were taken into consideration in order to study surface finishing. Table 1 presents the 27 sets of cutting parameters chosen for the test samples. Among them, the cutting speed is set at 950, 1150 and 1400 rpm; the feed rate is set at 0.05, 0.1, 0.15 mm rev^{-1}; the depth of cut is set at 0.5, 1.0 and 1.5 mm.

Data acquisition process consists of three different data collections which the first is the measurement of the tool vibration, the second is the temperature measurement on the working material and the third is the roughness measurement.

The tool vibration on the working machine was measured with four accelerometers connected with NI 9234 USB Data Acquisition Module, and analyzed using S & V Measurement Suite Software in order to get the acceleration signal in time domain. The machining process can be simplified as a cutting process of up-and-down (radial) and a feeding process of right-and-left (feed). Hence four single-axis accelerometers were placed near the cutting tool and the workpiece to measure the vibration in the radial and feed directions. It was observed that there were no chips hitting these accelerometers during the machining process. The RMS values of the acceleration signal measured in two directions were averaged as the input vibration value.

As the infrared thermometers have been used in more reports than any other method and there are many advantages in the use of infrared sensor. For surface temperature measurement, handheld infrared thermometer type (OS534E) with a built-in laser circle to dot switchable and RS-232 output was used and the measurements between cutting tool and workpiece surface are repeated three times while machining the workpiece.

The amount of standard surface roughness parameter (Arithmetic average deviation from the mean line Ra) was carried out using the surface roughness tester model Mahr Perthometer (MarSurf PS1, produced by Mahr GMbH, Germany). Three measurements for surface roughness were made and averaged for each test sample. Table 1 shows measurement results of 27 sets of cutting parameters.

Twenty seven (27) sets of data obtained in the experiment were used for the training and testing of neural network model. All the data was separated into two parts - i) 21 group used to train the prediction model and ii) the remaining 6 group used to test the validity of models. Surface temperature and tool vibration were yielded while machining workpiece, whereas they have some influence on surface roughness as well as cutting parameters. The relationship between these traits and surface roughness would be analyzed by correlation coefficients.

Table 1 Test samples and measurement results for training BP neural network models

NO.	S	F	D	VEx	TEx	RaEx
1	1120	0.05	0.5	0.961	62.34	0.856
2	850	0.05	0.5	0.729	58.81	0.975
3	630	0.05	0.5	0.692	55.86	1.036
4	1120	0.10	0.5	1.031	63.01	0.789
5	850	0.10	0.5	0.929	59.04	0.915
6	630	0.10	0.5	0.890	56.12	1.004
7	1120	0.15	0.5	1.172	64.04	0.754
8	850	0.15	0.5	1.036	60.17	0.901
9	630	0.15	0.5	0.945	56.76	0.981
10	1120	0.05	1.0	1.003	63.81	1.245
11	850	0.05	1.0	0.902	60.18	1.306
12	630	0.05	1.0	0.861	57.16	1.481
13	1120	0.10	1.0	1.261	64.05	1.123
14	850	0.10	1.0	1.123	60.88	1.275
15	630	0.10	1.0	0.968	57.83	1.304
16	1120	0.15	1.0	1.293	65.78	0.942
17	850	0.15	1.0	1.146	61.57	1.076
18	630	0.15	1.0	1.056	58.17	1.291
19	1120	0.05	1.5	1.121	67.34	1.472
20	850	0.05	1.5	1.093	63.42	1.679
21	630	0.05	1.5	0.993	60.14	1.848
22	1120	0.10	1.5	1.359	68.34	1.437
23	850	0.10	1.5	1.159	64.17	1.518
24	630	0.10	1.5	1.005	60.79	1.766
25	1120	0.15	1.5	1.577	68.65	1.335
26	850	0.15	1.5	1.304	64.65	1.401
27	630	0.15	1.5	1.166	61.32	1.623

S: Cutting speed (r/min), F: Feed rate (10^{-3}m/rev), D: Depth of cut (10^{-3} m), VEx: Experimental tool vibration (m/s^2), TEx: Experimental surface temperature (°C), RaEx: Experimental surface roughness (um).

BACK PROPAGATION (BP) NEURAL NETWORK METHODS

In this research, the inputs are cutting parameters (cutting speed, feed rate and depth of cut) and cutting responses (surface temperature or tool vibration), while the output is the surface roughness. Gomm et al. (1996) pointed out that BP neural network of three layers, namely the neural network only contains one hidden layer could be used to approximate almost any non-linear function with any accuracy if there are enough neurons in the hidden layer. Thus one hidden layer was used to constitute a three-layer BP neural network for roughness prediction.

The Back Propagation Algorithm

BP neural network's learning process consist of forward propagation and back propagation. In the forward process, input signals from input layer pass hidden layer and transmit to the output layer. If there is a difference which is defined as error value between the actual output values and known-correct output values, then BP network turns to the process of error back propagation. The error value is propagated backwards through the network, and the sensitivity of each neuron is calculated from the most outer layer. The neuron sensitivities of last layer are calculated with the following equation in matrix form.

$$\mathbf{s}^M = -2\dot{\mathbf{F}}^M\left(\mathbf{n}^M\right)(\mathbf{t}-\mathbf{a}), \qquad (1)$$

Matrix $\mathbf{t}$ consists of all target outputs. $\dot{\mathbf{F}}^M\left(\mathbf{n}^M\right)$ is the sensitivity function of respective neuron and is expressed as the following.

$$\dot{\mathbf{F}}^m\left(\mathbf{n}^m\right) = \begin{bmatrix} \frac{\partial f^m\left(n_1^m\right)}{\partial n_1^m} & 0 & \cdots & 0 \\ 0 & \frac{\partial f^m\left(n_2^m\right)}{\partial n_2^m} & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & \frac{\partial f^m\left(n_{Sm}^m\right)}{\partial n_{Sm}^m} \end{bmatrix}, \qquad (2)$$

where Sm is the number of neurons in layer m. The following equation is used for other layers.

$$\mathbf{s}^m = \dot{\mathbf{F}}^m\left(\mathbf{n}^m\right)\left(\mathbf{W}^{m+1}\right)^T \mathbf{s}^{m+1}. \qquad (3)$$

Finally, the weight and bias changes in each layer are calculated to reduce the error signal with selected update method, which may be referred as learning algorithm.

Drawback of Approximate Steepest Descent Method

In Approximate Steepest Descent (SD) method, momentum is used to smooth out the oscillations in the trajectory towards the optimum location. The weights and biases are updated with Approximate Steepest Descent method according to the learning rate and the momentum coefficient. However, there are some disadvantages:

(1) BP network is easy to get into the local least value, but cannot reach the global optimal circumstance.

(2) Learning speed is slow and network's training takes a long time.

(3) The network structure is forward structure not a nonlinear dynamics system. It is only a nonlinear mapping system.

(4) The selection of iterative step and inertial factor is determined by experiences. It maybe brings about network oscillation and stop learning convergent if it was not selected correct.

Traditional Strategy of Variable Learning Rate (TVLR)

Wong and Hamouda (2003) applied TVLR method during BP neural network training process for machinability data representation. The strategy was concluded as follows.

a) If the entire squared error increases by more than percentage ζ after a weight and bias update, then the update is discarded, the learning rate α is multiplied by factor ρ (< 1), and the momentum coefficient γ is set to zero.

b) If the entire squared error decreases after a weight and bias update, then the weight update is accepted and the learning rate is multiplied by factor η (>1). If momentum coefficient has been previously set to zero, it is reset to its original value.

c) If the entire squared error increases by less than ζ, then the weight and bias update is accepted but the learning rate and the momentum coefficient are unchanged.

Reinforced Strategy of Variable Learning Rate (RVLR)

The learning rate change coefficient ρ or η is chosen according to the entire squared error change in traditional strategy of variable learning rate and they are decisive factors in regard to the size of the weight adjustments made in each cycle. If the chosen value of ρ or η is too small, the descent will progress in very small steps, significantly increasing the total convergent time. In contrast, if the chosen value of ρ or η is too large, the searching path will oscillate about the ideal path and converges more slowly than a direct descent. Moreover, the factor ρ or η should be considered in each cycle iteration and the value cannot be changed during the training process. The authors proposed that the value of ρ or the value of η at each training cycle should be under different value in accordance with the increment of the entire squared error in order to improve the learning rate better. The factor ρ is calculated with the following equation.

$$\rho(k)=1-\frac{d(k)}{r_{initial}-r_{end}} \quad , \qquad (4)$$

Where $\rho(k)$ is the value of ρ in the kth training cycle and $d(k)$ represents the increment of the entire squared error in the kth training cycle. r_{initial} and r_{end} are the user defined values which indicate the entire squared error limit at the initial and the end of the training respectively. As general practice, the value of r_{initial} should be larger than r_{end}.

If the entire squared error decreases after a weight and bias update, the learning rate is multiplied by factor η(>1). The factor η is calculated with the following equation.

$$\eta(k)=1+\frac{d(k)}{r_{initial}-r_{end}} \quad , \qquad (5)$$

Where $\eta(k)$ is the value of η in the kth training cycle and $d(k)$ represents the decrement of the entire squared error in the kth training cycle.

The above mentioned strategy required less quantity of computational resources. Because the values of $\rho(k)$ and $\eta(k)$ are applied to reduce training circles.

MODELING AND PREDICTION OF SURFACE ROUGHNESS

Simple correlation coefficients between studied parameters illustrated in Table 2. Surface roughness showed strong and positive association with depth of cut (r=0.8869), whereas it exhibited moderate and negative correlation with cutting speed (r=-0.3583) and feed rate (r=-0.2409). After these traits, surface roughness recorded weak and positive association with experimental vibration (r=0.1871) and very weak and negative relationship with experimental temperature (r=-0.0379). Experimental vibration was significantly and positively associated with cutting speed (r=0.5332), feed rate (r=0.5632) and depth of cut (r=0.5757). Experimental temperature was strongly and positively correlated with cutting speed (r=0.8817) and experimental vibration (r=0.8378), but moderately and positively with depth of cut (r=0.3849) and feed rate (r=0.2486). From the data analysis, it is known that the depth of cut has the greatest direct effect on surface quality. Increasing cutting speed caused an great increase in surface temperature and consequently an decrease in surface roughness. And increasing feed rate also caused an decrease in surface roughness, but less than cutting speed. Results also showed that three different cutting parameters have almost same effect on experimental vibration. Surface temperature and tool vibration were measured as cutting responses while machining workpiece, whereas they have some influence on surface roughness as well as cutting parameters and are namely secondary parameters. In this study, these two secondary parameters were included as input with cutting parameters.

The experimental data (from NO.1 to NO. 21) listed in Table 1 were utilized to train the BP neural network. The purpose of network training is to find weight values with the least mean square errors. Surface temperature and tool vibration have some influence on surface roughness and are considered secondary parameters as neural network input. In order to find their affection on predicted surface roughness, three different models were trained with TVLR learning algorithm. The 1st model has four input variables, including three cutting parameters and tool vibration. The 2nd model also has four variables, but they are cutting parameters and surface temperature. In the 3rd model, both tool vibration and surface temperature were used to identify surface finish as indicators of cutting performance with cutting parameters. After training finished, other experimental data was used to test the above models. Figure 1 shows the effect of the measured surface roughness versus the predicted surface roughness with 1st model based on cutting parameters and surface temperature. Figure 2 shows the effect of the measured surface roughness versus the predicted surface roughness with 2nd model based on cutting parameters and tool vibration. It is seen that most points in Fig. 2 lie closer to the line than Fig. 1. Comparing Fig. 1 and Fig. 2, it is known that 1st model based on tool vibration had better prediction on surface roughness than 2nd model based on surface temperature. The effect of measured surface roughness versus the predicted surface roughness is shown in Figure 3. It is seen that most points lie very close to the line. The proposed in-process monitoring system of surface temperature and tool vibration is more useful to accurately predicted surface roughness.

Table 2 Correlation coefficients of studied traits

Trait name	S	F	D	VEx	TEx	RaEx
S	1					
F	___	1				
D	___	___	1			
VEx	0.5332	0.5632	0.5757	1		
TEx	0.8115	0.1545	0.5471	0.8325	1	
RaEx	-0.3583	-0.2409	0.8869	0.1871	0.1558	1

S: Cutting speed (r/min), F: Feed rate (10^{-3}m/rev), D: Depth of cut (10^{-3} m), VEx: Experimental tool vibration (m/s^2), TEx: Experimental surface temperature (°C), RaEx: Experimental surface roughness (um).

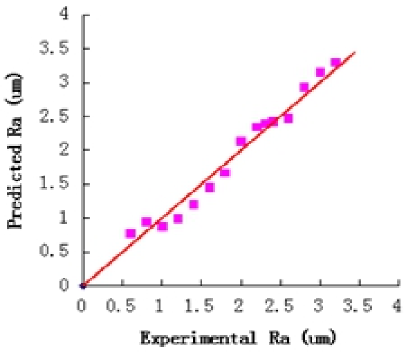

Fig. 1 Effect of measured Ra versus predicted Ra based on surface temperature

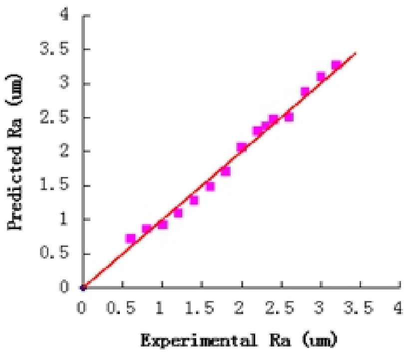

Fig. 2 Effect of measured Ra versus predicted Ra based on tool vibration

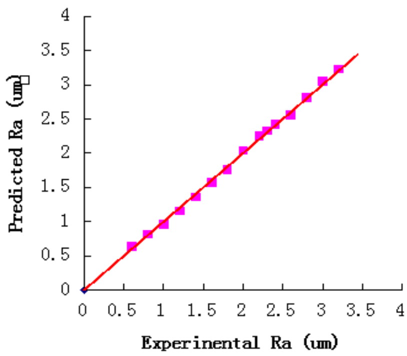

Fig. 3 Effect of measured Ra versus predicted Ra based on surface temperature and tool vibration

The trained model establishes the relationship between cutting parameters (S, F and D) and surface finish based on cutting responses (secondary parameters). Once cutting parameters and secondary parameters are inputted, the predicted surface roughness Ra can be easily outputted. Three different BP neural networks were utilized to train the experimental data listed in Table 1. They were approximate steepest descent with momentum (SD), traditional strategy of variable learning rate (TVLR) and reinforced strategy of variable learning rate (RVLR). For consistency, three-layer structure and the same nodes were used to train the experimental data in neural network models. The learning condition with ρ =0.95, η =1.05 was chosen to predict surface roughness in TVLR. For convenience, an adaptive function of the error and the error increment on consecutive updates was used as the value of ρ or η in RVLR.

The RVLR method has a wider scale selection of parameters which shows a higher convergence speed with a lower error result for every learning case. Besides, the learning scheme of RVLR makes the learning process converge almost to the same value —the global minimum despite the occurrence of a small oscillating phenomenon. Figure 4 shows the least mean square error of the new learning algorithm compared to the recommendation. The SD method has led the neural network towards a local minimum, around 26.18 m^2/min^2 mean square error. With the best trained- network, the maximum squared errors among the data sets with the SD method were recorded as 269.14 m^2/min^2. TVLR and RVLR were proven capable of exciting the learning of the network towards a new minimal point, if exists. The results show that the convergence iterations of TVLR were 6750000, but the convergence iterations of RVLR were reduced to 2800000. With either TVLR or RVLR, the network was able to avoid settling at the local minima and converge into its global minimum, around 9.0 m^2/min^2 as the best-record mean square error. But their respective least mean square errors of two well-trained networks were 9.23 m^2/min^2 and 8.21 m^2/min^2. The maximum squared errors were recorded as 287.55 m^2/min^2 and 269.14 m^2/min^2 for the TVLR and RVLR methods respectively. In RVLR, when 500000 learning cycles were completed (seen in Fig. 4) the learning error decreased sharply to 36.08 m^2/min^2 and kept unalterable until 1750000 iterations. Then the error converged slowly but continuously and finally to 8.21 m^2/min^2.

In term of processing rate, the RVLR method converged into its global minimal point at a faster speed compared to the TVLR method. Figure 5 shows that the RVLR method only required a quarter of the TVLR processing time to reach the "stable" region. At the begging of training, the entire squared error decreasing sharply, the learning rate in TVLR is multiplied by factor η =1.05, while RVLR's learning rate multiplied by factor $\eta(k)$ (k<500000) between 1.1 and 1.2. It made the learning error decrease very fast to 36.08 m^2/min^2, but got into the local or weak minima. After 1750000 learning cycles, the value of $\eta(k)$ made the solution away from the local or weak minima first, finally converged to the global minimum, 8.21 m^2/min^2, only with 600 second time. With either TVLR or RVLR, the network was able to avoid settling at the local minima and reach the close global minimum, but the RVLR method is always preferred provided having a reasonable processing time consideration.

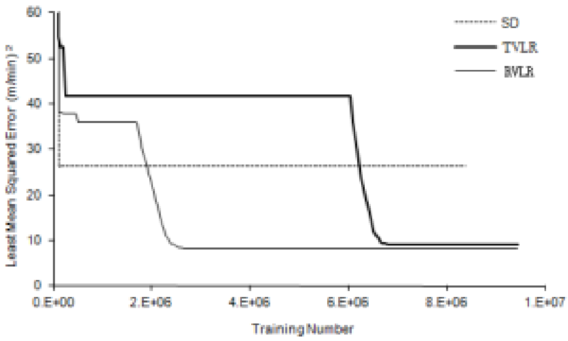

Fig. 4 Least mean square error in training history

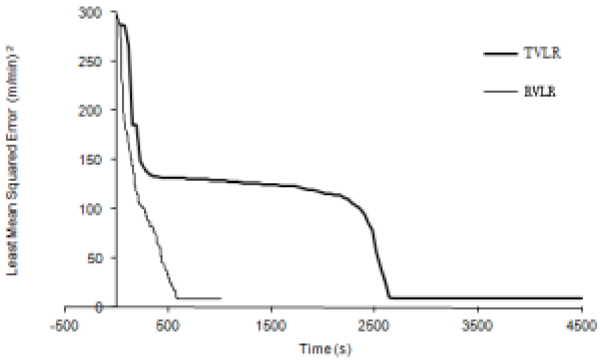

Fig. 5 Least mean square error in time history

Table 3 Results summary of SD, TVLR and RVLR

Model	error of NO. 22 (%)	error of NO. 23 (%)	error of NO. 24 (%)	error of NO. 25 (%)	error of NO. 26 (%)	error of NO. 27 (%)
SD	8.34	8.29	8.26	8.17	8.23	8.21
TVLR	4.58	4.62	4.56	4.52	4.53	4.54
RVLR	4.06	4.10	4.08	3.99	4.03	4.01

The implemented neural network algorithm was used to test the remaining data after the training procedures. Table 3 shows a summary of the results by different methods. It shows the TVLR model's prediction was as good, but the RVLR neural network gave the best prediction compared to the others.

CONCLUSIONS

This research proposes a new monitoring system to predict surface roughness based on tool vibration and surface temperature acquired during machining process. The correlation coefficients of cutting traits help in estimating the degree of relationship which could be used for predicting surface roughness. The experimental results show that surface temperature and tool vibration can be considered as secondary parameters and effectively used as indicators of cutting performance. The model based on cutting parameters and cutting responses (surface temperature and tool vibration) can identify surface roughness better than the model only based on cutting parameters.

Traditional strategy of variable learning rate (TVLR) was improved by introducing the self-help function to the learning algorithm and the RVLR method was proved to give better surface roughness prediction than SD method and TVLR. With SD method, the initial weights and biases have led the neural network towards a local minimum, but with either TVLR or RVLR, the network was able to avoid settling at the local minima effectively and reach the global minimum. The learning results showed that the RVLR method could predict the surface roughness with greater accuracy than TVLR. During simulation processes, it was also found that the new learning algorithm could accelerate the convergence speed helpfully. This method would be helpful in selecting cutting parameters and controlling of surface temperature and tool vibration for the required surface quality. This can also be used for optimization of machining conditions.

ACKNOWLEDGEMENT

The authors wish to express their gratitude to Shandong University of Engineering and Vocational Technology and Huazhong University of Science and Technology.

REFERENCES

Abouelatta, O., "Surface roughness and tool vibrations in turning operation," *Lap Lambert Academic Publishing*, Vol. 118, No. 1, pp. 269-277 (2012).

Assadi, H.M.A.A., Wong, S.V., Hamouda, A.M.S., Megat Ahmed, M.M.H., "Development of machine learning strategy for acquiring on-line machining skills during turning process," *Journal of Materials Processing Technology*, Vol. 155, No. 1, pp. 2087-2092 (2004).

Chien, W. T., Yao, C. F., "The development of the predictive model for metal machining parameters based on artificial neural network and genetic algorithm," *Proceedings of the 14th Mechanical Engineering*, CSME, Taichung, pp. 468-475 (1997).

Gomm, J.B., Williams, D., Evans, J.T., Doherty, S.K., Lisboa, P.J.G., "Enhancing the non-linear modelling capabilities of MLP neural networks using spread encoding," *Fuzzy sets and system*, Vol. 79 No. 1, pp. 113-126 (1996).

Hessainia, Z., Belbah, A., Yallese, M. A., Mabrouki, T., and Rigal, J. F., "On the prediction of surface roughness in the hard turning based on cutting parameters and tool vibrations, " Measurement, Vol. 46, No. 5, pp. 1671-1681 (2013).

Nalbant, M., Gokkaya, H., and Toktas, I., "Comparison of regression and artificial neural network models for surface roughness prediction with the cutting parameters in cnc turning," *Modelling & Simulation in Engineering*, Vol. 2007, No. 2, pp.1-14 (2007).

Ozel, T., Karpat, Y., "Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks," *International Journal of Machine Tools and Manufacture*, Vol. 45, No. 4-5, pp. 467-479 (2005).

Risbood, K. A., Dixit, U. S., Sahasrabudhe, A. D., "Prediction of surface roughness and dimensional deviation by measuring cutting forces and vibrations in turning process," *Journal of Materials Processing Technology*, Vol. 132, pp. 203-214 (2003).

Tangjitsitcharoen, S., "Prediction of surface roughness on CNC turning based on monitoring of cutting force and cutting temperature," *Advanced Materials Research*, Vol. 690-693, pp. 2540-2549 (2013).

Wong, S.V., Hamouda, A.M.S., "Machinability data representation with artificial neural network," *Journal of Materials Processing Technology*, Vol. 138, No. 1, pp. 538-544 (2003).

車削工件基於表面溫度和刀具振動的表面粗糙度BP神經網路預測

王彬，王丹桂，畢麗萍和王輝
山東工程職業技術大學
華中科技大學

摘要

機械加工中，許多車削工件對表面品質要求很高。因此機械加工條件的控制對改善表面品質顯得非常重要。本文介紹了一個加工過程中表面溫度和刀具振動的監控系統，並且基於表面溫度和刀具振動討論了表面粗糙度的預測。作者本文提出了一個新的BP神經網路學習規則，基於切削參數和切削性能來預測表面粗糙度，被稱為學習率變數加強方法（RVLR）。最後，本文給出表面粗糙度的預測結果。與最速下降法（SD）和學習率變數傳統方法（TVLR）相比，學習率變數加強方法（RVLR）需要更短的處

理時間收斂到全域最小值。最速下降法使神經網路模型陷入局部最小值，26.18 m^2/min^2。TVLR或者RVLR都使網路避免陷入局部最小值而達到全域最小值。然而，它們各自的最小均方差為9.23 m^2/min^2和8.21 m^2/min^2。此外，新的學習演算法只需要TVLR處理時間的1/4達到“穩定”的區域。為了達到表面品質要求，可以應用此方法選擇切削參數和控制表面溫度及刀具振動。