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ORIGINAL ARTICLE

An artificial neural network approach to investigate surface roughness and vibration of workpiece in boring of AISI1040 steels

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Abstract In metal cutting, tool failure and surface roughness are the important aspects that affect product quality and production cost, and these are affected mainly by vibration of workpiece. Current techniques do not have a proper method to measure vibration of a rotating workpiece so as to use it as a parameter to replace a cutting tool at an appropriate time. The purpose of the present work is therefore to use of laser Doppler vibrometer (LDV) to measure the vibration of workpiece without interfering the machining. Subsequent to obtaining the workpiece vibration data, artificial neural network (ANN) method was adopted to predict surface roughness and root mean square (RMS) velocity of workpiece vibration. According to Taguchi design of experiments, 18 experiments were prepared with two levels of nose radius and three levels of cutting speed and feed rate. Experiments were conducted on CNC lathe to obtain data of surface roughness and RMS of workpiece vibration velocity in boring of AISI 1040. A multilayer feedforward ANN model was developed and trained with the experimental data using back propagation algorithm. Further, the ANN was used to predict surface roughness and RMS velocity of workpiece vibration. The predicted values were compared with the collected experimental data and percentage error was computed. Less percentage of error was found between the experimental and predicted values.

Keywords ANN · Surface roughness · Tool vibration · Acousto-optic emission · Tool wear

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1 Introduction

Boring process is a difficult operation when compared with external turning process, and many variables affect the surface roughness. In boring process, tool vibration is the main factor that affects the tool life and surface finish. In boring operations, the length of boring bar is kept long, resulting in vibrations leading to tool failure, poor surface finish and chatter. Prasad et.al [1] stated that the texture of machined surface provides reliable information regarding the tool wear because tool wear affects the surface roughness dramatically. Machining error is one of the factors that is to be given attention to obtain good quality of work. Error in machining is wrong selection of cutting parameters that affect dimensional accuracy and surface quality. Chun and Tae [2] studied the effect of deflection of cutting tool, tool wear, depth of cut and thermal effects and machine tool errors on machining process. They found that deflection of tool and depth of cut are significant parameters affecting the surface quality and dimensional accuracy.

Chatter vibrations at high cutting speed can be measured accurately by laser Doppler vibrometer (LDV). Venkatarao et al. [3] and Balla et al. [4] also used LDV to observe vibration of workpiece and used a high-speed fast Fourier transform (FFT) preprocessor for generating features from online AOE signals to develop a database for appropriate decisions. The LDV is being used to observe high-frequency vibrations

Table 1 Chemical composition of AISI1040

Elements	Percentage
Carbon	0.37–0.44 %
Sulphur	0.05 % max
Manganese	0.6–0.9 %
Phosphorus	0.04 % max
Iron	Balance

during machining process. In this present work, a LDV was used to observe vibration of workpiece and FFT was used to process the acousto-optic emission (AOE) signals. Length-diameter ratio (L/D) of boring bar is one of the important factors causing tool vibration. In the present work, the L/D ratio was taken as 3 in order to minimize vibrations of tool and workpiece [3].

Surface quality is one of the important characteristics to estimate functional quality and life of a machined product. Good surface quality is essential for manufacturers to improve functional and technical quality of any product. Quintana et al. [5] stated that the surface roughness is influenced by various factors like cutting parameters, cutting tool characteristics, workpiece properties and cutting phenomena. Julie and Joseph [6] conducted experiments using Taguchi design to optimize surface quality. In the Taguchi design, they used cutting parameters like feed rate, spindle speed, depth of cut and tool type. In the present study, the Taguchi design is made with cutting speed, feed rate and nose radius.

According to Chang [7], the surface roughness and tool wear are strongly affected by the vibration amplitude and frequency. Improper tool geometry and the nose radius will produce more vibrations than the depth of cut. Two different nose radii were taken in the present work to evaluate effects of vibrations on tool life and surface roughness. Venkatarao et al. [3] mentioned in their work that two types of vibrations may occur in machining, such as forced vibration and self-excited vibration. Forced vibration is associated with bad gear drives, unbalanced machine tool components, misalignment, motors and pumps etc. Self-excited vibration occurs due to chatter which is caused by the interaction of the chip removal process and the structure of the machine tool and results in disturbances in the cutting zone. Chatter always indicates defects in the self-excited vibration. Junyun Chen, Qingliang Zhao [8] stated that vibration between tool and workpiece is more credible to estimate surface roughness. They have developed prediction models using vibration signals to predict surface roughness. Zahia Hessainia et al. [9] have studied effect of tool vibration along with cutting speed, depth of cut and feed rate on surface roughness. They have used response surface methodology to find out and optimum cutting parameters for minimum surface roughness with less tool vibration. In the present work, effects of vibration signals on workpiece vibration and surface quality were studied.

Tool condition monitoring (TCM) is an important characteristic in the automated manufacturing industries to assess ability of cutting tools for high production rates and good quality. Proper tool condition monitoring reduces tooling cost, and it helps in the reduction of product cost. Various authors reported different methods for online assessment of tool condition, such as process monitoring based on manipulation of sensor measurements like acoustic emission, cutting forces, vibration, temperature, stress-strain, vision and main motor current etc. to determine the state of the process. Estimation of tool wear is required for good quality of product and higher productivity. New tool is to be replaced when it loses its

Fig. 1 Workpieces

Fig. 2 Tool inserts

Table 2 Tool geometry of DNMG150608 and DNMG150604

Cutting edge length	15.5 mm
Cutting point angle	55°
Thickness	6.35 mm
Hole smallest dia	5.16 mm
Side clearance	0°

Table 3 Design of experiment (orthogonal array)

Trial no.	N R (mm)	Speed (m/min)	Feed (mm/rev)
1	0.4	170	0.10
2	0.4	170	0.13
3	0.4	170	0.16
4	0.4	190	0.10
5	0.4	190	0.13
6	0.4	190	0.16
7	0.4	210	0.10
8	0.4	210	0.13
9	0.4	210	0.16
10	0.8	170	0.10
11	0.8	170	0.13
12	0.8	170	0.16
13	0.8	190	0.10
14	0.8	190	0.13
15	0.8	190	0.16
16	0.8	210	0.10
17	0.8	210	0.13
18	0.8	210	0.16

cutting ability. Otherwise, it leads to reduced dimensional accuracy and additional costs. Sudhansu Ranjan Das et al. [10] stated that flank wear is affected by cutting parameters like cutting speed, feed rate and depth of cut. They have studied the effect of tool wear on the surface roughness and concluded that excessive wear on the tool gives poor product quality. Prasad et al. [4] stated that accurate detection of tool condition is one of the most important issues for replacing a new tool in time. ANN can monitor tool wear, chatter vibration and chip break during turning for real-time fault detection [11].

Artificial neural networks (ANNs) are also called as neural nets, artificial neural system, parallel distributed processing system and connectionist system. The ANNs are used to predict surface quality, tool wear, vibration of tool, tool life and cutting forces etc. [12]. Bozdemir and Aykut [13] stated that ANNs and expert systems are two main branches in artificial intelligence. Ramakotaiah et al. [14] used the ANN to predict cutting forces, surface roughness, and critical chatter locations in inward turning process. In the present paper, surface roughness and workpiece vibrations are predicted with the ANN.

Kishan et al. [15] explained the construction of neural network; the network is referred to as a directed graph that has a set of nodes (vertices) and set of connections (edges/links/arcs) between nodes. Each node contributes some kind of function like simple computation, and each connection transfers information or signal between nodes. Each connection between two nodes is labeled with a number called as connection strength or weight. The weight represents to what extent the signal is to be amplified or diminished by the connection.

The network with single node or fewer nodes cannot solve all the problems, and the networks which are constructed with large number of nodes are used to solve complex problems [12]. Kishan et al. [15] stated that the back propagation is a supervised learning process and it has more importance in the area of ANN and this is used in various applications like classification, prediction or forecasting, function and approximation. Marek et al. [16] developed appropriate control strategy with the help of neural networks to predict surface roughness and tool wear. Experimental data collected from tests were used as input parameters into neural network to identify the sensitivity among cutting conditions, tool wear monitoring parameters and surface roughness.

Fig. 3 Experimental setup for boring

Hsieh et al. [17] have used back propagation algorithm to train the network for tool wear monitoring based on the spindle vibration. Marimuthu and Chandrasekaran [18] used multi layered feedforward ANN to predict the surface roughness and tool wear during turning process of stainless steels. Palanisamy et al. [19] and Kalidas et al. [20] used feedforward back propagation ANN along with regression analysis for a proposed design of experiments to predict tool wear, and the predicted values were found within the trained range. Amir Mahyar et al. [21] used ANN to study the role of cutting factors on the prediction of tool life in milling process at various cutting conditions, and they found good correlation between the estimated and experimental values.

Pai et al. [22] used the ANN to estimate or classify certain wear parameters, using continuous acquisition of signals from multi-sensor systems. They proposed a new constructive learning algorithm named Growing Cell Structures that has been used for tool wear estimation in face milling operations, thereby monitoring the condition of the tool. Ramesh et al. [23] expressed that the cantilever shape of boring bar induces chatter vibrations and it leads to an increase in temperature and wear on tool. They predicted temperature and tool wear accurately using ANN model. Asilturk [11] has used the neural networks and multiple regressions for the prediction of surface roughness in machining of hardened AISI 1040 steel. They concluded that the neural network models can predict the machining characteristics better than regression analysis.

In the present study, a neural network was used to predict surface roughness and root mean square of vibration velocity of workpiece, when tool fails, i.e. flank wear reaches to 0.6 mm [ISO 3685:1993]. The network is constructed with four layers including input, output and hidden layers. Cutting speed, feed rate, volume of metal removed, hardness of workpiece and nose radius are taken as input neurons, and output neurons are surface roughness and root mean square of vibration velocity of workpiece.

2 Workpiece material and tool inserts

In the present work, experiments were conducted on AISI 1040 steel and its chemical composition is shown in the Table 1. It is hardenable by heat treatment, quenching and tempering to develop tensile strength. It is widely used in industrial applications. The material is provided in a raw state from steel industries for manufacturing of crankshafts, couplings and cold-headed parts [4, 11, 24, 25]. The workpieces used in the experiment are shown in Fig. 1.

Physical vapour deposition (PVD)-coated tungsten carbide tool inserts were used in this experiment with two nose radii of 0.8 mm (DNMG150608) and 0.4 mm (DNMG150604). The insert geometry is shown in Fig. 2 and corresponding parameters in Table 2.

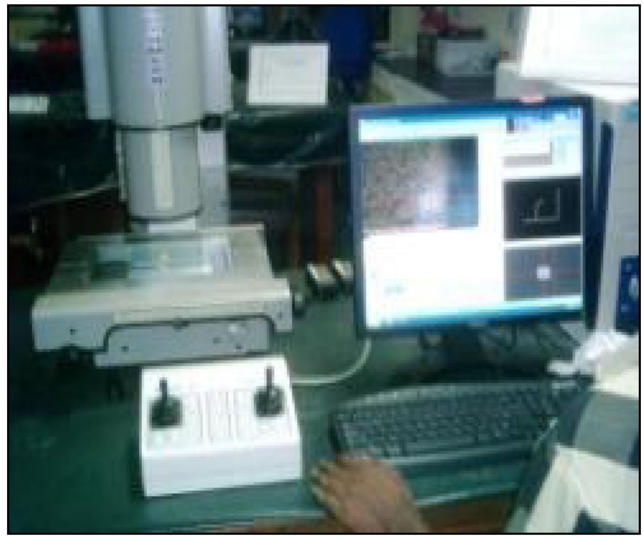

Fig. 4 Machine vision system

A sharp cutting tool is expected to give more cutting ability for a long duration of time in an effective and smooth manner. There are two types of wears that occur on cutting tool due to loss of material in metal cutting [3]. According to International Standards Organization (ISO 3685:1993), tool life criteria are considered only with the leading edge groove. For uneven wear, the maximum flank wear or wear land width (VBmax) should be less than 0.6 mm.

3 Design of experiments and experimentation

A specially designed orthogonal array of Taguchi (Table 3) is used to investigate the effects of the machining parameters through the small number of experiments, and it takes less

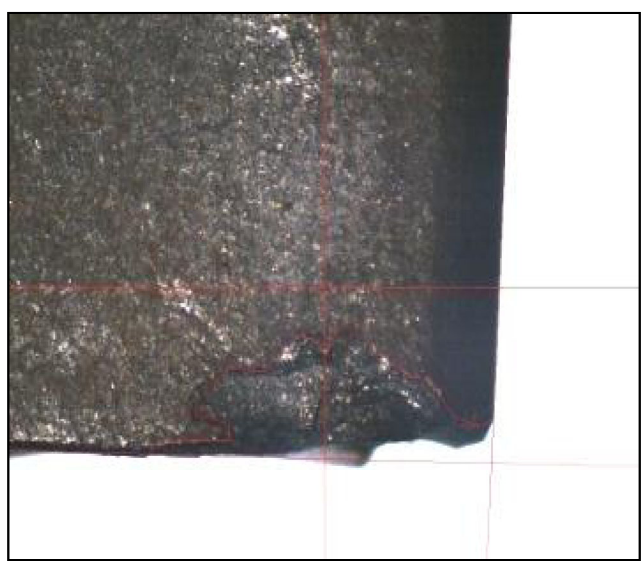

Fig. 5 Flank wear

Table 4 Experimental data for trial 1

Pass	Ra (μm)	Rms (mm/s)	VB (mm)	Vol (mm^3)	Hardness HRB
1	1.23	1.1140	0.1759	1721.55	95.25
2	1.60	1.0780	0.2147	3463.20	95.50
3	1.78	1.0400	0.2946	5202.18	95.50
4	2.00	1.0530	0.3214	6946.92	95.75
5	2.45	1.1554	0.3846	8697.42	96.00
6	3.10	1.1820	0.4857	10,453.68	96.25
7	3.54	1.2170	0.6107	12,215.70	96.50
8	6.20	1.4870	0.6874	13,983.48	96.75

time for the experimental investigations. The design of experiments is shown with three columns representing two levels of nose radius and three levels of cutting speed and feed.

The experiments were conducted on CNC lathe DX200 model. The metal used in this experiment is AISI1040 with a length of 90 mm, outer diameter of 100 mm and inner diameter of 56 mm.

The following sequential procedure was used to carry out the experiment under dry condition. The experiments were conducted according to design of experiments (orthogonal array of L_{18}) as shown in Table 3.

1. Each test was started with a fresh cutting edge with one test condition (trial) and machining was stopped at the end of each pass. After each pass, the depth of cut was increased by 0.2 mm (fixed depth of cut was given in each pass) until the tool failed.
2. Vibration signals from the rotating workpiece were measured in the machining process using LDV and the setup of experiment is shown in Fig. 3.
3. After each pass, the tool insert was removed and its flank wear was measured with machine vision system which is shown in Fig. 4. Flank wear on the tool inserts is shown in Fig. 5.
4. After each pass, the workpiece was also removed and its surface roughness and its hardness were measured.
5. Steps 1 to 4 were continued until the tool failed, and beyond that, 2 or 3 passes were performed on the workpiece to observe the behaviour of tool wear.
6. A new workpiece and new tool insert were loaded to the machine, and the above steps were followed with a new working condition (trial).
7. In each trial, surface roughness and RMS of workpiece vibration velocity were identified when the tool failed based on flank wear (VB). Experimental data for trial 1 was shown in Table 4. At pass 7, the flank wear just crossed 0.6107 mm (ISO 3685:1993) and it indicated tool failure and it was shown with green colour.

The above procedure was followed for all the trials, and in each trial, the cutting parameters were changed as per design of experiments. Eight to ten passes were conducted in each trial for a new tool. After each pass, the workpiece and tool were removed to measure surface roughness of workpiece and flank wear on the tool. Workpiece vibrations were measured with LDV online while the machining is in progress.

Behaviour of surface roughness and RMS of workpiece vibration velocity for 18 trials was shown in Fig. 6. As said in the procedure, 0.2 mm depth of cut was given in each pass. It was observed from the figure that surface roughness and root mean square of workpiece vibration velocity are increased in the next passes. RMS of workpiece vibration velocity was observed above 1.00 mm/s for the trials 1, 2, 3, 11, 12 and 13.

4 Results and discussion

In this study, a neural network is used to predict surface roughness and root mean square of vibration velocity of workpiece when tool fails, i.e. flank wear reaches 0.6 mm [ISO

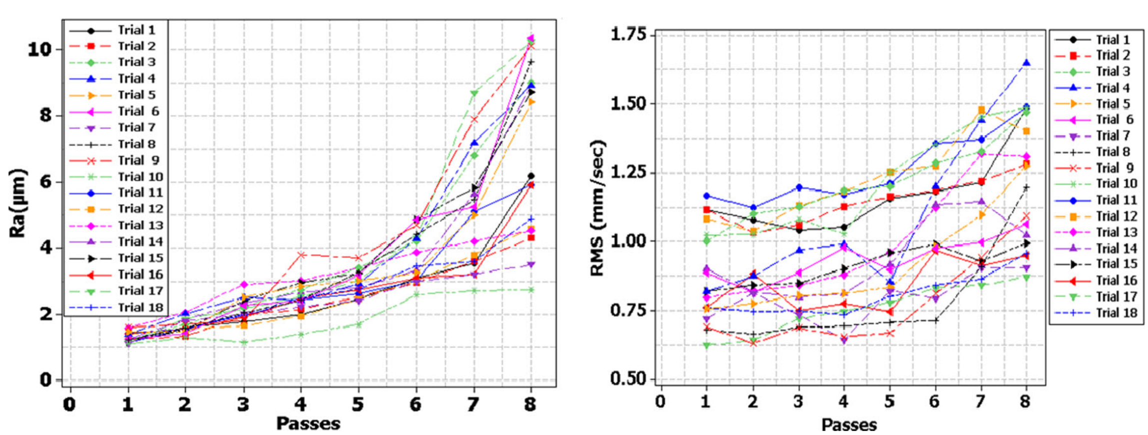

Fig. 6 Surface roughness and RMS of workpiece vibration velocity for 18 trials

Table 5 Experimental results of surface roughness and RMS of workpiece vibration velocity

Trial no.	N R (mm)	Speed (m/min)	Feed (mm/rev)	Ra	RMS
1	0.4	170	0.10	3.54	1.2170
2	0.4	170	0.13	3.60	1.2210
3	0.4	170	0.16	4.20	1.2850
4	0.4	190	0.10	4.29	1.2021
5	0.4	190	0.13	3.25	0.9820
6	0.4	190	0.16	4.86	0.9760
7	0.4	210	0.10	3.50	0.9037
8	0.4	210	0.13	5.46	0.9080
9	0.4	210	0.16	4.70	0.8110
10	0.8	170	0.10	2.75	1.4870
11	0.8	170	0.13	5.11	1.3723
12	0.8	170	0.16	3.80	1.4780
13	0.8	190	0.10	4.53	1.3085
14	0.8	190	0.13	5.64	1.1438
15	0.8	190	0.16	5.83	0.9275
16	0.8	210	0.10	3.20	0.9137
17	0.8	210	0.13	4.68	0.8418
18	0.8	210	0.16	3.60	0.8646

3685:1993]. Experimental results of surface roughness (Ra) and RMS of workpiece vibration velocity for VB=0.6 mm are given in Table 5 for all the trials.

A feedforward four-layered back propagation neural network was constructed as shown in Fig. 7. The network was constructed with four layers including input, output and two hidden layers. Each layer was constructed by grouping neurons. The network consists of one input layer with five neurons, one output layer with two neurons and two hidden layers with 14 and 8 neurons. The input neurons are cutting speed, nose radius, volume of metal removed, hardness of workpiece and feed and output neurons are surface roughness and RMS of workpiece vibration velocity. Neurons in the hidden layers were determined by examining different neural networks. Easy NN plus software was used for training of this network, and the ANN was trained with back propagation algorithm. Weights of network connections were randomly selected by the software. Chinnaswamy et al. [26] and Asilturk [11] have used the neural networks and multiple regressions for the prediction of surface roughness in machining of hardened AISI 1040 steel. They changed the weights of connections in the net work until the predicted values were closer to the actual (experimental) values.

In the present work, the network was trained at different combinations of neurons and hidden layers. The criterion for choosing the best combination of neurons and hidden layers for optimal training is that the values of average training error and validating errors should always be less than the target error. At a combination less than 14 and 8, the criterion was not satisfied. Learning or training of network is a process that consists of adapting weights to the connections between neurons in the each layer. The learning of neural network was done with feedforward back propagation algorithm as shown in Fig. 8. The neural network was trained with 80 samples and validated with 20 samples. The process of learning was stopped after 10,700 cycles when the average training error was less than target error which was set as 0.01. The network was trained at 0.6 learning rate and at the momentum of 0.8. The software used in this study itself selected the weights for the connections according to the given experimental data. It has selected 56 as weight for the connections between input layer and hidden layer 1, 98 as weight for the connections between hidden layer 1 and hidden layer 2 and 28 as weight for the connections between hidden layer 2 and output layer. As shown in Fig. 8, the average training error was found as 0.003067 that is less than the target error, i.e. 0.01.

The neural network was trained with 80 samples, validated with 20 samples and tested for 18 samples. Figure 8 shows maximum, minimum and average training error and one validating error. Among the three training errors, the software

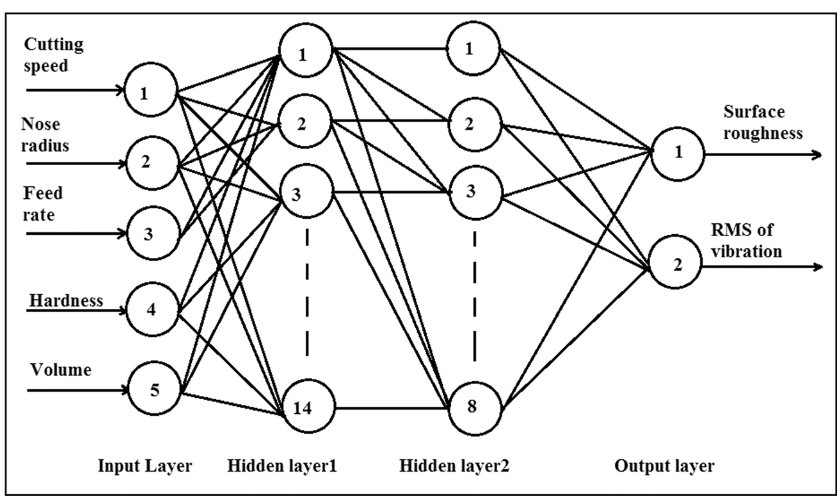

Fig. 7 Neural network architecture (5-14-8-2)

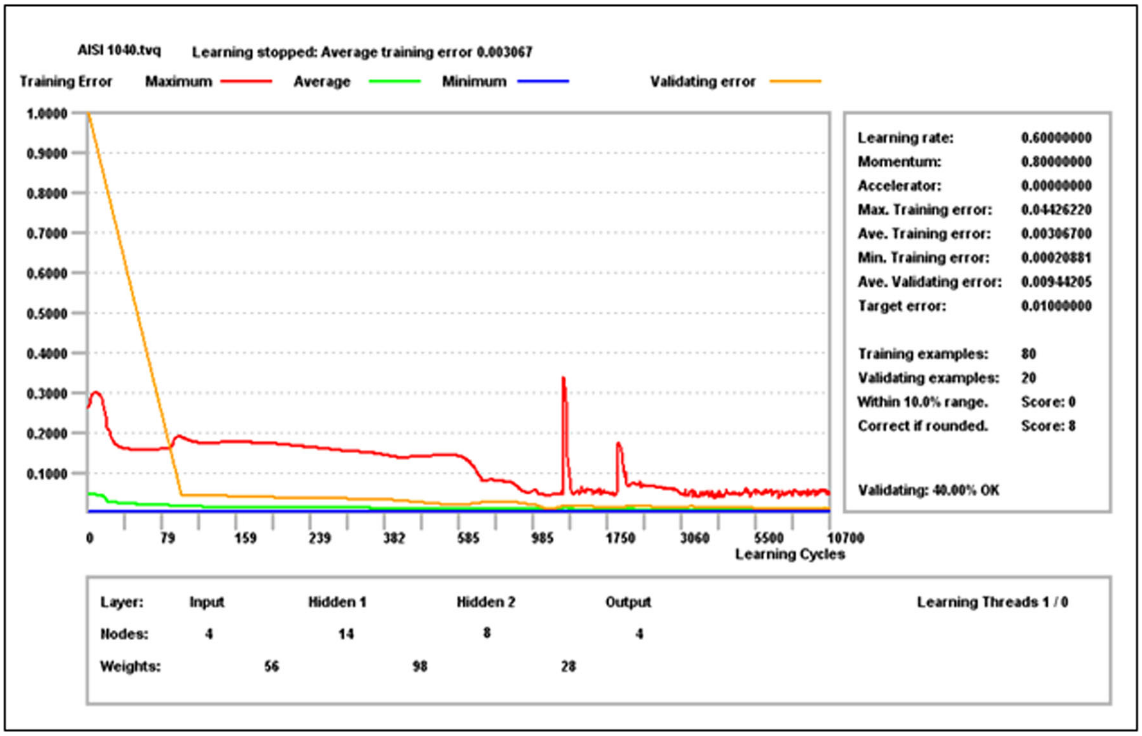

Fig. 8 Learning progress graph with maximum, average and minimum training error

takes the average error into consideration. When the average training error and the validating error becomes less than the target error, learning or training of network was stopped. Table 5 was presented with experimental values of surface roughness and RMS of workpiece vibration velocity corresponding to tool failure in each trail. The trained neural network was used to predict the surface roughness and RMS of workpiece vibration velocity for the tested 18 trails. The ANN-predicted values for the 18 trails are presented in Table 6.

Table 6 Experimental data and ANN predicted data for 18 trials

Trial no.	Exp. Ra	Pred. Ra	% Error	Exp. RMS	Pred. RMS	% Error
1	3.54	3.560	0.56	1.2170	1.2785	4.81
2	3.60	3.546	0.02	1.2210	1.2974	5.88
3	4.20	3.942	6.14	1.2850	1.3074	1.71
4	4.29	4.464	4.05	1.2021	1.1985	0.29
5	3.25	3.194	1.72	0.9820	0.9547	2.78
6	4.86	4.598	5.39	0.9760	0.8929	8.51
7	3.50	3.542	1.20	0.9037	0.9341	3.25
8	5.46	5.253	3.79	0.9080	0.9622	5.63
9	4.70	4.875	3.72	0.8110	0.7946	2.02
10	2.75	2.821	2.58	1.4870	1.4993	0.82
11	5.11	4.867	4.75	1.3723	1.3947	1.60
12	3.80	3.834	0.89	1.4780	1.4214	3.82
13	4.53	4.491	0.86	1.3085	1.2048	7.92
14	5.64	5.352	5.10	1.1438	1.2197	6.22
15	5.83	5.542	4.93	0.9275	0.9428	1.62
16	3.20	3.453	7.90	0.9137	0.9571	4.53
17	4.68	4.854	3.71	0.8418	0.9014	6.61
18	3.60	3.412	5.22	0.8646	0.8246	4.62
Mean of % error			3.47	Mean of % error		4.03

Table 6 compares the experimental values and predicted values of surface roughness and RMS of workpiece vibration for testing data. The predicted values are closer to experimental values. But there is slight error between the experimental and predicted values, and it is computed as 3.47 and 4.03 % for surface roughness and RMS of vibration velocity, respectively. The ANN was used successfully by different authors in different machining processes to predict surface roughness, tool life, temperature in machining, machining time and etc. [19–21, 23, 26].

5 Conclusions

The present work focused on the prediction of surface roughness and RMS of workpiece vibration velocity in boring of AISI 1040 steel. According to orthogonal array of L_{18}, 18 experiments were conducted on CNC lathe by varying input parameters of nose radius, cutting speed and feed rate. A predictive model of neural network was developed with two hidden layers. The network was trained with feedforward back propagation algorithm using 80 samples and validated for 20 samples. The following conclusions can be drawn from the present work:

1. In each trial of experiments, a strong correlation among the dependent and independent variables was found.
2. LDV is proven to be a non-invasive technique to measure vibration of workpiece. Without LDV measurements, the conclusions could not be more authentic.
3. In measurement of vibration, it was found that the use of LDV is easy and it takes less time to measure vibration of workpiece. Setup of LDV is easy when compared with setup of accelerometer.
4. The neural network can help in selection of proper cutting parameters to reduce tool vibration and tool wear and reduce surface roughness.
5. It was found that there is good agreement between experimental data and neural network-predicted values for surface roughness (3.47 % of error) and RMS of workpiece vibration velocity (4.03 % of error).

Conflict of interest The authors declare that they have no conflict of interest.

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