# Prediction of cutting tool wear, surface roughness and vibration of work piece in boring of AISI 316 steel with artificial neural network

**Article** *in* Measurement · May 2014

DOI: 10.1016/j.measurement.2014.01.024



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Measurement 51 (2014) 63–70

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

# Prediction of cutting tool wear, surface roughness and vibration of work piece in boring of AISI 316 steel with artificial neural network

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ARTICLE INFO

*Article history:*
Received 15 November 2013
Received in revised form 12 December 2013
Accepted 16 January 2014
Available online 28 January 2014

*Keywords:*
ANN
Surface roughness
Boring
Tool vibration
Acousto-optic emission
Tool wear

ABSTRACT

Machining of stainless steel is difficult due to their hardening tendency. In boring of stainless steels, tool wear and surface roughness are affected by vibration of boring bar. In this paper, tool wear, surface roughness and vibration of work piece were studied in boring of AISI 316 steel with cemented carbide tool inserts. A Laser Doppler Vibrometer was used for online data acquisition of work piece vibration and a high-speed Fast Fourier Transform analyzer was used to process the acousto optic emission signals for the work piece vibration. Experimental data was collected and imported to artificial neural network techniques. A multilayer perceptron model was used with back-propagation algorithm using the input parameters of nose radius, cutting speed, feed and volume of material removed. The artificial neural network was used to predict surface roughness, tool wear and amplitude of work piece vibration. The predicted values were compared with the collected experimental data and percentage error was computed.



## 1. Introduction

Tooling cost is an important factor which should be reduced in order to keep the manufacturing cost to a minimum. Tool failure can be identified by observing higher power consumption, poor surface finish, dimensional inaccuracy, appearance of a burnishing band on machined surface, tool vibrations or work piece vibration, among others. Prasad and Sarcar [3] stated that the texture of machined surface provides reliable information regarding the extent of the tool wear because tool wear affects the surface roughness dramatically. Stainless steels are widely used in commercial and industrial applications due to their excellent corrosive resistance. It is difficult to machine stainless steels due to their hardening tendency during machining process.

In boring operations, the length of boring bar is kept long, resulting in vibrations leading to tool failure, poor surface finish and chatter. Length-diameter ratio ($L/D$) of boring bar is one of the important factors causing tool vibration. Kuster and Gygax [11] explained the vibrations of boring, boring bar fixation, machine tool condition and selection of cutting conditions. Korkut and Kucuk [7] identified that the best $L/D$ ratio for less vibration in boring process is 3. The $L/D$ ratio in the current study was taken as 3.

Laser Doppler Vibrometers (LDV) are being used to observe high frequency vibrations during machining process. In this present work, a LDV was used to observe vibration of work piece and Fast Fourier Transform (FFT) analyzer used to transform the acousto-optic emission (AOE) signals into frequency domain. Nakagawa et al. [17] used LDV to

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http://dx.doi.org/10.1016/j.measurement.2014.01.024
0263-2241/

observe the chattering behaviors of the end-mill shank. Chatter vibrations at high cutting speed were measured accurately by LDV. Venkatarao et al. [25] and Prasad et al. [2] also used LDV to observe vibration of work piece and used a FFT preprocessor for generating features from online AOE signals to develop a database for appropriate decisions.

According to Chang [5], 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. Luke et al. [14] pointed 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, or 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.

Lin and Chang [12] showed that vibrations have strong correlation with surface roughness. Accordingly, various features of vibration signals have been chosen to estimate surface quality. In the present work, effects of vibration signals on tool wear and surface quality were studied. Salgado et al. [21] studied the cutting parameters, feed, spindle speed, depth of cut, tool nose radius, nose angle and vibration data which are the input information for evaluation of tool life. Marimuthu and Chandrasekaran [16] stated that, optimization of cutting parameter is required for good quality of products and production rate. In this work, the tool life was evaluated using the Taguchi method with two levels of spindle speed, feed and nose radius.

## 2. Artificial neural networks (ANN)

Artificial neural networks are also called neural nets, artificial neural system, parallel distributed processing system and connectionist system. Mehrotra et al. [10] explained the construction of a neural network; the network is referred to as a directed graph having 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 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. Some of the networks are fully connected networks, layered networks, acyclic networks, feed forward networks or modular networks. Colin [6] explained different types of learning methods in ANN such as supervised learning, unsupervised learning and reinforcement learning. The behavior of the network changes according to the changes in the weights of connections in the network. The changes in the weights of ANN are referred to as learning. Changes in the weights are affecting the synaptic efficiencies in real ANN. Sha and Edwards [22] stated that the ANNs are well established, and prominent in literature, when computational based approaches are involved.

Mehrotra et al. [10] stated that back propagation is a supervised learning process which is important in the area of ANN. It is used in various applications like classification, prediction or forecasting, function, and approximation. Marimuthu and Chandrasekaran [16] used multi layered feed forward ANN to predict the surface roughness and tool wear during turning process of stainless steels. Palanisamy et al. [19] and Kalidas et al. [9] used feed forward 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. Khorasani et al. [1] used ANN to study 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. [24] used 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 aid was used for tool wear estimation in face milling operations, thereby monitoring the condition of the tool. Ramesh et al. [20] expressed that cantilever shape of boring bar induces chatter vibrations and it leads to increase in temperature and wear on tool. They predicted temperature and tool wear accurately using ANN model. Vrabel et al. [15] developed appropriate control strategy with the help of ANN to predict surface roughness and tool wear. Experimental data collected from tests were used as input parameters into ANN to identify the sensitivity among cutting conditions, tool wear and monitoring parameters and surface roughness.

Natarajan et al. [18] stated that the use of back-propagation feed forward ANN in the prediction of tool life will reduce computational time. Benardos and Vosniakos [4] presented a neural network modeling approach for the prediction of surface roughness for a Taguchi design of experiments (DOE) method. Lin et al. [13] derived a relationship between the force and wear using multiple regression analysis and ANN models were used for further improvement of accuracy in predicting tool wear. Tsai et al. [26] presented an in-process system for surface recognition in end milling based on ANN. In their work they used an accelerometer to get vibration of the machine tool and work piece.

Shie [23] used ANN to find an optimal combination of cutting parameters for the optimization of dry machining parameters in end milling process. Zhang and Chen [8] applied Taguchi design to optimize the surface quality in a computer numerical control drilling operation with the control factors of feed, spindle speed, tool type. Yalcin et al. [27], studied the effect of cutting parameters on the surface roughness, cutting force and temperature by using ANN which were trained by using experimental results obtained from Taguchi's L8 orthogonal design. In this study, the network is constructed with four layers consisting of one input layer with four neurons, one output layer with three neurons and two hidden layers with fourteen and eight neurons. The cutting speed, feed, volume of metal removed and nose radius are taken as input neurons and output neurons are surface roughness, tool wear and work piece vibrations.

## 3. Tool life criteria

A sharp cutting tool is expected to give more cutting ability for long time in an effective and smooth manner. Two types of wears occur on cutting tools. Wear on the face and flank termed as crater wear and flank wear (VB) respectively. The flank wear is also called as wear land, which affects the tool life and its cutting ability. According to International Standards Organization (ISO 3685:1993), tool life criteria are considered only with the leading edge groove. If the profile is uniform, the tool can be used unless the average value VB is greater than 0.3 mm. For uneven wear, the maximum wear land width (VBmax) should be less than 0.6 mm.

## 4. Work piece material and tool inserts

AISI 316 stainless steel having the chemical composition is shown in Table 1 was used in this study. It has good corrosion resistance is regarded as marine grade. The machinability of this steel is rated at 45% with respect to the AISI 1112 alloy having 100% machining rated steel. The work pieces used in the experiment are shown in Fig. 1.

**Table 1**
chemical composition of AISI 316.

| Elements | Percentage (%) |
|---|---|
| C | 0.08 max |
| Mn | 2.0 |
| Si | 0.75 |
| p | 0.045 |
| S | 0.03 |
| Cr | 16–18 |
| Ni | 10–14 |
| N | 0.1 |
| Fe | Balance |

**Fig. 1.** Work pieces.

**Table 2**
Tool geometry of DNMG150608 and DNMG150604.

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

**Fig. 2.** Tool inserts.

Physical vapor deposition 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 Table 2 and Fig. 2.

## 5. Experimental procedure

The experiment was conducted on CNC lathe DX200 model. The metal used in this experiment is AISI 316 with 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 conditions. In this paper, $L_8$ is a Taguchi orthogonal array used to analyze the experimental results obtained from boring process. The

**Table 3**
Design of experiments.

| Trail | Speed (m/min) | Nose radius (mm) | Feed (mm/rev) |
|---|---|---|---|
| 1 | 210 | 0.10 | 0.8 |
| 2 | 210 | 0.16 | 0.8 |
| 3 | 210 | 0.10 | 0.4 |
| 4 | 210 | 0.16 | 0.4 |
| 5 | 170 | 0.10 | 0.8 |
| 6 | 170 | 0.16 | 0.8 |
| 7 | 170 | 0.10 | 0.4 |
| 8 | 170 | 0.16 | 0.4 |

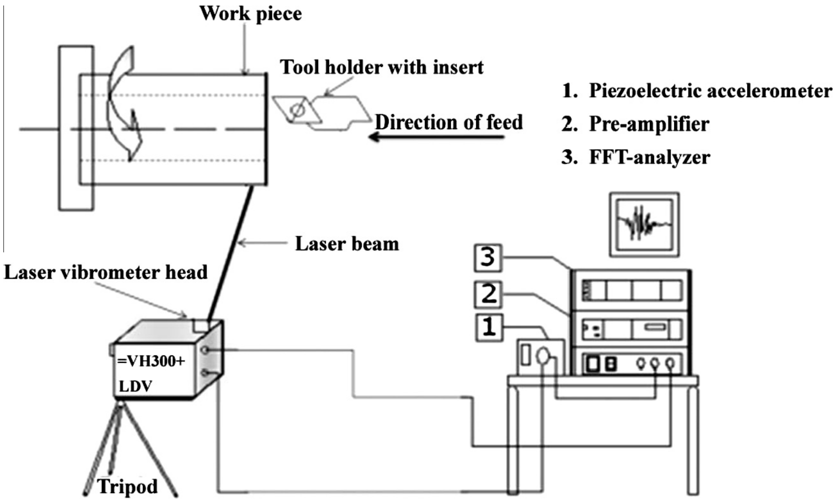


**Fig. 3a.** Schematic diagram for setup.

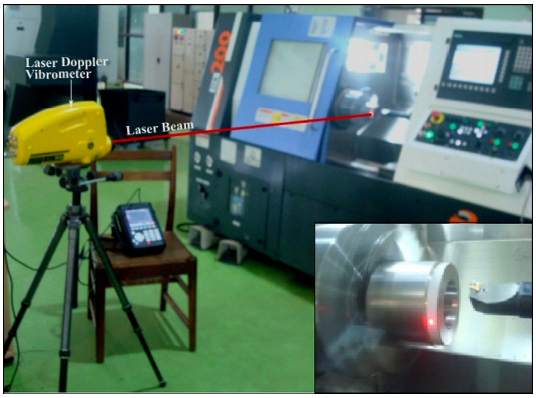


**Fig. 3b.** Experimental set up for boring.

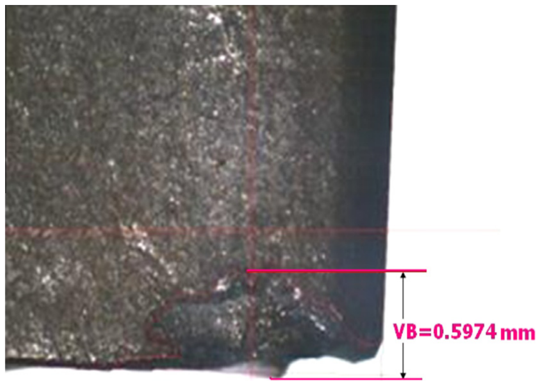


**Fig. 4.** Flank wear.

$L_8$ orthogonal array or design of experiments was prepared 8 trails having 2 levels of cutting speed, nose radius and feed as shown in Table 3. The experiments were conducted according to design of experiments.

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 work piece were measured in the machining process using LDV. The experimental set-up used is shown in Figs. 3a and 3b.
3. After each pass, the tool insert is removed and flank wear was measured with a machine vision system. Amount of flank wear on the tool inserts is shown in Fig. 4.
4. After each pass, the work piece is also removed and its surface roughness is measured using talysurf.

The step 1–4 were continued until the tool failed and beyond that 2 or 3 passes were performed to observe the behavior of tool wear after tool failed. Experimental data for trial 1 is given in Table 4. In addition to experimental data, the volume of metal removed is also presented in Table 4. Row number 7 in Table 4 is shown with bold values that represents tool failure as VB is closer to 0.6 mm (ISO 3865: 1993).

5. A new work piece and new tool insert were loaded in the machine and the above steps were followed with a new working condition (trial).
6. In each trial, the surface roughness, tool wear and amplitude of work piece vibrations were recorded when the tool is failed.

The Experimental data in all the trials when tool failed is shown in Table 5.

Ten passes were conducted in each trial for a new tool having nose radius of 0.8 mm and eight passes were conducted for the 0.4 mm nose radius tool. After each pass the work piece and tool were removed to measure the surface roughness of work piece and flank wear on the tool. However the amplitude of work piece vibrations were

**Table 4**
Observations in the trial 1.

| Pass | Surface roughness (Ra) μm | RMS of vibration (mm/s) | Amplitude (*Y*) mm | Flank wear (VB) mm | Vol. of metal ($mm^3$) |
|---|---|---|---|---|---|
| 1 | 1.50 | 0.7601 | 0.3512 | 0.1254 | 17.639 |
| 2 | 1.65 | 0.8823 | 0.2859 | 0.1652 | 35.326 |
| 3 | 1.80 | 0.8610 | 0.2911 | 0.1972 | 53.074 |
| 4 | 1.98 | 0.8469 | 0.2904 | 0.1257 | 70.883 |
| 5 | 2.10 | 0.9228 | 0.3065 | 0.2135 | 88.753 |
| 6 | 2.30 | 0.9115 | 0.3214 | 0.4521 | 106.692 |
| **7** | **3.20** | **0.8393** | **0.3251** | **0.5974** | **124.693** |
| 8 | 3.60 | 0.9240 | 0.3354 | 0.6841 | 142.754 |
| 9 | 3.80 | 0.9267 | 0.3548 | 0.7242 | 160.885 |
| 10 | 4.10 | 0.9449 | 0.3661 | 0.8426 | 179.074 |

**Table 5**
Design of experiments and experimental results.

| Trial No. | Design of experiments | | | Surface roughness (μm) | Flank wear (mm) | Amplitude of vibration (mm) |
|---|---|---|---|---|---|---|
| | Speed (m/min) | Nose radius (mm) | Feed (mm/rev) | | | |
| 1 | 210 | 0.10 | 0.8 | 3.20 | 0.5974 | 0.3251 |
| 2 | 210 | 0.16 | 0.8 | 3.21 | 0.6145 | 0.3227 |
| 3 | 210 | 0.10 | 0.4 | 3.80 | 0.6043 | 0.3239 |
| 4 | 210 | 0.16 | 0.4 | 4.20 | 0.698 | 0.3903 |
| 5 | 170 | 0.10 | 0.8 | 3.20 | 0.6775 | 0.5371 |
| 6 | 170 | 0.16 | 0.8 | 3.42 | 0.6203 | 0.5373 |
| 7 | 170 | 0.10 | 0.4 | 4.20 | 0.6143 | 0.5419 |
| 8 | 170 | 0.16 | 0.4 | 4.55 | 0.822 | 0.8633 |

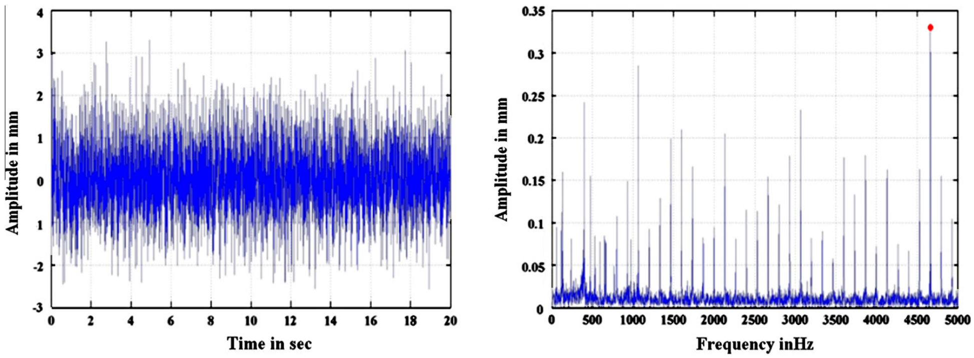


**Fig. 5.** Time and frequency domain spectrograph in boring in the first pass.

measured with LDV on-line during machining, the time and frequency domain spectrograph at the first pass and on tool fail are shown in Figs. 5 and 6 respectively. Fig. 7 shows graphical representation of experimental results of surface roughness, amplitude of work piece vibration and flank wear all passes in 8 trails. The tool wear development for two nose radii of cutting tools at different trials is also shown in Fig. 7.

## 6. Results and discussion

A feed-forward four layered back propagation neural network is constructed in Fig. 8. The network is constructed with four layers including with input, output and hidden layers. The ANN with one hidden layer gave errors significantly high. Hence two layer network was considered. The input neurons are cutting speed, nose radius, volume of metal removed and feed and output neurons are surface roughness, tool wear and amplitude of work piece vibration. 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 are randomly selected by the software.

The learning of neural network is shown in Fig. 9. The red[1] line is the maximum example error, the blue line is the minimum example error and the green line is the average example error. The orange line is the average validating error. Learning progress graph shows the maximum, average and minimum training error. The average validating error is shown if any validating examples rows are included. The

[1] For interpretation of color in Fig. 9, the reader is referred to the web version of this article.

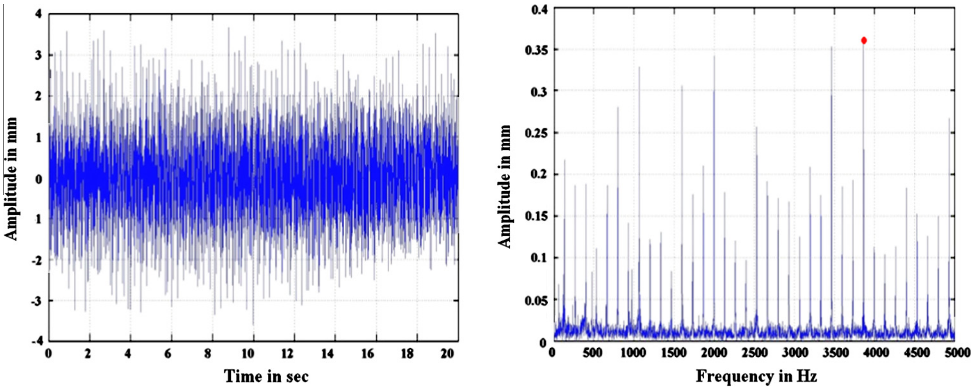


**Fig. 6.** Time and frequency domain spectrograph in boring when the tool failed.

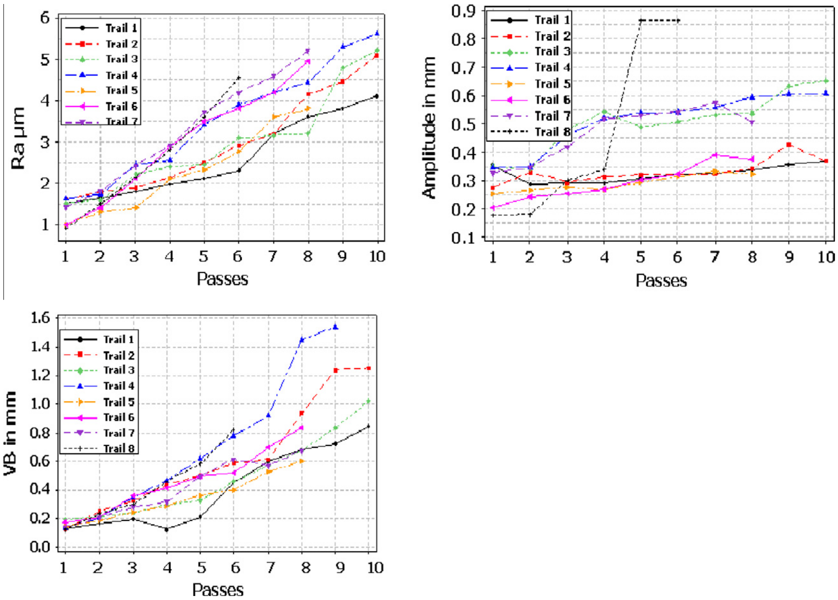


**Fig. 7.** Graphical representation of experimental results for surface roughness, amplitude of work piece vibration and flank wear.

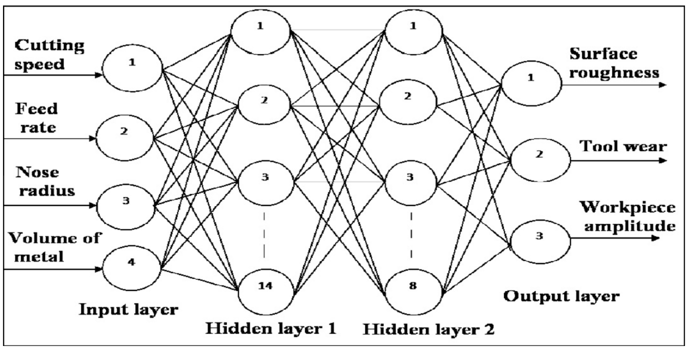


**Fig. 8.** Neural network architecture (4-14-8-3).

neural network was trained with 54 examples and validated with 15 examples.

The neural network was trained with 54 examples, validated with 15 examples and tested for 8 examples. Predicted values of surface roughness and work piece vibration amplitudes are given in Table 6. Percentage of error between experimental values and predicted values for the surface roughness, tool wear and vibration of work

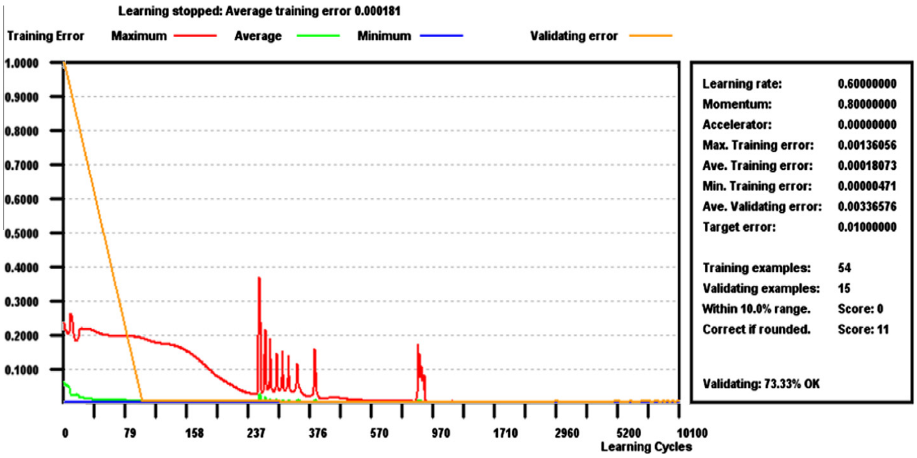


**Fig. 9.** Learning progress graph with maximum, average and minimum training error.

**Table 6**
Predicted surface roughness and vibration amplitude.

| Trial No. | Exp. Ra | Pred-Ra | Error (%) | Exp. *Y* | Pred-*Y* | Error (%) | Exp. VB | Pred-VB | Error (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 3.20 | 3.0544 | 4.5500 | 0.3251 | 0.3189 | 1.9071 | 0.5974 | 0.5985 | 0.1841 |
| 2 | 3.21 | 3.2458 | 1.1152 | 0.3227 | 0.3023 | 6.3216 | 0.6145 | 0.6279 | 2.1806 |
| 3 | 3.80 | 4.0770 | 7.2894 | 0.3239 | 0.2975 | 8.1506 | 0.6043 | 0.6109 | 1.0921 |
| 4 | 4.20 | 4.3514 | 3.6047 | 0.3903 | 0.3648 | 6.5334 | 0.698 | 0.6422 | 7.9942 |
| 5 | 3.20 | 3.4124 | 6.6375 | 0.5371 | 0.5426 | 1.0240 | 0.6775 | 0.7024 | 3.6752 |
| 6 | 3.42 | 3.2271 | 5.6403 | 0.5373 | 0.5446 | 1.3586 | 0.6203 | 0.6226 | 0.3707 |
| 7 | 4.20 | 4.3147 | 2.7309 | 0.5419 | 0.5851 | 7.9719 | 0.6143 | 0.5916 | 3.6952 |
| 8 | 4.55 | 4.3416 | 4.5802 | 0.8633 | 0.8565 | 0.7876 | 0.822 | 0.8565 | 4.1970 |
| Mean error | | | 4.5185 | Mean error | | 4.2568 | Mean error | | 2.9237 |

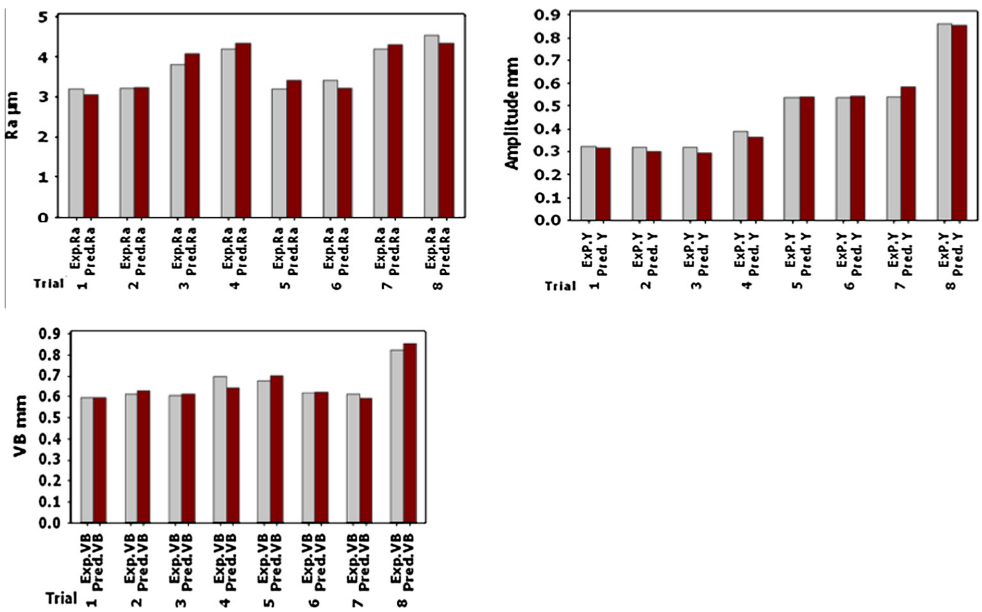


**Fig. 10.** ANN model for surface roughness, amplitude of vibration and tool wear.

piece is calculated. Mean error percentage was found as 4.5185%, 4.2568% and 2.9237% for surface roughness, amplitude of work piece vibration and tool wear respectively. From Fig. 10, it was found that the predicted values are very close to the experimental values. From these results, it can be deemed that the proposed network model is capable of predicting the tool wear, surface roughness and amplitude of vibration. It also helps in the selection of cutting parameters for good surface quality and extended tool life.

## 7. Conclusions

In this work, eight experiments were conducted according to a proposed design of experiments with two levels of cutting parameters such as cutting speed, tool insert nose radius and feed. In each trial of experiment, a strong correlation among the dependent and independent variables was found. A neural network (4-14-8-3) was used to learn the collected experimental data. The ANN was trained with 54 examples, validated with 15 examples and tested with 8 examples. The trained ANN was used to predict the surface roughness, tool wear and work piece vibration. It was found that there is agreement between experimental data and predicted values for surface roughness (4.5185% of error), work piece vibration (4.2568% of error) and tool wear (2.9237% of error). Then it is possible to change the cutting tool at correct time in order to get good quality of products. The neural network can help in selection of proper cutting parameters to reduce tool vibration and tool wear and reduce surface roughness.

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