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ORIGINAL ARTICLE

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A neural-network-based methodology for the prediction of surface roughness in a turning process

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Abstract A neural-network-based methodology is proposed for predicting the surface roughness in a turning process by taking the acceleration of the radial vibration of the tool holder as feedback. Upper, most likely and lower estimates of the surface roughness are predicted by this method using very few experimental data for training and testing the network. The network model is trained using the back-propagation algorithm. The learning rate, the number of neurons in the hidden layer, the error goal, as well as the training and the testing dataset size, are found automatically in an adaptive manner. Since the training and testing data are collected from experiments, a data filtration scheme is employed to remove faulty data. The validation of the methodology is carried out for dry and wet turning of steel using high speed steel and carbide tools. It is observed that the present methodology is able to make accurate prediction of surface roughness by utilising small sized training and testing datasets.

Keywords Artificial neural networks · Dry and wet turning · Surface roughness · Vibration

1 Introduction

Automated intelligent control of computerised numerically controlled (CNC) machines has been attracting the attention of a number of researchers. Attempts are being made to impart human-like intelligence to the machine tools. The artificially intelligent machine tool is supposed to predict the job quality based on the sensory feedback and proper analysis of the feedback signals. Based on the predictions, the machine tool should also be able to take a corrective action.

One important attribute of job quality in the turning process is surface roughness. A reasonably good surface finish is desired for improving the tribological properties, fatigue strength, corrosion resistance and aesthetic appeal of the product. On the other hand, excessively better surface finish may involve more cost of manufacturing. Hence, much attention was paid to the estimation of surface roughness. A review of important works has been presented in recent papers by Risbood, Dixit and Sahasrabudhe [1] and Feng and Wang [2].

The surface finish prediction strategy has been developed using four main methods: the multiple regression technique [2–4], mathematical modelling based on the physics of the process [5], the fuzzy-set-based technique [6] and neural network modelling [1, 7–9]. Among these, neural network modelling seems to be more promising because of the ability of neural networks to model complex processes and its similarity with the human-cognitive system. Chryssolouris and Guillot [10] compared the neural network model with the regression model and observed the superiority of former. On the other hand, Feng and Wang [9] found multiple regression models and neural network models to be equally effective.

It should be noted that the effectiveness of a neural network model is very much dependent on choosing various network parameters and the size of training and testing data and is often done using inefficient trial and error procedure. Dixit and Chandra [11] developed a strategy for choosing the network parameters as well as training and testing data for predicting upper, lower and most likely estimates of roll force and roll torque in a cold flat rolling process. The present work employs a similar methodology for predicting the surface roughness in a turning process. Since the training and testing data are collected from experiments, there may be some noisy data due to randomness of the process and measurement errors. A data filtration scheme is employed to eliminate spurious data. The proposed methodology has been validated using experimental data on dry and wet turning of steel using high speed steel (HSS) and carbide tools.

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2 Surface roughness prediction strategy

A feed forward artificial neural network trained using the back-propagation algorithm [12] has been employed. The process parameters considered are cutting speed (v), feed (f) and depth of cut (d). A feedback of the radial vibration (a) is also obtained for online prediction of center line average (CLA) surface roughness (Ra). Thus, the input layer of the neural network contains four neurons while the output layer has a single neuron corresponding to the predicted value of surface roughness. The accuracy, reliability and effectiveness of the neural network depends on a number of factors like number of training and testing data, learning rate, number of hidden layers, number of neurons in the hidden layers and processing function used. By modelling different problems, it was observed that both *logsig* and *tansig* produce almost the same performance. Hence, only the *logsig* processing function has been used, in this work. Also, only single hidden layer networks are used. Preliminary numerical experiments did not show any advantage of double hidden layer network over single hidden layer network. A typical network architecture with three neurons in the hidden layer is shown in Fig. 1. The optimum number of neurons in the range of two to six is decided by the computer code.

The entire methodology is illustrated in the form of a flow chart in Fig. 2. Based on this flow chart, a computer code was written in object oriented C++ language in a modular fashion. The initial training and testing dataset is chosen on the basis of effect of feed, depth of cut and cutting speed on the surface roughness. Then the best possible network is chosen, learning rate, number of neurons in hidden layer and error goals being decided automatically by the code. If the best possible network is not able to achieve the desired accuracy, size of dataset is increased and the procedure is repeated. A data filtration module sorts out the data with unusually high level of error compared to its partners. A replicate experiment is performed for that data. Various modules are described in the following subsections.

2.1 Selection of initial training and testing dataset

The size of the training and testing set is very crucial when the generation of data is a costly affair, for example, in the turning of costly material. As the performance of a neural network is much

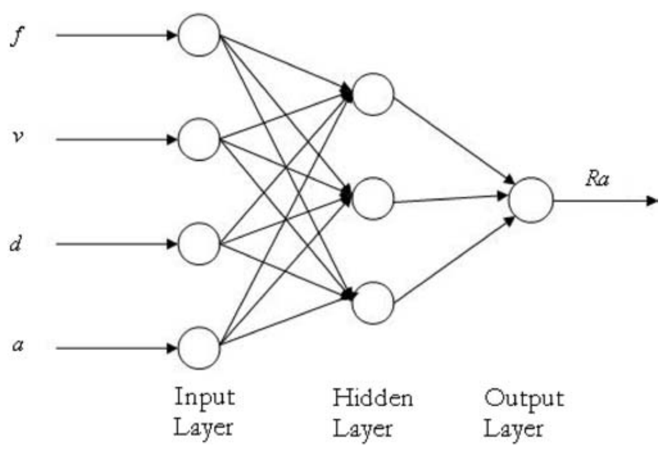

Fig. 1. A typical neutral network architecture

better in interpolation than in extrapolation, for n inputs, the minimum number of training datasets should include all the corners of an n-dimensional space. In addition, the parameter, which has a higher effect on the surface roughness value, should have more representation in the training dataset. The effect of a factor can be evaluated as [13]:

$$\text{Effect of a factor} = \frac{\sum \text{responses at high levels} - \sum \text{responses at low levels}}{\text{half the number of runs in the experiment}} \, . \tag{1}$$

In the present work, there are three controllable process parameters: cutting speed, feed and depth of cut. Two levels of each of these parameters correspond to minimum (low level) and maximum (high level) values in the considered range of the parameters. First, eight experiments are performed in order to compute effects of these parameters. The factor with the least influence is assigned two levels. The levels of other factors are taken in proportion to their effect and additional experiments are performed to represent these levels in the training dataset. For example, if the influence levels for depth of cut, feed, and cutting speed come out to be 2, 3, and 5 respectively, then one additional level of feed and three additional levels of cutting speed have to be generated. Thus, for feed, one value in the middle of range is chosen and other process parameters corresponding to this are taken at random. Similarly, in the case of cutting speed, three additional levels are chosen to have a total of five equally spaced levels in the range. Thus the initial training dataset of 2^3 is increased by one level of feed and three levels of cutting speed, making the training data 12. If the magnitude of effect of a factor is less than one fifth of the magnitude of effect of the most influential parameter, the factor is considered insignificant and is not considered.

The size of testing dataset is important from the point of view of reliability. If the network has been fitted with large number of testing data, it is expected to be more reliable, i.e., there will be fewer cases in which the error in prediction will be more than prescribed. However, the data generation process may be costly and time consuming. A simple method to decide the minimum number of testing data is proposed here.

Supposing that in validation data, the percentage of data having an error greater than a prescribed value is p. The network is always fitted in such way so that in no prediction, the error is more than the prescribed value. For a testing data size of n, the probability that in this dataset, all of the predictions fall within the limit is given by

$$P_0 = \left(1 - \frac{p}{100}\right)^n \, . \tag{2}$$

Using this expression, one can find the testing dataset size n, if P_0 and p are known. For example, if the requirement is that, in general, 75% of the time the prediction error should come out to be less than the prescribed value and the probability that a network will have poorer predictive capability is 0.1. Then, putting $p = 25$ and $P_0 = 0.1$ into the expression Eq. 2 gives $n = 8$. Hence, in the present work, minimum testing data size is kept as 8.

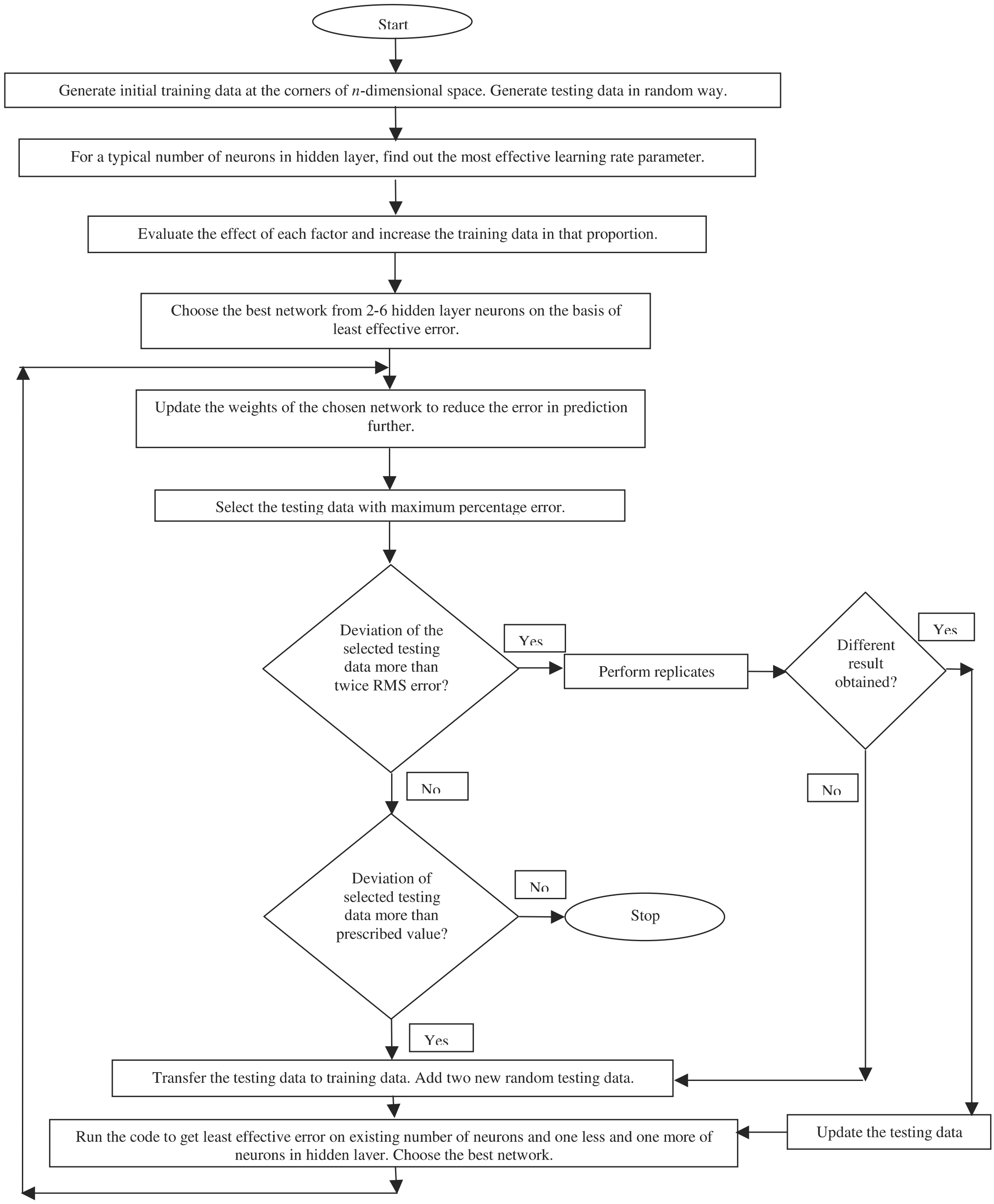

Fig. 2. Flow chart of the methodology adopted

2.2 Normalisation

The numerical values of different input parameters lie in different ranges. The four input parameters (depth of cut, feed, cutting speed and vibration) are normalised such that their values lie between 0.1 and 0.9. In order for the percentage error in the prediction to be more or less uniform, normalised values of logarithmic surface roughness are used [1].

2.3 Setting the optimum learning rate

The learning rate is decided by running the neural network code for different values of η on a prescribed error goal for a typical number of neurons (three in the present case) in the hidden layer. The best learning rate is the one taking the minimum number of epochs. It was observed that network performance was not very sensitive to learning rate near the optimum η of the network.

2.4 Best network topology

In this module, the best network topology is selected. Using the learning rate value calculated earlier, the network is trained with different number of neurons (varying from two to six) in the hidden layer. The maximum number of epochs allowed in each run is 25,000. At each network topology, the code is run five times with different initial random weights. Thereafter, maximum of training and testing root mean squared functional error, called *effective error*, is calculated. The root mean squared functional error is given by:

$$RMS_{err}^{f} = \sqrt{\sum \frac{\left(R_a - \hat{R}_a\right)^2}{n R_a^2}}\,, \tag{3}$$

where R_a is the measured CLA value of surface roughness and $\hat{R}_a$ is the predicted most likely value. The effective error is compared after every 100 epochs. If the effective error starts increasing, the run is terminated, and the weights corresponding to the minimum error of network are considered the best weights. Among all network topologies, the best network topology is the one having the least effective error. The program stores the best weights achieved and the corresponding number of neurons in the hidden layer. The program is run further by taking the best weights and the optimum number of neurons in the hidden layer until the effective error starts increasing. This further updates the weights, providing the best possible network architecture and weights possible with a given training dataset.

2.5 Increasing the size of training and testing dataset

If the desired accuracy is not obtained with the given dataset size, new training and testing data are added. The procedure for increasing the data set is as follows. Transfer one dataset of the testing set having maximum error to the training set and create two datasets in the testing set in lieu of it. Thus, the training and testing datasets increase by one pattern. With a new training dataset, the network is fitted again. This time only three network architectures are searched, the network with existing number of neurons and networks having one less and one more neuron in the hidden layer. The best network topology is selected based upon the least effective error. This procedure of shifting the dataset from testing dataset to training dataset is repeated until the desired accuracy is attained.

2.6 Data filtration

The data filtration module informs the user about the possible presence of a spurious data that might be caused by error in data collection. A mathematical approach of recognising such a case is as follows. Error in the predicted data may be normally distributed. However, approximating the error distribution in prediction by a sine wave, root mean squared error e can be represented in terms of maximum fractional error a_0 as

$$e^2 = \int_0^{\pi} \frac{a_0^2 \sin^2(\theta)\, \mathrm{d}\theta}{\pi} = \frac{a_0^2}{2}\,. \tag{4}$$

Thus, the maximum fractional error is 1.414 times that of RMS_{err}^{f} error. If the fractional error of any case is more than the maximum fractional error, then it implies that the particular case is violating the assumed variation of error. Thus, this particular case can be considered spurious and replicates of the data are needed for confirmation. In practice, the variation of error need not be sinusoidal and hence the data is considered spurious if maximum fractional error is more than twice the RMS_{err}^{f} error.

2.7 Lower and upper estimate

The present methodology predicts lower and upper estimates along with the most likely estimate of surface roughness. Prediction of lower and upper estimates provides a range within which the surface roughness value can lie. Surface roughness can thus be represented as a fuzzy number with a membership grade of 1 attached to most likely value and 0.5 to the lower and upper estimates.

A methodology to predict the lower and upper bound of any non-linear function has been proposed by Ishibuchi and Tanaka [14], which requires a simple modification of the back-propagation algorithm. In the back-propagation algorithm the error is propagated backwards such that it adjusts the weights of the network. In case of the prediction of an upper estimate, the prediction should be a value greater than the experimental value. Hence, if the predicted value is slightly greater than the experimental value, reduced value of the error is propagated backwards for modifying the weights. On the contrary, if the predicted value is less than the experimental value, complete error is propagated backwards. This is to ensure that the prediction is more than the experimental value. Thus, the error function is given by the following equation:

$$e_p = \begin{cases} \left(d_p - o_p\right)^2/2 & d_p \geq o_p \\ w(u)\left(d_p - o_p\right)^2/2 & d_p < o_p \end{cases}\,. \tag{5}$$

Here u, d_p, o_p denote number of iterations of the learning algorithm, experimental value and network output for a particular pattern (p), respectively. Factor, $w(u)$ is a monotonically decreasing function such that, $0 < w(u) \leq 1$ and $w(u) \to 0$ as $u \to \infty$. The decreasing function used here is

$$w(u) = \frac{1}{1 + (u/500)^3}\,. \tag{6}$$

In a similar way, a lower estimate of the data can be determined. In this case, the error function is given by:

$$e_p = \begin{cases} \left(d_p - o_p\right)^2/2 & d_p < o_p \\ w(u)\left(d_p - o_p\right)^2/2 & d_p \geq o_p \end{cases}\,. \tag{7}$$

3 Validation using experimental data

Experiments of turning mild steel with HSS and carbide tools were conducted at Indian Institute of Technology, Guwahati [1]. More experiments were added to existing database. For carrying out the experiments an HMT NH-26 lathe machine was employed. In this lathe, a three phase 11 kW induction motor, providing 23 speeds between 40 and 2040 rpm, drives the spindle. The work-piece is held in a hydraulic chuck. The work-pieces used for surface roughness study were cut from rolled steel bars containing about 0.35% carbon. The hardness of steel was 130 BHN, the yield strength was 290 MPa and the ultimate tensile strength 477 MPa. For studying the influence of cutting parameters on the surface roughness, few experiments were conducted on work-pieces of diameters ranging between 30–46 mm, job lengths of 240 mm and cutting lengths of 110 mm. It was observed that length and diameter of the job have an insignificant effect on surface roughness compared to cutting speed, feed, depth of cut, acceleration of radial vibration of the tool holder and the use of cutting fluid. For measuring the CLA surface roughness values (*Ra*), Pocket Surf (Mahr, GmbH) was used. Its measuring range is 0.03–6.35 μm. The surface roughness evaluation length in each case was taken as 2.4 mm. A piezoelectric type vibration meter (Syscon, SI-327A01) measures acceleration of radial vibration of the tool holder. It has a resolution of 0.01 m/s^2 and linearity of ±2% of full-scale output.

The proposed methodology is used to train the network for dry and wet turning of steel with HSS and carbide tools. The results obtained are discussed in the following subsections.

3.1 Wet turning by HSS tool

In the case of wet turning using an HSS tool, four input neurons of cutting speed, feed, depth of cut and vibration are considered.

Table 1. Range, effect and levels of a cutting variable in wet turning by the HSS tool

Cutting variable	Range	Effect of factor	No. of levels
Cutting speed	25–110 m/min	−1.43	5
Feed	0.04–0.16 mm/rev	2.03	7
Depth of cut	0.3–0.6 mm	0.62	2

The best network topology is the one with four hidden neurons. A learning rate of 1.0 is used. Three additional levels for cutting speed and five levels for feed are included in training data based on the effect of factors as shown in Table 1. For maximum allowable percentage error in prediction of 15%, network required 19 training data and 11 testing data, which are presented in Tables 2 and 3, respectively. The performance of the network is assessed by means of 29 validation data (Table 4). Figure 3 provides a visual depiction of the results. It is seen that experimental value of surface roughness lies between predicted lower and upper estimates, except in two cases. Somewhat larger differences in the two estimates is due to inherent randomness of the turning process. The deviation of the predicted most likely estimate from the experimental data is as follows. The percentage RMS_{err}^{f} error in prediction for validation data is 15.01%. It is seen that in 23 cases the error in prediction is less than 20%. Only in three cases was the error more than 25%, with the maximum error being 27.47%. The coefficient of determination for the predicted surface roughness values is found to be 74.34%, which is higher than 68.57%, the value obtained in [1].

3.2 Dry turning by HSS tool

In the case of dry turning using the HSS tool, four input neurons of cutting speed, feed, depth of cut and vibration are considered. The best network topology is the one with five hidden neurons.

Table 2. Training data set in wet turning by the HSS tool

S. No.	v(m/s)	d (mm)	f (mm/rev)	a (m/s^2)	R_a (μm)
1	107.80	0.3	0.04	0.55	1.74
2	105.12	0.3	0.16	0.97	3.23
3	104.80	0.6	0.04	2.92	2.74
4	106.02	0.6	0.16	2.66	2.91
5	27.71	0.3	0.04	0.95	2.06
6	26.99	0.3	0.16	0.88	5.20
7	27.71	0.6	0.04	0.59	2.87
8	26.99	0.6	0.16	1.42	6.20
9	46.55	0.3	0.08	0.73	3.21
10	64.56	0.4	0.04	0.66	2.13
11	78.10	0.6	0.12	2.10	4.57
12	73.95	0.3	0.05	0.76	2.52
13	38.50	0.3	0.06	0.47	3.37
14	34.71	0.6	0.08	0.63	3.67
15	74.13	0.4	0.10	2.48	4.80
16	36.87	0.5	0.12	1.07	4.55
17	48.14	0.6	0.08	0.58	4.52
18	106.47	0.3	0.08	0.65	2.26
19	23.45	0.3	0.04	0.42	1.99

Table 3. Testing data set in wet turning by the HSS tool

S. No.	v (m/s)	d (mm)	f (mm/rev)	a (m/s^2)	R_a (μm) Experimental	LE	MLE	UE	Deviation* (%)
1	42.98	0.4	0.10	0.67	4.24	3.62	4.05	5.22	4.54
2	35.96	0.3	0.12	0.95	5.21	4.01	4.71	6.08	9.56
3	76.43	0.6	0.05	1.23	2.91	2.45	3.24	3.66	−11.39
4	72.92	0.6	0.04	0.79	2.81	2.40	2.95	3.43	−4.96
5	32.87	0.3	0.12	0.48	4.29	4.00	4.59	5.92	−6.89
6	48.75	0.6	0.04	0.65	3.18	2.56	3.19	3.83	−0.15
7	103.55	0.6	0.08	3.66	3.59	2.45	3.46	3.71	3.52
8	47.52	0.6	0.16	1.73	5.43	5.42	5.80	6.18	−6.72
+9	47.17	0.3	0.04	0.90	2.31	2.11	2.49	3.00	−7.93
10	27.35	0.6	0.08	0.72	4.00	3.41	3.82	5.28	4.53
11	54.28	0.6	0.04	0.55	2.78	2.65	3.17	3.67	−14.04

*Deviation of most likely value from experimental value
LE: Predicted lower estimate of surface roughness
MLE: Predicted most likely estimate of surface roughness
UE: Predicted upper estimate of surface roughness

Table 4. Validation data set in wet turning by the HSS tool

S. No.	v(m/s)	d (mm)	f (mm/rev)	a (m/s^2)	R_a (μm)
1	34.71	0.6	0.08	0.63	3.67
2	64.56	0.4	0.04	0.66	2.13
3	29.39	0.6	0.16	1.12	5.22
4	20.88	0.4	0.12	0.67	4.79
5	54.91	0.4	0.08	2.80	3.53
6	38.50	0.3	0.06	0.47	3.37
7	34.71	0.6	0.08	0.57	3.73
8	48.14	0.6	0.08	0.58	4.52
9	64.56	0.4	0.04	0.54	2.84
10	32.87	0.3	0.12	0.55	5.26
11	54.28	0.6	0.04	0.71	3.76
12	29.39	0.6	0.16	0.98	5.44
13	20.88	0.4	0.12	0.73	3.76
14	54.91	0.4	0.08	0.73	3.48
15	38.50	0.3	0.06	0.56	3.77
16	48.70	0.4	0.04	0.54	2.39
17	61.88	0.5	0.08	0.98	4.68
18	60.56	0.5	0.08	0.77	3.14
19	100.85	0.5	0.16	1.49	3.11
20	26.48	0.4	0.04	0.37	2.03
21	49.25	0.3	0.06	0.86	3.13
22	106.34	0.3	0.04	0.94	2.65
23	45.95	0.6	0.06	1.16	3.70
24	101.80	0.6	0.06	2.70	2.51
25	45.99	0.3	0.16	1.15	5.87
26	104.20	0.3	0.16	2.23	3.36
27	45.95	0.6	0.16	2.28	5.06
28	46.97	0.6	0.16	2.43	6.35
29	103.10	0.6	0.16	3.32	4.72

A learning rate of 1.0 is used. One additional level for cutting speed is included in training data based on the effect of factors as shown in Table 5. For the maximum allowable percentage error in prediction of 15%, the network required nine training data and eight testing data, which are presented in Tables 6 and 7, respectively. The performance of the network is assessed by means of 26 validation data (Table 8). Visual depiction of the results is provided in Fig. 4. It is seen that the experimental value of sur-

Table 5. Range, effect and levels of a cutting variable in dry turning by the HSS tool

Cutting variable	Range	Effect of factor	No. of levels
Cutting speed	25–110 m/min	−2.25	3
Feed	0.04–0.16 mm/rev	1.59	2
Depth of cut	0.3–0.6 mm	−0.33	2

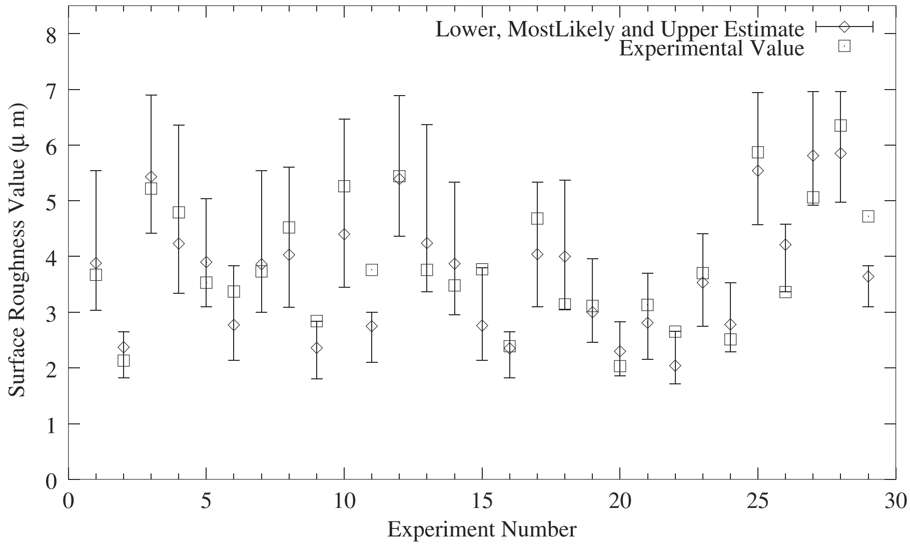

Fig. 3. Predicted values versus experimental value of surface roughness in turning by the HSS tool in the presence of coolant

Table 6. Training data set in dry turning by the HSS tool

S. No.	v(m/s)	d (mm)	f (mm/rev)	a (m/s^2)	R_a (μm)
1	107.82	0.3	0.04	0.56	2.44
2	105.12	0.3	0.16	1.05	3.23
3	104.80	0.6	0.04	2.69	2.21
4	106.02	0.6	0.16	2.28	4.45
5	27.71	0.3	0.04	2.36	5.68
6	26.99	0.3	0.16	2.18	6.14
7	27.71	0.6	0.04	0.62	3.32
8	26.99	0.6	0.16	1.26	6.20
9	45.95	0.3	0.16	1.39	5.56

Table 7. Testing data set in dry turning by the HSS tool

S. No.	v (m/s)	d (mm)	f (mm/rev)	a (m/s^2)	R_a (μm) Experimental	LE	MLE	UE	Deviation* (%)
1	48.14	0.6	0.08	0.89	3.84	3.05	3.58	5.02	6.82
2	42.98	0.4	0.10	1.33	4.65	3.99	4.83	6.61	−3.86
3	36.87	0.5	0.12	1.11	4.90	4.36	5.29	6.81	−7.92
4	35.96	0.3	0.12	0.87	4.76	4.17	4.82	6.58	−1.22
5	78.10	0.6	0.05	0.84	2.06	1.91	1.98	2.21	3.98
6	27.35	0.3	0.08	1.76	6.35	4.51	5.59	6.95	11.99
7	42.31	0.3	0.04	11.84	3.67	3.37	4.15	7.02	−13.19
8	104.67	0.6	0.04	8.27	3.96	3.27	4.21	6.99	−6.21

face roughness lies between predicted lower and upper estimates, except in two cases. The deviation of the predicted most likely estimate from the experimental data is as follows. The percentage RMS^f_{err} error in prediction for validation data is 16.05%. It is seen that in 19 cases, the error in prediction is less than ±20%. Only in five cases is the error more than 25%, with the maximum being 29.94%. The coefficient of determination for the predicted surface roughness values is found to be 63.82%, which is higher than 38.99%, the value obtained in [1]. It is also worth noting that in [1], a total of 26 data (18 training and eight testing) were used for fitting the network, whereas in the present work total 17 data are enough.

3.3 Wet turning by carbide tool

In the case of wet turning using carbide tools, experiments at 13 feed levels were conducted at three different cutting speeds, each at the same depth of cut (0.6 mm). The network required 21 training data and 10 testing data (Tables 9 and 10, respectively). The best network has three neurons in the hidden layer.

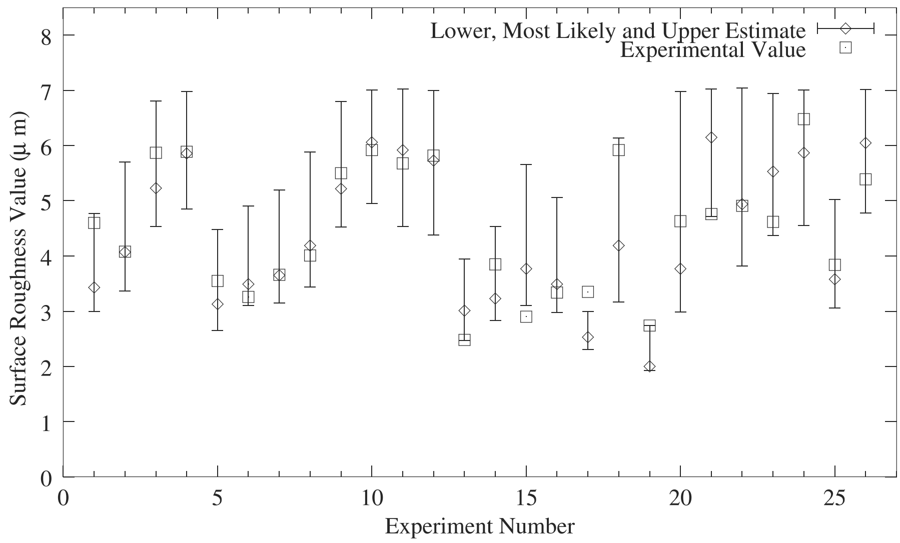

Fig. 4. Predicted values versus experimental value of surface roughness in turning by the HSS tool in the absence of coolant

Table 8. Validation data set in dry turning by the HSS tool

S. No.	v(m/s)	d (mm)	f (mm/rev)	a (m/s^2)	R_a (μm)
1	32.17	0.4	0.06	0.47	4.60
2	24.96	0.6	0.06	0.69	4.08
3	45.06	0.3	0.16	0.78	5.87
4	39.57	0.4	0.16	1.29	5.89
5	70.60	0.3	0.08	1.20	3.55
6	67.31	0.6	0.12	0.87	3.26
7	32.17	0.4	0.06	0.68	3.66
8	24.96	0.6	0.06	0.77	4.01
9	45.06	0.3	0.16	0.97	5.50
10	39.57	0.4	0.16	1.58	5.92
11	70.60	0.3	0.08	4.13	5.68
12	67.31	0.6	0.12	3.04	5.82
13	33.85	0.4	0.04	0.43	2.48
14	55.81	0.5	0.08	0.90	3.85
15	42.92	0.3	0.04	1.54	2.90
16	73.95	0.3	0.12	1.06	3.34
17	46.97	0.6	0.04	0.67	3.35
18	46.97	0.6	0.04	1.92	5.92
19	72.92	0.6	0.04	1.06	2.74
20	103.10	0.6	0.04	10.10	4.63
21	41.66	0.3	0.12	2.53	4.76
22	41.65	0.3	0.12	11.25	4.91
23	70.60	0.3	0.12	2.66	4.62
24	103.10	0.3	0.16	3.67	6.48
25	48.14	0.6	0.08	0.89	3.84
26	47.52	0.6	0.16	1.97	5.39

A learning rate of 0.05 is used. A maximum error of 20.15% is observed in the case of testing data. The performance of the network is assessed by means of 20 validation data (Table 11). Figure 5 provides a visual depiction of the results. It is seen that the experimental value of surface roughness lies between the predicted lower and upper estimates, except in three cases. The deviation of the predicted most likely estimate from the experimental data is as follows. The percentage RMS_{err}^{f} error in prediction for validation data is 17.66%. It is seen that in 15 cases, the error in prediction is less than ±20%. In three cases, error is more than 25%. The coefficient of determination for the predicted surface roughness values is found to be 71.27% that is somewhat lower than the 84.25% obtained in [1]. Slightly inferior performance of the network, in the present case is due to probabilistic nature of network fitting.

3.4 Dry turning by carbide tool

In the case of dry turning using a carbide tool, four input neurons of cutting speed, feed, depth of cut and vibration are considered.

Fig. 5. Predicted values versus experimental value of surface roughness in turning by the carbide tool in the presence of coolant

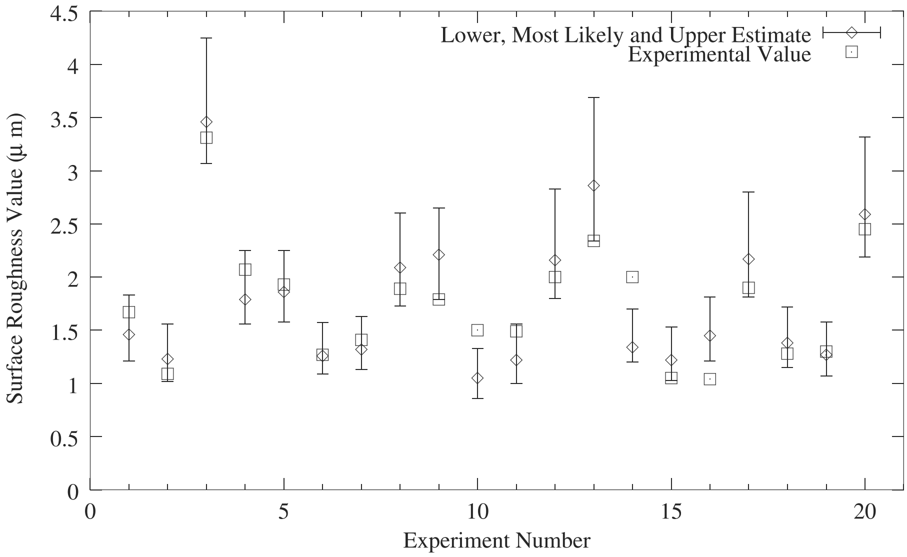

Table 9. Training data set in wet turning by the carbide tool

S. No.	v(m/s)	f (mm/rev)	a (m/s^2)	R_a (μm)
1	134.42	0.05	1.61	2.99
2	134.42	0.07	1.65	1.62
3	134.42	0.10	1.41	1.29
4	134.42	0.14	2.35	0.96
5	134.42	0.20	1.61	1.75
6	134.42	0.28	1.32	2.63
7	134.42	0.36	2.61	4.37
8	174.88	0.05	3.80	1.94
9	174.88	0.07	4.55	1.86
10	174.88	0.10	6.91	1.40
11	174.88	0.14	8.54	1.56
12	174.88	0.20	9.10	1.85
13	174.88	0.28	8.41	2.02
14	174.88	0.36	10.90	2.46
15	227.64	0.05	1.39	1.14
16	227.64	0.07	1.60	1.29
17	227.64	0.10	1.94	1.57
18	227.64	0.14	1.75	1.68
19	227.64	0.20	2.01	1.46
20	227.64	0.28	2.80	2.68
21	227.64	0.36	2.82	3.43

Table 11. Validation data set in wet turning by the carbide tool

S. No.	v(m/s)	f (mm/rev)	a (m/s^2)	R_a (μm)
1	134.41	0.08	1.62	1.67
2	134.41	0.16	1.73	1.09
3	134.41	0.32	2.15	3.31
4	174.88	0.06	4.29	2.07
5	174.88	0.24	7.61	1.93
6	227.64	0.06	1.49	1.27
7	227.64	0.08	1.73	1.41
8	227.64	0.24	2.11	1.89
9	138.40	0.06	1.96	1.79
10	136.70	0.12	1.25	1.50
11	135.00	0.16	1.07	1.49
12	140.80	0.24	0.84	2.00
13	139.00	0.28	0.87	2.34
14	178.60	0.06	1.97	2.00
15	176.38	0.12	1.48	1.05
16	174.10	0.16	1.39	1.04
17	171.82	0.24	1.00	1.90
18	185.50	0.14	1.20	1.28
19	183.20	0.12	1.80	1.30
20	181.00	0.28	1.85	2.45

Table 10. Testing data set in wet turning by the carbide tool

S. No.	v (m/s)	f (mm/rev)	a (m/s^2)	R_a (μm)				Deviation* (%)
				Experimental	LE	MLE	UE	
1	134.41	0.06	1.46	2.76	1.91	2.20	2.82	20.15
2	134.41	0.12	1.65	1.17	0.88	1.07	1.36	8.46
3	134.41	0.24	1.85	2.09	1.73	2.06	2.67	1.45
4	174.88	0.08	5.69	1.89	1.40	1.63	2.06	14.03
5	174.88	0.12	7.50	1.52	1.29	1.50	1.87	1.03
6	174.88	0.16	9.10	1.85	1.35	1.58	1.93	14.52
7	174.88	0.32	10.10	2.38	1.94	2.21	2.66	7.38
8	227.64	0.12	1.30	1.82	1.24	1.48	1.82	18.64
9	227.64	0.16	1.85	1.75	1.40	1.67	2.04	4.33
10	227.64	0.32	2.84	2.58	2.41	2.83	3.60	- 9.85

In this case, somewhat greater difference in the magnitude of RMS^{f}_{err} value of radial vibration was obtained as the tool moved from the free end to the chuck end. Hence, the work-piece was divided into three zones and the mean values of vibration and surface roughness were recorded for each zone. To accommodate for more variation in vibration levels in a particular case, the initial training dataset consisted of two levels of vibration for all the high and low level combinations of the three process parameters. Thus a set of $2 \times 8 = 16$ data is used to find effect of the parameters. One additional level for speed and three levels for feed are included based on the effect of the factor as shown in Table 12. The best network architecture has 3 neurons in the hidden layer. For maximum allowable percentage error in prediction of testing data to be 20%, the network required 21 training data and nine testing data that are presented in Tables 13 and 14, respectively. The performance of the network was assessed by means of 80 validation data (Table 15). Figure 6 provides a visual depiction of the results. It is seen that experimental value of surface roughness lies between predicted lower and upper estimates, except in seven cases. The deviation of the predicted most likely estimate from the experimental data is as follows. The percentage RMS^{f}_{err} error in prediction for validation data is 16.64%. It is seen that in 60 cases the error in prediction is less than ±20%. In 11 cases the error is more than 25%, with the maximum being 33.43%. The coefficient of determination for the predicted surface roughness values is found to be 65.12%.

Table 12. Range, effect and levels of a cutting variable in dry turning by the carbide tool

Cutting variable	Range	Effect of factor	No. of levels
Cutting speed	90–240 m/min	−0.54	3
Feed	0.04–0.32 mm/rev	0.93	5
Depth of cut	0.1–1.0 mm	−0.43	2

Table 13. Training data set in dry turning by the carbide tool

S. No.	v(m/s)	d (mm)	f (mm/rev)	a (m/s^2)	R_a (μm)
1	102.87	0.1	0.32	5.75	4.89
2	102.87	0.1	0.32	6.42	4.72
3	235.84	0.1	0.04	5.91	3.43
4	235.84	0.1	0.04	4.41	2.50
5	226.87	0.1	0.32	4.98	3.53
6	226.87	0.1	0.32	5.24	3.28
7	236.48	1.0	0.04	6.20	2.43
8	236.48	1.0	0.04	7.03	2.48
9	106.26	0.1	0.04	2.45	2.32
10	106.26	0.1	0.04	2.86	2.53
11	96.12	1.0	0.04	12.84	3.38
12	96.12	1.0	0.04	6.83	2.72
13	97.04	1.0	0.32	5.16	3.65
14	97.04	1.0	0.32	5.11	3.46
15	238.41	1.0	0.32	11.47	2.43
16	238.41	1.0	0.32	13.50	2.24
17	191.49	0.6	0.16	19.40	3.20
18	130.89	0.1	0.20	8.58	6.16
19	197.92	0.3	0.12	8.32	2.22
20	138.19	0.6	0.24	11.13	3.99
21	232.00	0.1	0.16	7.51	2.40

Table 14. Testing data set in dry turning by the carbide tool

S. No.	v (m/s)	d (mm)	f (mm/rev)	a (m/s^2)	R_a (μm)				Deviation* (%)
					Experimental	LE	MLE	UE	
1	130.31	0.1	0.24	5.87	5.62	4.02	4.89	6.92	13.03
2	197.42	0.6	0.12	14.12	2.87	2.06	2.66	3.41	7.32
3	184.06	0.1	0.30	6.81	4.70	4.24	5.22	6.91	−11.09
4	87.15	0.6	0.32	5.94	6.26	4.62	5.63	6.96	10.17
5	221.67	0.6	0.16	15.87	2.33	1.90	2.43	3.16	−4.30
6	89.90	0.6	0.28	12.06	5.72	5.06	6.05	6.99	−5.79
7	233.55	0.6	0.08	5.59	2.41	1.88	2.31	2.93	4.39
8	212.27	1.0	0.12	8.80	2.35	1.78	2.22	2.89	5.64
9	228.15	0.1	0.28	5.55	3.52	2.37	2.86	4.19	18.74

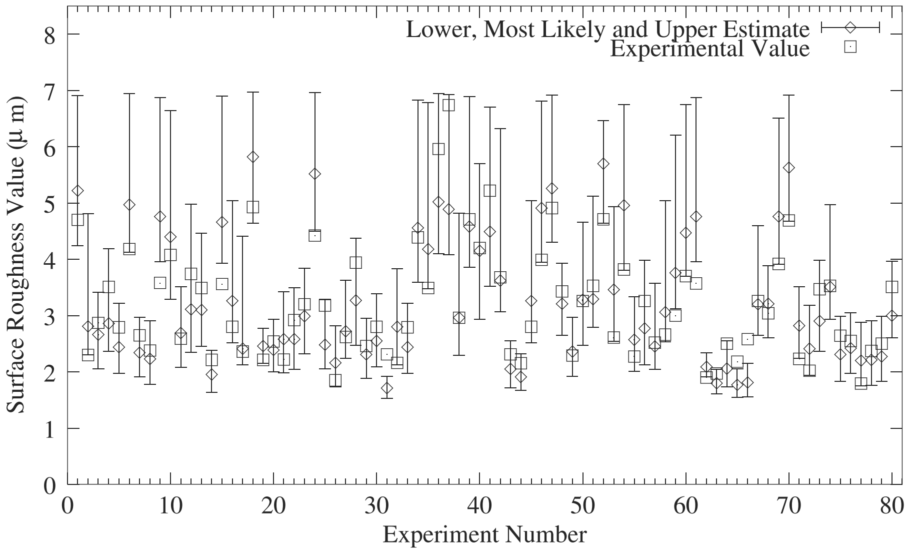

Fig. 6. Predicted values versus experimental value of surface roughness in turning by the carbide tool in the absence of coolant

Table 15. Validation data set in dry turning by the carbide tool

S. No.	v(m/s)	d (mm)	f (mm/rev)	a (m/s^2)	R_a (μm)	S. No.	v(m/s)	d (mm)	f (mm/rev)	a (m/s^2)	R_a (μm)
1	184.06	0.1	0.30	6.81	4.70	41	158.89	0.1	0.20	6.41	5.22
2	160.42	0.1	0.16	4.89	2.22	42	163.45	0.1	0.24	4.38	3.68
3	197.42	0.6	0.12	14.12	2.87	43	199.89	0.1	0.12	5.52	2.31
4	228.15	0.1	0.28	5.55	3.62	44	197.92	0.1	0.16	4.84	2.15
5	203.86	0.6	0.28	8.69	2.79	45	196.90	0.1	0.20	6.81	2.80
6	103.32	0.1	0.28	6.29	4.18	46	188.52	0.1	0.28	6.79	3.81
7	223.67	1.0	0.08	8.66	2.65	47	184.06	0.1	0.32	6.48	4.91
8	120.37	1.0	0.16	7.53	2.38	48	235.84	0.1	0.04	5.92	3.43
9	135.70	0.3	0.32	4.51	3.58	49	234.56	0.1	0.08	5.83	2.29
10	132.06	0.1	0.12	6.42	4.08	50	229.44	0.1	0.20	11.16	3.26
11	201.88	0.1	0.08	6.62	2.59	51	226.87	0.1	0.32	4.98	3.53
12	159.65	0.1	0.12	6.04	3.74	52	131.47	0.3	0.04	11.50	4.43
13	126.97	0.6	0.20	6.70	3.49	53	129.72	0.3	0.08	6.92	2.61
14	224.64	0.3	0.20	5.16	2.31	54	126.22	0.3	0.16	8.45	3.62
15	129.14	0.1	0.32	5.14	3.56	55	150.33	0.3	0.08	5.96	2.27
16	196.90	0.1	0.20	6.81	2.80	56	147.11	0.3	0.12	6.26	3.26
17	105.81	0.1	0.08	2.61	2.36	57	144.83	0.3	0.16	4.72	2.52
18	131.47	0.1	0.16	9.50	4.94	58	142.55	0.3	0.20	4.60	2.66
19	202.86	0.1	0.04	4.62	2.21	59	140.27	0.3	0.24	4.44	2.84
20	128.48	1.0	0.04	4.93	2.54	60	137.98	0.3	0.28	4.62	3.50
21	192.97	0.3	0.12	8.32	2.22	61	135.70	0.3	0.32	4.51	3.57
22	131.53	0.6	0.16	6.72	2.92	62	236.51	0.3	0.04	3.02	1.90
23	191.40	0.6	0.16	19.40	3.20	63	233.55	0.3	0.08	3.30	1.97
24	157.37	0.1	0.28	7.28	4.42	64	221.67	0.3	0.24	5.17	2.50
25	218.70	0.3	0.28	5.71	3.18	65	230.58	0.3	0.12	3.89	2.18
26	215.72	0.6	0.24	6.74	1.85	66	227.61	0.3	0.16	4.45	2.58
27	197.92	0.6	0.32	7.69	2.62	67	212.76	0.3	0.32	5.79	3.26
28	103.33	0.6	0.08	8.53	3.94	68	142.93	0.6	0.04	7.83	3.04
29	222.16	1.0	0.08	7.84	2.46	69	134.11	0.6	0.28	8.87	3.82
30	114.50	1.0	0.24	8.61	2.80	70	127.10	0.32	0.6	9.63	4.69
31	233.28	0.1	0.12	4.54	2.31	71	203.36	0.08	0.6	11.15	2.23
32	194.95	0.3	0.16	9.92	2.06	72	179.61	0.24	0.6	7.19	2.02
33	203.86	0.6	0.28	8.69	2.79	73	173.68	0.28	0.6	7.72	3.47
34	104.90	0.1	0.12	5.71	4.39	74	167.73	0.32	0.6	6.81	3.53
35	104.53	0.1	0.16	4.93	3.29	75	227.61	0.12	0.6	8.92	2.64
36	104.23	0.1	0.20	6.38	5.96	76	183.57	0.08	1.0	10.10	2.55
37	102.87	0.1	0.32	6.17	6.74	77	166.49	0.16	1.0	9.46	1.79
38	132.64	0.1	0.08	4.86	2.97	78	158.89	0.20	1.0	10.51	2.37
39	129.72	0.1	0.28	5.06	4.71	79	151.36	0.24	1.0	9.98	2.50
40	166.50	0.1	0.08	8.35	4.20	80	136.08	0.32	1.0	10.75	3.51

4 Conclusions

The present work is concerned with predicting the surface roughness by taking the feedback of the radial vibration of the tool holder in the turning process. To this purpose, a neural-network-based code is developed, in which, the size of training and testing data is increased until desired prediction accuracy is obtained. The code also predicts the upper and lower estimates of surface roughness. Thus, the prediction can be represented in the form of a fuzzy number, which provides an idea about the error in a prediction and allows for a fuzzy-based control of the process. The data filtration module incorporated in the code removes the spurious data.

The proposed methodology has been validated by means of experimental data on wet and dry turning of steel using HSS and carbide tools. The methodology is found to be quite effective and utilises fewer training and testing data. It is observed that in most of the cases, the experimental value is close to the most likely estimate and within the upper and lower estimates.

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