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MODELLING SURFACE ROUGHNESS OF EN8 TURNED COMPONENT USING ARTIFICIAL NEURAL NETWORK

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Surface Roughness;

Neural Network;

EN-8 Material;

CNC Machine;

Prediction;

Matlab.

Abstract

Shafts demand different surface roughness's at different sections along its length to mount different components. This requires setting machining parameters at various levels and need operator skills. Sometimes finishing processes are to be implemented that add to the machining time and cost. In the present work, neural network has been implemented to predict the surface roughness of the turned component of EN8 shaft material using tungsten carbide tool on CNC machine. The surface roughness data for training and testing was generated by measuring surface roughness values on turned components using recommended values of machining parameters - spindle speed, feed rate, depth of cut and tool nose radius from Machining Data Hand book using L_{27} orthogonal array (OA). Neural networks of different configurations i.e with one and two hidden layers with different number of neurons in each were tested and compared by calculating MSE for each during training and it was found that the network with 4-8-1 configuration was found to be best network. Three additional practical data of surface roughness were generated by turning the material using different combinations of input parameters to serve as validation data. The neural network predicted the roughness values in close approximation to the practical values which established the robustness of the network.

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1. Introduction

Machining is a versatile process widely used to produce metallic components in small to medium batch size. It is used to produce features like through and blind holes, cavities, key ways using milling and drilling processes. Machined components get assembled with other components and hence require a particular surface finishing and dimensional accuracy. Fatigue life of components depends not only on internal integrity of the material but also on its surface roughness and hence it has become a key quality characteristic. Though machining on CNC machine is an established process, selection of machining parameters for desired surface finish are not available in the machining data books and depends on skills of the operator.Manufacturing industries often face problems of high rejections due to low quality products produced during manufacturing.

Over the last three decades, researchers have embraced artificial neural network (ANN) methodology and applied it successfully in different domains. ANN was applied to diffetent manufacturing domains. D. Benny Karunakar & G. L. Datta [7] applied ANN to predict the major defects in sand castings against variation of six input parameters, M. P. Lightfoot et. Al. [2005] [10] developed ANN model to predict weld induced deformation in 6-8 mm thick D and DH 36 grade steel plate. Abdulkadir Cevika et.al. (2008) [1] modelled ultimate capacity of arc spot welding in terms of weld strength, average welding thickness and diameter. Performances of non conventional machining processes were also modelled. Angelos P. Markopoulos et al.(2008) [2] modelled surface roughness in EDM process, Assarzadeh & M. Ghoreishi (2008) [15] MRR and surface roughness in die sinking EDM process, Srijib Kr. Dhara et al (2008) [19] laser micro machining of tungsten molybdenum high speed steel for high depth of grove with small thickness of recast layer.

In traditional machining, Mondal S.C., Mandal P., 2014 [16] modelled surface of pin of C40 material during centreless grinding with 3-5-1 architecture of NN under the influence of wheel speed, depth of cut and coolant flow.Experimental data was generated using L_{27} array of experiment. Chen Lu et.al.2009 [6] used radial basis function neural network to determine FFT vector of surface profile for three cutting parameters for in-process evaluation of surface profile quality that was intended to replace complexity of integrating many factors at a time. Prasad

M.V.R.D. et. al. 2014 [11] modelled surface roughness of Inconel 718 during machining with CBN tool, using principal component analysis model. Experimental data was generated using L_9 orthogonal array for three cutting parameters. The cutting parameters associated with lowest surface roughness were found. Anuja Beatricea et.al. 2014 [3] used a 3-7-7-1 neural network model to predict surface roughness during hard turning of AISI H13 steel with an aim to use minimal cutting fluid. L_{27} orthogonal array was used to generate the surface roughness data which was entirely for training the network. Marek Vrabeet.et. al. (2012) [12] used NN to identify the sensitivity among cutting conditions,tool wear and surface roughness during drilling of nickel based superalloy UDIMET to develop software for mahine tool control for online monitoring of surface roughness. Farid Boukezz et al. (2017) [8] used NN model to predict surface roughness in turing C38 material using P20 carbide tool. Tool wear and surface roughness were modeled in turning steel under MQL condition P30 grade carbide tool S. M. Ali, and N. R. Dhar, 2010[17].T. Deepan Bharathi Kannan et al. (2014) [20] modeled roughness of drilled surfaces of copper against feed rate and spindle speed and later compared GA and PSO methods to optimize input parameters. M M Koura et al. (2014) [9] modeled surface roughness of steel component using carbide inserts. Samya Dahbi et.al. 2016 [18] modelled surface roughness of AISI42 steel during turning against four maching parameters including tool nose radius. N.Fang et.al. (2015) [13] compared the performance of two ANN models MLP and RBF for studying the effect of eight input parameters on performance of five surface roughness parameters on aluminum during turning.

Cylindrical components are widely used as shafts that demand a very fine surface finish at certain sections. Though grinding operations are inevitably used, the cost of grinding adds to cost of component. EN8 is one of the preferred materials for making power transmission shafts and other cylindrical parts.The present study has been undertaken with the objective of studying the effect of four machining parameters i.e. cutting speed, feed rate, depth of cut and tool nose radius on surface finish of EN8 component during turning operation using ANN.

2.0 Artificial Neural Network

The human brain consists of ten billion neurons, each of which is connected, on average, to several thousand other neurons through connections called as synapses. Being a simple processing unit, each neuron contains a soma, which is the body of the neuron, an axon, and a number of dendrites (Fig.1). A neuron receives inputs from other neurons along its dendrites, and when this input signal exceeds a certain threshold, the neuron "fires",in fact, a chemical reaction occurs, which causes an electrical pulse, known as an action potential, to be sent down the axon (the output of the neuron), toward synapses that connect the neuron to the dendrites of other neurons [5]

Artificial neural networks are modeled like human brain and consist of a number of artificial neurons. Neurons in artificial neural networks tend to have fewer connections than biological neurons, and neural networks are all (currently) significantly smaller in terms of number of neurons than the human brain.

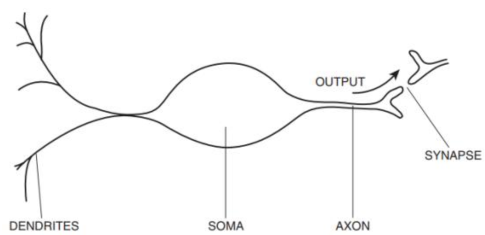

Fig. 1: Simplified biological neuron [5]

For neural networks to learn, the weight associated with each connection (equivalent to a synapse in the biological brain) can be changed in response to particular sets of inputs and events.

3. 0 Experimental setup

The raw data for surface roughness for the neural network was generated by experimentation. Identical cylindrical work samples of EN8 were turned on CNC turning machine under different cutting conditions and roughness values were measured using portable surface roughness tester.

3.1 The work samples

The selected material for this study was EN8 which is a carbon steel. The material is widely used for power transmission shafts under light to medium duty conditions. The material is available in the market in form of round bar, square bar, hexagon and plates. The material was procured in round bar shape. For systematic experimentation for generating meaningful data, orthogonal arrays (OA) L_{27} was used and a total 18 work pieces were cut with 50mm outer diameter and 30mm length. A schematic diagram of the single work piece is as shown in fig. 2 and procured round bars and cut samples are shown in fig. 3. Table 1 shows the chemical composition of work samples.

Table 1: Chemical composition of AISI 1040

Component	Carbon (C)	Silicon (Si)	Manganese (Mn)	Sulfur (S)	Phosphorus (P)
Weight %	0.36-0.44	0.10-0.40	0.60-1.00	0-0.05	0-0.05

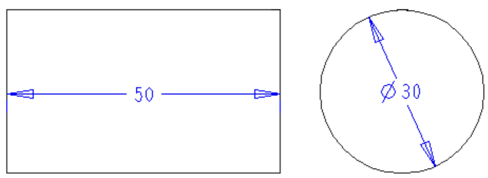

Figure 2: Schematics of work piece

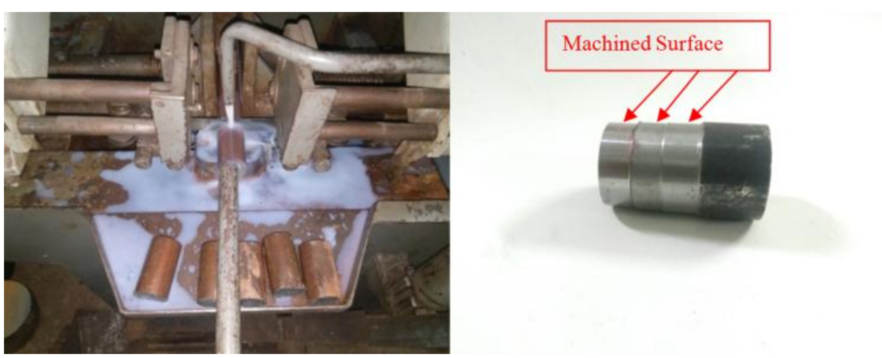

Figure 3: Raw material sample and machined work piece sample

3.2 The machine

In this project Jyoti DX200 series machine was used (Fig.4) with the specifications mentioned in table 2.

Table 2: Specification of Jyoti DX200

Chuck size	170 mm
Max. Turning Diameter	320 mm
Max. Turning Length	300mm
Travel (X / Z Axis)	175 / 300 mm
Rapid Feed (X / Z Axis)	30 m/min
Spindle Power - Siemens	10.5/ 7 kW

Figure 4: CNC machine Jyoti DX200

3.3 The surface roughness tester

A portable roughness tester Handysurf E-35A-B is used for measuring the surface roughness.as shown in fig.5 was used for measuring roughness depth (Rz) as well as the mean roughness value (Ra) in micrometers or microns (µm). Table 3 mentions its specificstions.

Figure 5: Handysurf E-35A-B

Table 3: Specifications of Handysurf E-35A-B tester

Sampling length L (mm)	**Evalution length L (mm)**	**Range of Ra (µm)**	
		Over	**Under**
0.08	0.4	0.006	0.02
0.25	1.25	0.02	0.1
0.8	4	0.1	2
2.5	12.5	2	10
8	40	10	80

3.4 Cutting tool

Cemented Carbide tool was used for turning the worksamples prepared above. Three different nose radiuses were selected to study the effect of nose radius on roughness.

4.0 Methodolgy

4.1 Data generation

To develop neural metwork model, surface roughness data was generated by performing systematic experimentation of turning the component using L_{27} orthogonal array (OA). Table 4 shows the factors and their levels selected for the experimentation. The four machining parameters – cutting speed (m/min.), feed rate (mm/rev.), depth of cut (mm) and tool nose radius (mm) each at three different levels were considerd. Levels of first three parameters were selected on the basis of recommednded range of these parameters in the machining databook [4] .Levels of nose radius were selected on the basis of standard carbide tips available in the market. Table 5 shows L_{27} array that is followed for experimentation. Each of 27 experiments was performed twice and average values of roughness were taken. Three different surfaces were generated on each of the 18 samples providing 54 surfaces, two surfaces for each experimental run.

Table 4: Factors and their levels

	Level 1	**Level 2**	**Level 3**
Cutting speed (rpm)	1300	1900	2600
Feed rate (mm/rev.)	0.05	0.15	0.25
Depth of cut (mm)	0.1	0.3	0.5
Tool nose radius (mm)	0.4	0.8	1.2

Table 5: L_{27} array [14]

Experi-mental	Spindle Speed	Feed Rate	Depth of cut	Tool nose
1.	1	1	1	1
2.	1	1	2	2
3.	1	1	3	3
4.	1	2	1	2
5.	1	2	2	3
6	1	2	3	1
7	1	3	1	3
8	1	3	2	1
9	1	3	3	2
10	2	1	1	1
11	2	1	2	2
12	2	1	3	3
13	2	2	1	2
14	2	2	2	3
15	2	2	3	1
16	2	3	1	3
17	2	3	2	1
18	2	3	3	2
19	3	1	1	1
20	3	1	2	2
21	3	1	3	3
22	3	2	1	2
23	3	2	2	3
24	3	2	3	1
25	3	3	1	3
26	3	3	2	1
27	3	3	3	2

4.2 Selecting ANN Model and Architecture

In this study, feed forward network was selected but different structures with one and two hidden layers with different number of neurons were tested so as to obtain the architecture that produces best performace parameters - mean of error percentage and standard deviation of error percentage [21]. The network parameters learning rate = 0.01; learning algorithm = cyclical weight/Bias rule; and activation function = Linear which were kept constant for all the networks.

In this work, R2013a MATLAB version is used for developing and testing the networks. The values of input and output parameters were first normalized for ANN models. Out of 27 experimental data, 18 were used as training data and rest were used as testing data. The performance of different networks based on estimation of mean of percentage error (eq. 1) and standard deviation of error percentage (eq.2) are as shown in table 6.

Table 6: Performance of the different networks with different structures

NN Index	**Structure of NN**	**Mean of Error %**	**Std. deviation of Error %**	**NN Index**	**Structure of NN**	**Mean of Error %**	**Std. deviation of Error %**
1	4-5-1	23.1	19.14	17	4-5-5-1	28.9	18.46
2	4-5-1	25.38	18.01	18	4-5-5-1	22.96	14.43
3	4-5-1	35.93	23.24	19	4-5-5-1	28.56	24.32
4	4-5-1	31.83	28.54	20	4-5-5-1	24.42	20.26
5	4-8-1	20.96	29.37	21	4-5-8-1	25.41	14.93
6	**4-8-1**	**5.89**	**3.93**	22	4-5-8-1	26.52	30.01
7	4-8-1	10.43	5.42	23	4-5-8-1	26.46	29.82
8	4-8-1	8.97	5.72	24	4-5-8-1	27.18	27.08
9	4-11-1	22.81	16.17	25	4-5-11-1	39.56	28.25
10	4-11-1	22.72	24.09	26	4-5-11-1	35.13	27.66
11	4-11-1	27	25.05	27	4-5-11-1	37.14	26.01
12	4-11-1	25.22	24.11	28	4-5-11-1	37.08	26.08
13	4-14-1	24.48	35.01	29	4-5-14-1	21.92	29.14
14	4-14-1	27.31	27.97	30	4-5-14-1	19.29	24.75
15	4-14-1	28.16	33.76	31	4-5-14-1	19.30	29.91
16	4-14-1	23.28	25.14	32	4-5-14-1	19.58	25.47

Mean of error percentage,

$$\mu \quad = \frac{Sum\ \ of\ \ all\ \ the\ \ experimantal\ \ \ values}{Number\ \ of\ \ Experiments} \qquad \text{……….. (1)}$$

Standard deviation of error percentage

$$S = \sqrt{\frac{\sum(x-\bar{x}\,)^2}{n-1}}$$

………….(2)

Where,

x = observed values of the sample

$\overline{x}$ = mean value observations

n = the number of observations in the sample.

The minimum values of mean of error percentage and standard deviation of error percentage were found to be 5.89 and 3.93 respectively for the architecture 4-8-1. Fig. 6 shows the schematics of the selected NN architecture.

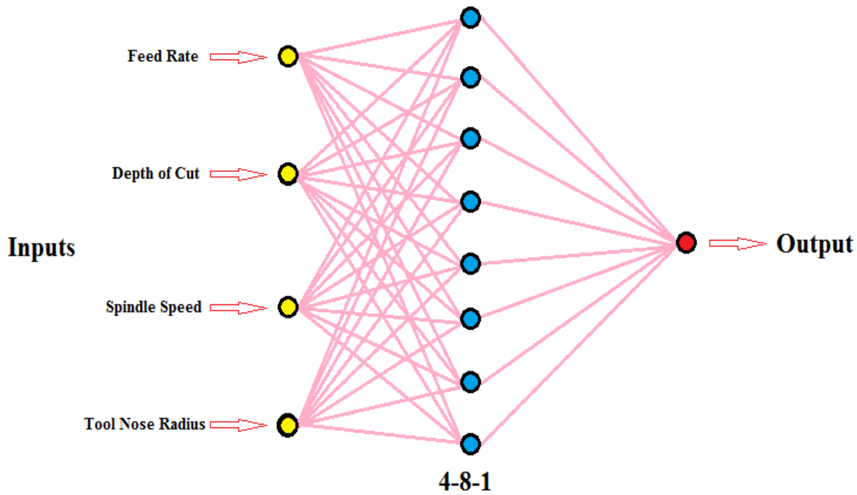

Figure 6: Schematics of selected neural network

5.0 Results and Analysis

The selected network was trained with 18 data sets and table 7 shows the results of surface roughness predicted by the network after training and testing. The numbers of epochs were fixed at 1000 but the error was not fixed.

Table 7: Performance of selected network during training and testing

S.No.	Spindle speed	Feed rate	Depth of cut	Tool nose radius	Experimental values	ANN values

Training Data						
1	1300	0.05	0.1	0.4	1.360	1.339
2	1300	0.05	0.5	1.2	1.215	1.207
3	1300	0.15	0.1	0.8	1.325	1.426
4	1300	0.15	0.5	0.4	1.595	1.140
5	1300	0.25	0.1	1.2	1.265	1.278
6	1300	0.25	0.5	0.8	1.355	1.358
7	1900	0.05	0.1	0.4	1.015	1.287
8	1900	0.05	0.5	1.2	1.095	1.090
9	1900	0.15	0.1	0.8	1.240	1.171
10	1900	0.15	0.5	0.4	1.055	1.065
11	1900	0.25	0.1	1.2	1.205	1.111
12	1900	0.25	0.5	0.8	1.350	1.346
13	2600	0.05	0.1	0.4	2.005	2.031
14	2600	0.05	0.5	1.2	0.890	0.991
15	2600	0.15	0.1	0.8	1.695	1.695
16	2600	0.15	0.5	0.4	2.040	2.047
17	2600	0.25	0.1	1.2	0.935	0.993
18	2600	0.25	0.5	0.8	1.720	1.715
Testing Data						
19	1300	0.05	0.3	0.8	1.305	1.288
20	1300	0.15	0.3	1.2	1.235	1.208
21	1300	0.25	0.3	0.4	1.415	1.352
22	1900	0.05	0.3	0.8	1.160	1.140
23	1900	0.15	0.3	1.2	1.145	1.063
24	1900	0.25	0.3	0.4	1.100	1.303
25	2600	0.05	0.1	0.4	2.005	2.031
26	2600	0.15	0.3	1.2	0.905	0.995
27	2600	0.25	0.3	0.4	2.090	2.070

Fig.7 shows the graphical interface of neural network tool box in MATLAB 2013(B). Fig. 8 shows the graphical representation of performance of the selected ANN with 4-8-1 architecture. 18 data sets were carefully selected for training the network in order to maximize the variatioin of values of the four parameters. The remaining 9 data sets were used for testing of the trained network. The performance of network during training was measured by calculating values of MSE against the number of epochs. This is represented by blue curve. The graph between mean squared error (MSE) and the number of epochs shows the decrement in MSE with the number of epochs which was set at 1000. At the end of 1000 epochs, the value of MSE lies between 10^{-03} to 10^{-04}. The network was then fed with the data sets reserved for testing. The red curve on the fig. 8 represents the performance of the network during testing. During testing the value of MSE increases till 100 epochs and then starts decreasing till 300 epochs. It does not change appreciably after approx 300 epochs and closes to 10^{-02} on MSE axis.The green curve indicates validation of the network that follows the trend of the testing curve but lies on the higher side of it. From the fig. it is also clear that MSE for testing as well as that for validation are higher than that for training for the number of epochs selected. The values of MSE for testing and validation are not quite close but also they are not far apart which indicate a fair generalization capability of the network.

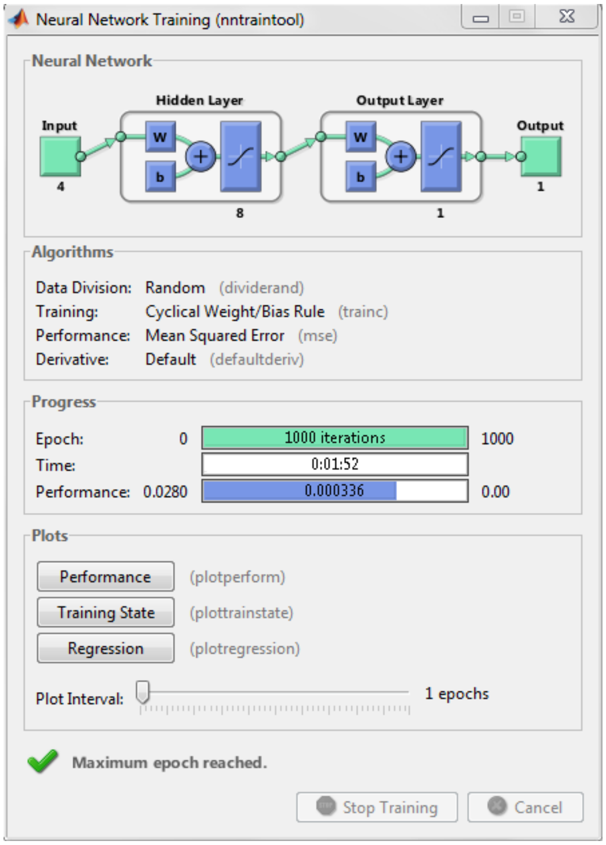

Figure 7: User Interface of network performance with 4- 8-1 architecture

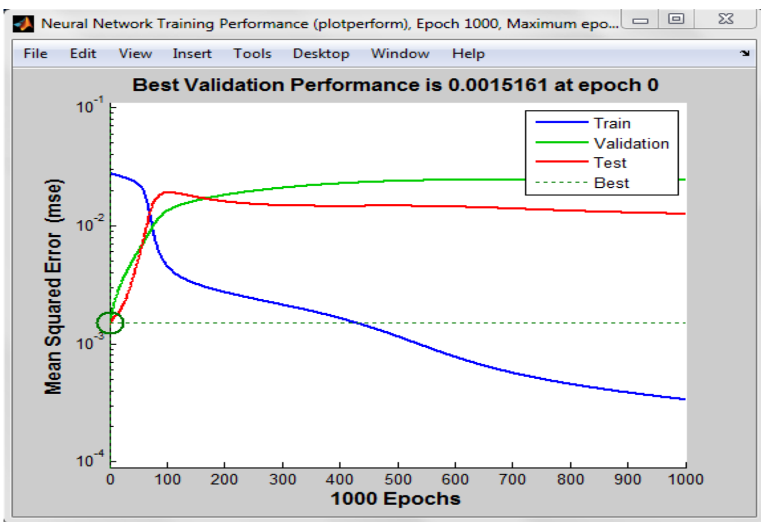

Figure 8: Graphical representation of neural network training

Fig.9 shows the best fit regression line for the entire 27 sets of data. It shows the correlation between experimental data and neural network output. The best linear fit function is calculated as: A=0.922T+0.934, while the correlation coefficient was calculated, R^2=0.899. The result confirms that that the neural network can predict the output data required for unknown input data in a satisfactory manner for the tool work piece combination and with the condition that input data values vary within limits.

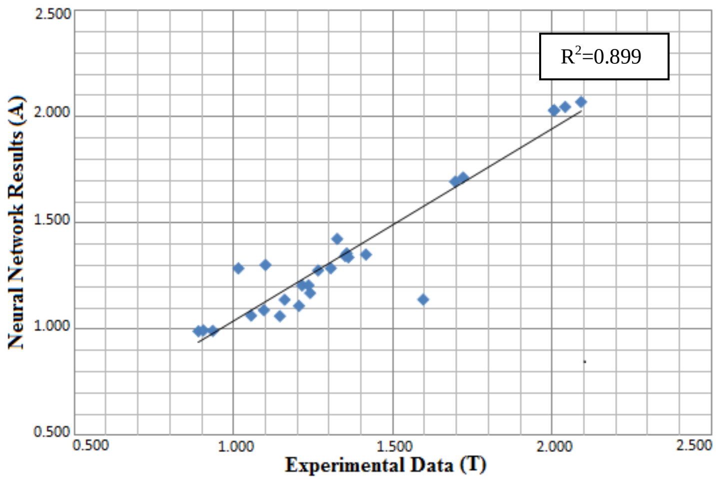

Figure 9: Correlation of actual outputs and predicted outputs

6.0 Conclusion

In the present work, prediction of surface roughness of EN8 turned component under different cutting conditions was investigated. With an aim to minimize surface roughness of machined component, the turning process was modeled using ANN as tool and different structures. The data for training and testing the network was generated on CNC machine using the concept of L_{27} orthogonal array. The feed forward architecture was adopted and out of several configurations with one and two hidden layers, a three layered feed forward network 4-8-1 was found suitable for prediction which was trained with eighteen data sets and tested with nine data sets. The epochs were limited to 1000. Though the coefficient of determination (R^2) was less for training data, it was improved for testing data. The overall performance of the trained network was further estimated and it was found the network is performing satisfactory with the coefficient of determination (R^2) as 0.899.

A group of three data sets was further used to verify the performance of network that produced a maximum error 3.28% and performed satisfactorily within the range of cutting parameters ans so it can be concluded that the model is effective for the present application and can be used for selecting optimal cutting parameters for desired roughness on select work materials.

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