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Investigations into Effect of Cutting Conditions On Surface Roughness Under MQL Turning of AISI 4340 by ANN Models

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Abstract

Enormous usage of cutting fluid in industries is reporting the issues related to health of employee, environmental pollution which promotes the Minimum Quantity Lubrication (MQL). The study reports surface roughness modelling in CNC turning under minimum quantity lubrication of EN 24, taking into account effect of cutting environment, cutting conditions using artificial neural networks (ANN). The optimisation of models are processed using the input-output data sets, ANN model, the repetitions in training the neural network, rate, hidden nodes and the training function. ANN analysis with multilayer feed forward structure under MATLAB is adopted in the analysis. Finally, After the training, the ANN is tested in order to evaluate its predictive and generalization performances. Testing the ANN is carried out by applying a new input data set, which was not included in the training process. The well known statistical tools coefficient of determination is used for this benchmarking. The adequacy of the ANN is evaluated by considering the coefficient of correlation (R).

Keywords: *MQL, ANN, Surface roughness*

1.0 Introduction

Controlling total manufacturing cost with maintaining quality is of great challenge in manufacturing industries especially related to machining operations. So many researchers have focused on analysis of machinability related characteristics. Cutting fluid improves components surface along with increase in tool life. Large amount of cutting fluid usage during cutting process increases cost of machining. Even in some cases Klocke and Eisennblatter (1997) noted that cutting fluid cost is larger than cutting tools. Hence if possible; the reduction in use of cutting fluid may benefit economics during machining process. Minimum quantity lubrication (MQL) uses 50-500 ml/h range of cutting fluid which is very less than in flooded cooling condition (Dhar et. al., 2007). Varadarajan et. al., (2002) in their work to evaluate the performance of MQL; observed the parameters which are forces during cutting, life of tool, surface roughness and tool-chip contact length. Vikram Kumar (2007) reported with the Taguchi analysis in turning of hard component, feed as the major contributing factor on surface roughness. Dhar et. al. (2007) studied machining of EN24 under MQL which shows significant reduction in tool wear, surface roughness. Fair results are observed with use of MQL while turning AISI 1040. Dhar et. al. (2006) noted that reduction in temperature with use of MQL reduces friction, maintains cutting edge results into good dimensional accuracy.

Artificial Neural Networks (ANNs) are used extensively in manufacturing process to model the process viz. turning, milling and drilling (Ezugwua et al., 2005). ANN has got the learning and generalization capabilities, it accommodates non linear variables as well as it adapts to changing environment and missing data. Modelling and machining process monitoring is the area wherein ANN is finding its way (Sick, 2002). The numerous applications of ANN in this manufacturing sector are controlling of cutting processes, predicting the responses such as tool wear, surface roughness, forces (Liu and Wang, (1999), Karri, (1999)). Elanayar and Shin (1995) proposed use of radial basis function to predict the flank and crater wear and its effect on forces. Ghasempoor et al. (1999) proposed ANN in turning for tool wear classification and monitoring. Liu and Altintas (1999) derived using various inputs an expression to calculate flank wear. The ANN was supplied with the input of wear, force ratio, feed and cutting speed.

From a literature (Powar et. al., 2016) it can be noted that experiments are performed with various output parameters under different lubrication condition. The present work shows study of MQL specific parameters alongwith the various levels of cutting conditions and use of ANN to model the process.

20 Methods And Materials

2.1 Component and Machine Tool

The component AISI 4340 (EN 24) steel used in this work is hardened to 42 (+/-)2 HRc. Total 25 components with sizes of 30 mm and length 160 mm are used in experiment. The compositions of EN24 steel (CMTI, 2011) is shown in Table 1. The tests are conducted on CNC lathe using developed MQL set up.

Machining is carried out using carbide insert and a tool holder DCLNR 25 25 M is used for the mounting.

Table 1: AISI 4340 Component Composition

C	Si	Mn	Cr	Ni	Mo
0.35 – 0.45	0.1 – 0.35	0.4 – 0.7	0.9 – 1.3	1.25 – 1.75	0.2 – 0.35

2.2 Input Parameter Selection

In this work, alongwith cutting conditions, the MQL performance is studied. The cutting fluid mixture and distance in cutting point-nozzle block are considered as additional parameters. It is decided to use five levels of each input parameters and on the basis of manufacturer catalogue, experts from industry values of cutting conditions are selected. To direct a good mixture of cutting oil and air, the distance and quantity of mixture is decided with five levels. MQL range reported in the literature is considered as the rate of mixture of cutting fluid for the operation. Table 2 shows various input parameters (Dhar et. al., 2006) used during experiment with different levels and values.

2.3 Selection of Orthogonal Array and Measurement of Surface Roughness as Output Parameter

As outlined in earlier section, with five input parameters and five levels each, L25 orthogonal array (Taguchi et.a l., 2004) is used with 25 experimental runs. The output parameter decided in this experiment is surface roughness. Online measurement of surface roughness is not possible therefore the offline measurement of surface roughness is done using surface roughness tester. The surface roughness of component is measured at three different locations, 120^{o} apart a plane and three measurements per plane. Surface roughness is measured at a distance of 10 mm as plane 1, two more planes are considered i.e. plane 2 and plane 3 each at 10

Table 2: Input Parameters With Their Levels

Input Parameters	(A) Quantity of Mixture (Q) (ml/hr)	(B) Distance of block (Dist) (cm)	(C) Cutting Speed (V) (m/min)	(D) Feed (f) (mm/rev)	(E) Depth of cut (d) (mm)
Level 1	100	2.5	100	0.1	0.1
Level 2	200	3.5	110	0.15	0.2
Level 3	300	4.5	120	0.2	0.3
Level 4	400	5.5	130	0.25	0.4
Level 5	500	6.5	140	0.3	0.5

mm distance. Normalisation, was conducted using the "the lower-the-better" approach.

2.4 Artificial Neural Network

Studies have reported that a comprehensive dataset is not required for the successful network training (Marinkovic V. et al., 2011). Proper network choice, architecture, algorithm for training and various ANN parameters are important though the data is collected during experimentation. Quantity of cutting fluid mixture (E), distance of nozzle block from the cutting point (D), cutting speed (V), feed rate (f) and depth of cut (d) are the inputs used in this study to develop an ANN network. Different algorithms are tested and 'tansigmoid' and purelin transfer function is used in the hidden and output layer respectively. Levenberg-Marquardt (LM) feed forward back propagation algorithm is used for training. Neurons in hidden layer are found by trial and error method (Asilturk I. et al., 2011). Coefficient of determination (R) is calculated, to find the optimal network architecture for every network.

In this study, the optimum architecture of a three-layer BP ANN is selected. Readings from the original L25 orthogonal array are used to test this ANN. Randomly, 80% of the dataset is used for training and the remaining 20% for testing the trained network (Ali S. M. et al., 2010, Masud Md. Abdulla Al et al., 2011). The MATLAB version 7.0.1 (R14) is used to develop and to check the performance. The results obtained using ANN are reported here in later phases.

2.4.1. Artificial Neural Network (setting up ANN models)

Artificial Neural Network (ANN) approach is similar to that of human learning process. Using the approach and model developed with the help of ANN, the data available is used for training and testing and also to understand the relationship between variables. This enables the ANN approach to predict the responses based on inputs provided in the given range. (Rege, Tock W., 1996).

2.4.2. Components of Artificial Neural Network

The ANN model includes neurons. The neurons in artificial neural network (ANN) model communicates with each other. The components used to develop the ANN requires to be connected with each other to form a complete structure. However there are some set of factors that are required to be follow in order to get the results. These set of factors are used in designing of model, implementation of model and finally using the model to predict the results. There are some input output processing activation functions and patterns. The teaching pattern is nothing but the training of the network and allows network adjustment to give the results.

2.5 Procedure used to Develop ANN using Neural Network Toolbox

Manual implementation of ANN is easy for the cases and problems which carries the smaller set of instructions. Even for small set of neurons the use of ANN may help to predict the results. But as the trial and error procedure is used every now and then, manual way of predicting the result may found difficult in large size of network, since large size network requires more number of neurons. Therefore, to solve the complex problems, it is beneficial to use computers and software available. There are many such software available which will develop the ANN to predict the results. One such toolbox which is used in this study is "Neural Network Toolbox" available in MATLAB.

The backpropagation algorithm is used in many cases to solve the specific problems. Choosing and selecting the suitable architecture and parameters for the same is a very important task in ANN. Further there is no prescribed solution or theoretical set of instructions and or guidance to set up the ANN model.

Artificial neural network uses a training function updates ANN parameters by reducing error of the system. It updates every time when the network is trained to get a good result and reaches a steady state.

The training algorithms used in this study are evaluated by following steps:

1. The Feedforward backpropagation network and its processing parameters are initially determined with all the trials for all different training functions.
2. Supplying inputs/outputs selected/measured for trials for training. Input and output is the dataset values.

Initially the data set available is divided randomly into various sets such as training and testing.

3. In each trial, ANN developed model is trained to check results. Once the training process completes, then the output is generated using ANN model.
4. With the available network the best possible network is selected on the bases of performance indicator.

In this research, the data has been divided into two groups randomly training data, accounting for 75 to 80 per cent, validation data and testing data, making up 20 per cent of the total dataset.

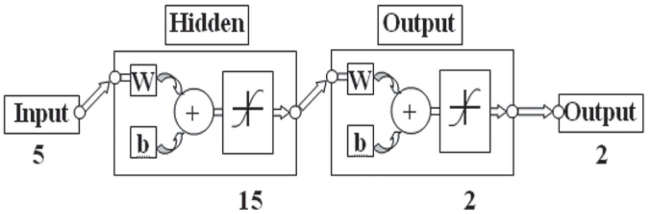

Figure 1: ANN Network Used To Analyze Surface Roughness

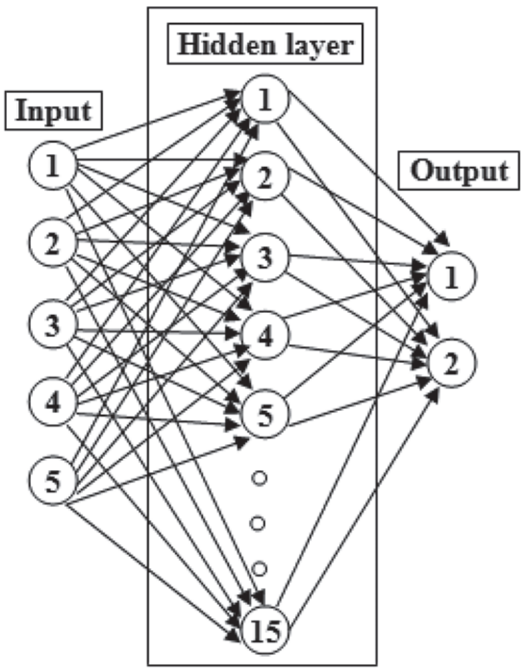

Figure 2: ANN Architecture Used To Analyse Surface Roughness

With the many techniques available for training ANN, the backpropagation (BP) training is used to operate as a multilayer fully-interconnected feed-forward ANN. The widely used algorithm for BP is the Levenberg-Marquardt (L-M) algorithm, especially for smaller and moderate ANNs.

After the training to evaluate the productiveness, new dataset is used to test the ANN, which are not the part of the training process. While training the network, no. of hidden layers and epochs are selected from the condition where the error is satisfactory. Trial and error method with initially 5 neurons and then increasing in a step of 5 is followed to reach to a good conformance stage. The adequacy of the ANN is evaluated by considering the coefficient of determination (R). The ANN network with five (5) input nodes viz. quantity of mixture, distance of nozzle block, cutting speed, feed, depth of cut, as shown in Figure 1. is used in this study. Similarly the ANN architecture used in this analysis is shown in Figure 2. The network shown in Figure 1 is used to analyse the surface roughness.

In the present study randomly 80% of experimental readings are used to train the network and remaining 20% are used to test the developed network. The success of ANN, depend largely on the larger dataset. Dataset initially selected is based on the Taguchi orthogonal array. With 5 input variables with each of 5 levels, Taguchi suggests L25 OA. The same are used during the experimentation and trials. Further sometimes small data gives unsatisfied results. Hence, the existing dataset is expanded by interpolating available data within the discrete values of input and response. Total 121 readings are generated by the interpolation assuming each discrete points are linearly varying to give desired output and response.

2.5.1. The Assessment of the Model

The well known statistical tool coefficient of determination is used for this benchmarking. The adequacy of the ANN is evaluated by considering the coefficient of correlation (R) using an equation (1).

The correlation coefficient values are obtained with the following equation:

$$R = 1 - \frac{\sum j\,(t_j - o_j)^2}{\sum j\,(o_j)^2} \qquad \text{... (1)}$$

3.0 Results and Discussion

3.1. Training and Testing of Models Developed for AISI 4340

As discussed in earlier section, the training of data is performed using the ANN network shown in Figure 3. The regression plot generated by an ANN model is shown in Figure 4 which shows the closeness of predicted results. The plots represent the training, validation and testing of all data. The results indicate a good fit.

The network is trained with 80% of readings available from the experimental dataset. The predicted values of surface roughness from the ANN network shown in Figure 3 are compared to the experimental result. The Table 3 shows the results of responses obtained from the developed ANN model for the training dataset. It shows the experimental and

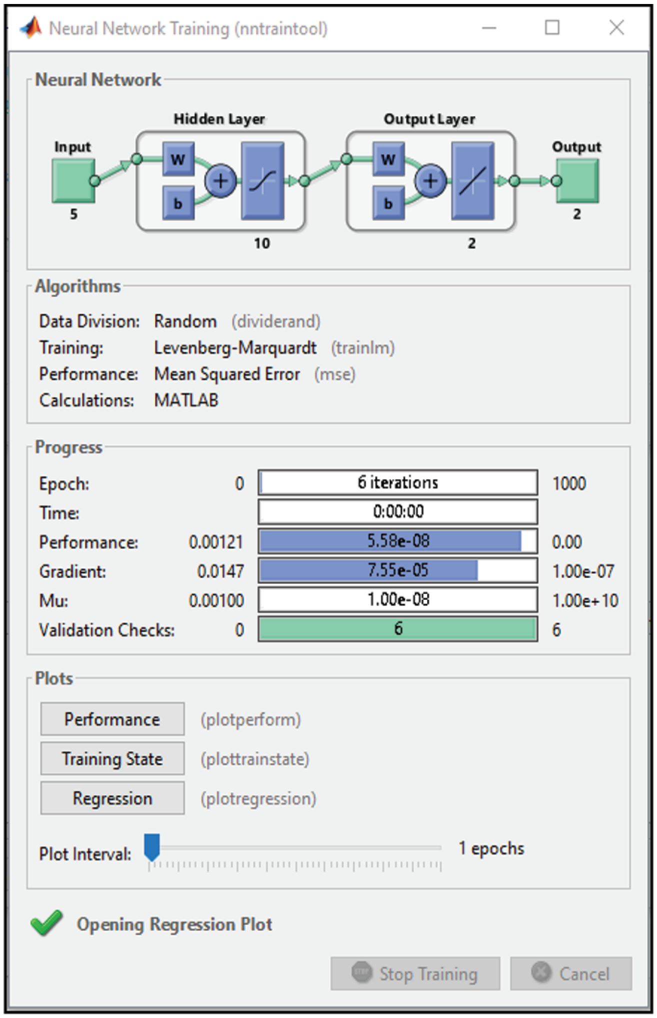

Figure 3: Network for AISI 4340

predicted values of surface roughness. It can be seen from Figure 5 that the results are in good agreement.

The Table 4 shows the data obtained from the testing dataset. The comparison of the predicted and experimental data which shows closeness of the values obtained.

A comparison of values to determine the deviation between the experimental and predicted value that comes out from ANN models have been conducted which is shown in Table 5. The R for the training sets = 0.93 (93%) and for testing sets is = 0.94 (94 %) which shows a closeness of readings obtained.

Sometimes small dataset used to develop ANN may give unsatisfactory results. So the expansion of dataset is necessary to generate more number of data sets. Hence the interpolation of data set is carried out and Artificial Neural Network (ANN) model is also developed and tested for the effectiveness.

3.2. Interpolation of Data and Network Developed for AISI 4340

The original orthogonal array of L25 from the experiment for the readings of surface roughness is used in this section. The total number of experimental results available is twenty five (25) in number which is less in number to model the ANN network. This may lead to poor performance and fitting. Therefore the available

database in this study is expanded using interpolation. The new data points within the range are obtained by interpolating the data points available in original L25 array. The linear

Table 3: Experimental and Predicted Values of Training Network

Trial No	Experimental (surface roughness)(μm)	Predicted (surface roughness) (μm)	Trial No	Experimental (surface roughness) (μm)	Predicted (surface roughness) (μm)
2	1.049	0.610	15	1.147	0.737
4	1.139	1.057	16	1.012	1.293
5	1.189	1.245	17	1.048	0.655
6	1.135	0.753	18	1.234	1.088
7	1.063	0.853	19	1.166	0.690
8	0.994	0.802	20	0.705	1.410
9	0.850	1.158	21	1.043	1.097
11	1.300	0.801	22	1.192	0.954
12	0.806	1.297	24	0.661	1.220
14	1.144	0.703	25	1.053	1.166

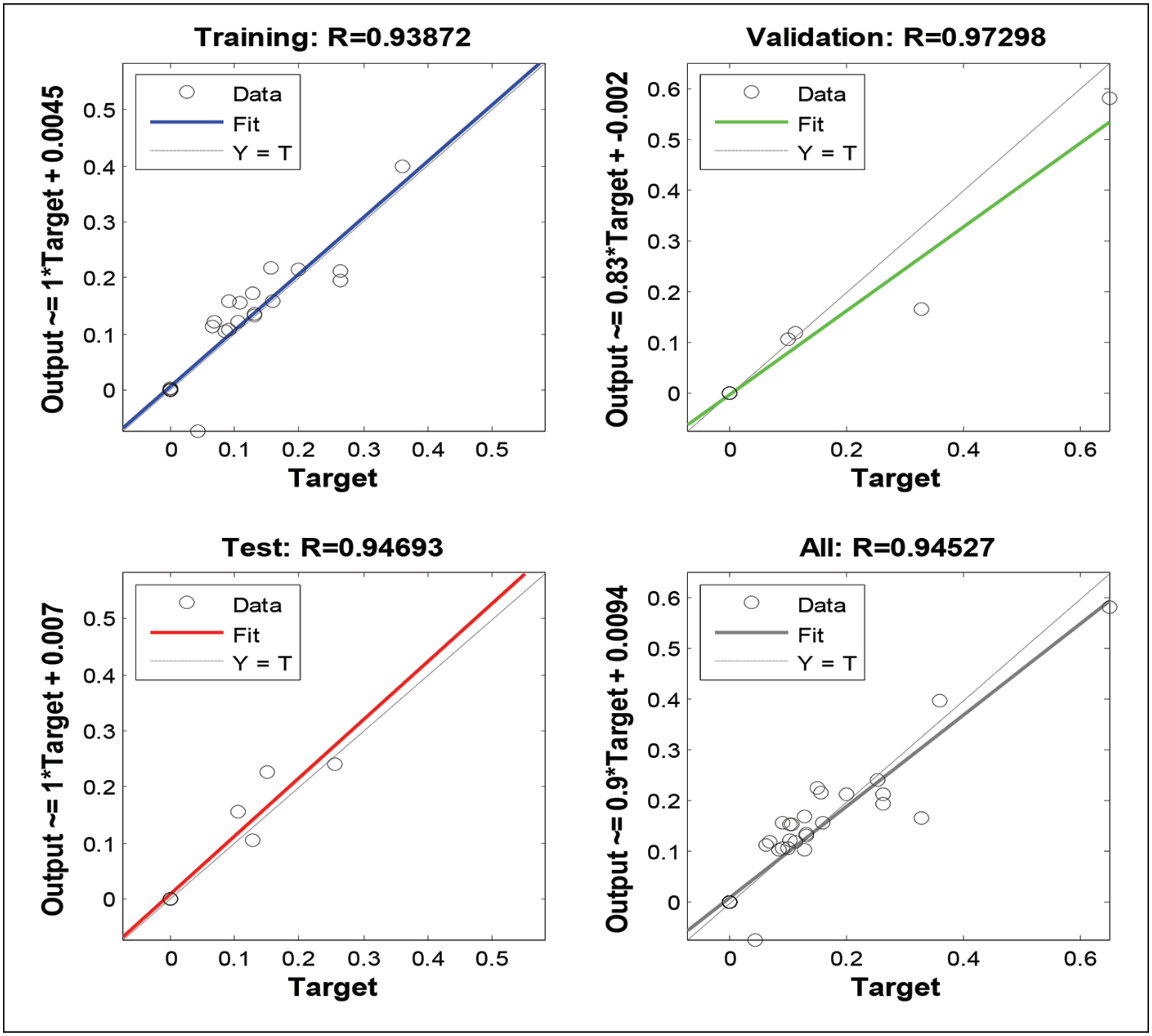

Figure 4: Regression Plot for Network of AISI 4340

interpolation is performed to calculate the interpolation step value. It assumes that the change between two values is linear. In a procedure of training ANN model, ANN network uses some part of database to train the network based on which it uses part of it for validating and remaining for testing the results. The expanded dataset after performing interpolation is shown in Table 6.

The Table 6 shows the expanded values of experiment, designed using Taguchi orthogonal approach alongwith the measured values of surface roughness. The total 121 readings are generated using

Table 4: Experimental and Predicted Values of Testing Network

Trial No	Experimental (surface roughness) (µm)	Predicted (surface roughness) (µm)
1	0.875	0.807
3	1.085	0.737
10	1.125	0.751
13	0.912	1.379
23	0.524	1.456

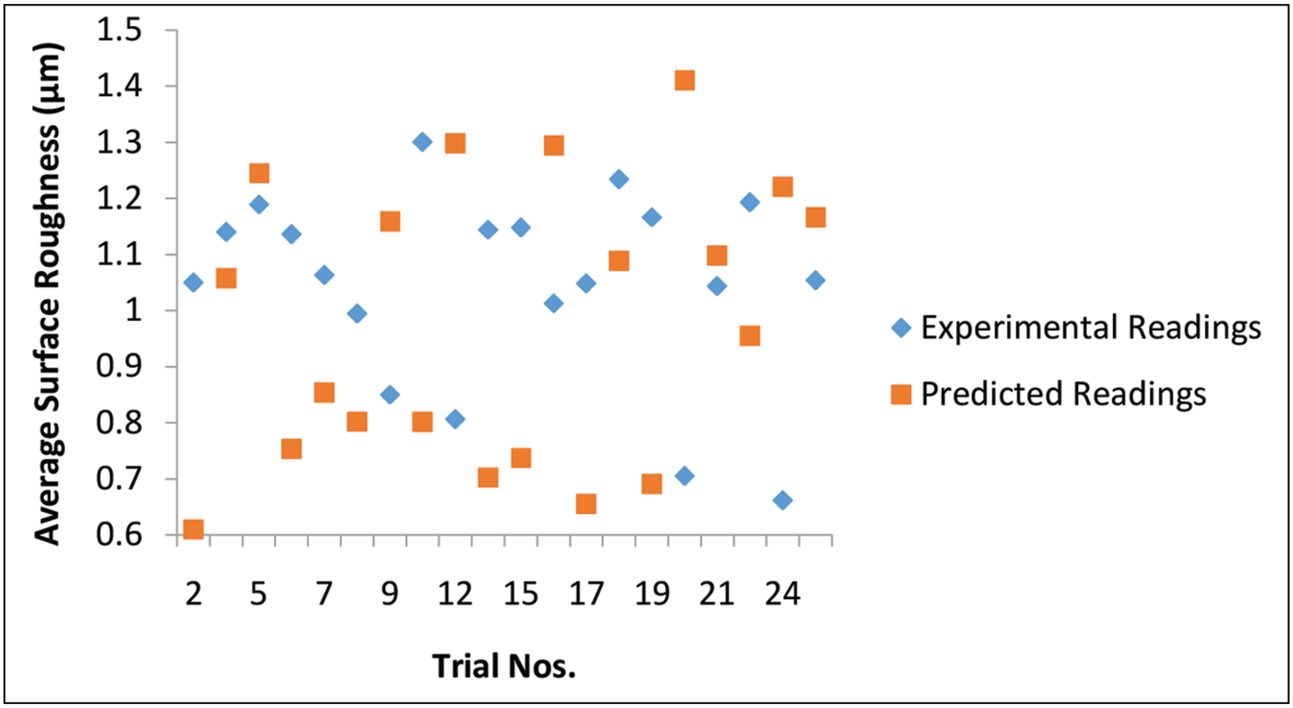

Figure 5: Comparison of 80% of Experimental Values of Surface Roughness Considered for Training Purpose

Table 5: Adequacy Check for the Model

Adequacy check	Training (80 %)	Testing (20 %)	Focused Experiment	Confirmation Experiment
R	0.93	0.94	0.97	0.97

the interpolation. The earlier same procedure is used to develop the network in MATLAB. The ANN network is selected through the observations of regression plots of neural network prediction. Figure 6 shows the ANN model used to predict the results and Table 7 shows the regression plot which shows good agreement in the readings obtained.

The predicted values of surface roughness are given in Figure 7. These are also shown graphically in the Figure 8.

The comparison of predicted values with the experimental values from Table 8 shows that the R for the 96 readings (80%) out of 121 interpolated readings is = 0.96 (96%) and for the remaining 25 readings (20%) is = 0.96 (96%). This shows that predicted values are in good relation with the observed values.

The comparison of results shown in Table 5 to the accuracy values of the results shown in Table 8 are generally found to be close to the directly measured data. However, as can be seen from the performance criterion in Table 8, ANN produces the better results using larger dataset generated after interpolation compared to Table 5. It is important to note that the ANN model with large dataset is successful at all the stages viz training, testing, focused and confirmation experiment.

Table 6: Modified Database of AISI 4340 to Model the ANN Network

	Quantity of mixture (ml/hr)	Distance of Block (cm)	Cutting Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Surface roughness (mm)
1	100	2.5	100	0.1	0.1	0.0008
2	100	2.7	102	0.11	0.12	0.0009
3	100	2.9	104	0.12	0.14	0.0009
4	100	3.1	106	0.13	0.16	0.0009
5	100	3.3	108	0.14	0.18	0.0010
6	100	3.5	110	0.15	0.2	0.0010
7	100	3.7	112	0.16	0.22	0.0010
8	100	3.9	114	0.17	0.24	0.0010
9	100	4.1	116	0.18	0.26	0.0010
10	100	4.3	118	0.19	0.28	0.0010
11	100	4.5	120	0.2	0.3	0.0010
12	100	4.7	122	0.21	0.32	0.0010
13	100	4.9	124	0.22	0.34	0.0011
14	100	5.1	126	0.23	0.36	0.0011
15	100	5.3	128	0.24	0.38	0.0011
16	100	5.5	130	0.25	0.4	0.0011
17	100	5.7	132	0.26	0.42	0.0011
18	100	5.9	134	0.27	0.44	0.0011
19	100	6.1	136	0.28	0.46	0.0011
20	100	6.3	138	0.29	0.48	0.0011
21	100	6.5	140	0.3	0.5	0.0011
22	120	5.7	134	0.28	0.48	0.0011
23	140	4.9	128	0.26	0.46	0.0011
24	160	4.1	122	0.24	0.44	0.0011
25	180	3.3	116	0.22	0.42	0.0011
26	200	2.5	110	0.2	0.4	0.0011
27	200	2.7	112	0.21	0.42	0.0011
28	200	2.9	114	0.22	0.44	0.0011
29	200	3.1	116	0.23	0.46	0.0010
30	200	3.3	118	0.24	0.48	0.0010
31	200	3.5	120	0.25	0.5	0.0010
32	200	3.7	122	0.26	0.42	0.0010
33	200	3.9	124	0.27	0.34	0.0010
34	200	4.1	126	0.28	0.26	0.0010
35	200	4.3	128	0.29	0.18	0.0010
36	200	4.5	130	0.3	0.1	0.0009
37	200	4.7	132	0.26	0.12	0.0009
38	200	4.9	134	0.22	0.14	0.0009
39	200	5.1	136	0.18	0.16	0.0009
40	200	5.3	138	0.14	0.18	0.0008

	Quantity of mixture (ml/hr)	Distance of Block (cm)	Cutting Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Surface roughness (mm)
41	200	5.5	140	0.1	0.2	0.0008
42	200	5.7	132	0.11	0.22	0.0009
43	200	5.9	124	0.12	0.24	0.0009
44	200	6.1	116	0.13	0.26	0.0010
45	200	6.3	108	0.14	0.28	0.0010
46	200	6.5	100	0.15	0.3	0.0011
47	220	5.7	104	0.18	0.28	0.0011
48	240	4.9	108	0.21	0.26	0.0011
49	260	4.1	112	0.24	0.24	0.0012
50	280	3.3	116	0.27	0.22	0.0012
51	300	2.5	120	0.3	0.2	0.0013
52	300	2.7	122	0.26	0.22	0.0012
53	300	2.9	124	0.22	0.24	0.0011
54	300	3.1	126	0.18	0.26	0.0010
55	300	3.3	128	0.14	0.28	0.0009
56	300	3.5	130	0.1	0.3	0.0008
57	300	3.7	132	0.11	0.32	0.0008
58	300	3.9	134	0.12	0.34	0.0008
59	300	4.1	136	0.13	0.36	0.0008
60	300	4.3	138	0.14	0.38	0.0008
61	300	4.5	140	0.15	0.4	0.0009
62	300	4.7	132	0.16	0.42	0.0009
63	300	4.9	124	0.17	0.44	0.0010
64	300	5.1	116	0.18	0.46	0.0010
65	300	5.3	108	0.19	0.48	0.0010
66	300	5.5	100	0.2	0.5	0.0011
67	300	5.7	102	0.21	0.42	0.0011
68	300	5.9	104	0.22	0.34	0.0011
69	300	6.1	106	0.23	0.26	0.0011
70	300	6.3	108	0.24	0.18	0.0011
71	300	6.5	110	0.25	0.1	0.0011
72	320	5.7	114	0.23	0.18	0.0011
73	340	4.9	118	0.21	0.26	0.0010
74	360	4.1	122	0.19	0.34	0.0010
75	380	3.3	126	0.17	0.42	0.0010
76	400	2.5	130	0.15	0.5	0.0010
77	400	2.7	132	0.16	0.42	0.0010
78	400	2.9	134	0.17	0.34	0.0010
79	400	3.1	136	0.18	0.26	0.0010
80	400	3.3	138	0.19	0.18	0.0010
81	400	3.5	140	0.2	0.1	0.0010

	Quantity of mixture (ml/hr)	Distance of Block (cm)	Cutting Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Surface roughness (mm)
82	400	3.7	132	0.21	0.12	0.0010
83	400	3.9	124	0.22	0.14	0.0011
84	400	4.1	116	0.23	0.16	0.0011
85	400	4.3	108	0.24	0.18	0.0011
86	400	4.5	100	0.25	0.2	0.0012
87	400	4.7	102	0.26	0.22	0.0012
88	400	4.9	104	0.27	0.24	0.0012
89	400	5.1	106	0.28	0.26	0.0011
90	400	5.3	108	0.29	0.28	0.0011
91	400	5.5	110	0.3	0.3	0.0011
92	400	5.7	112	0.26	0.32	0.0010
93	400	5.9	114	0.22	0.34	0.0009
94	400	6.1	116	0.18	0.36	0.0008
95	400	6.3	118	0.14	0.38	0.0007
96	400	6.5	120	0.1	0.4	0.0007
97	420	5.7	124	0.13	0.38	0.0007
98	440	4.9	128	0.16	0.36	0.0008
99	460	4.1	132	0.19	0.34	0.0009
100	480	3.3	136	0.22	0.32	0.0009
101	500	2.5	140	0.25	0.3	0.0010
102	500	2.7	132	0.26	0.32	0.0010
103	500	2.9	124	0.27	0.34	0.0011
104	500	3.1	116	0.28	0.36	0.0011
105	500	3.3	108	0.29	0.38	0.0011
106	500	3.5	100	0.3	0.4	0.0011
107	500	3.7	102	0.26	0.42	0.0010
108	500	3.9	104	0.22	0.44	0.0009
109	500	4.1	106	0.18	0.46	0.0007
110	500	4.3	108	0.14	0.48	0.0006
111	500	4.5	110	0.1	0.5	0.0005
112	500	4.7	112	0.11	0.42	0.0005
113	500	4.9	114	0.12	0.34	0.0005
114	500	5.1	116	0.13	0.26	0.0006
115	500	5.3	118	0.14	0.18	0.0006
116	500	5.5	120	0.15	0.1	0.0006
117	500	5.7	122	0.16	0.12	0.0007
118	500	5.9	124	0.17	0.14	0.0008
119	500	6.1	126	0.18	0.16	0.0008
120	500	6.3	128	0.19	0.18	0.0009
121	500	6.5	130	0.2	0.2	0.0010

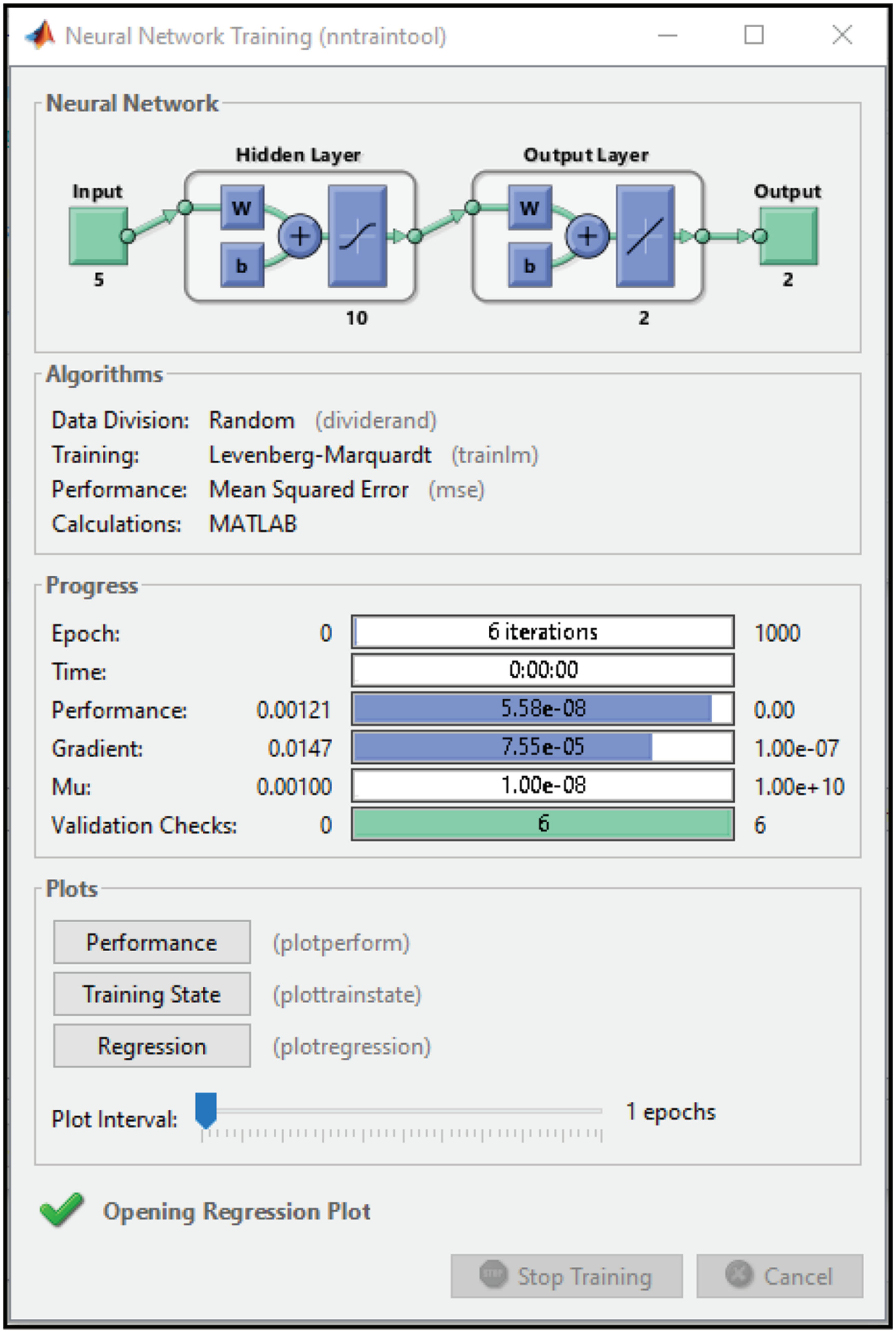

Figure 6: Network developed for expanded data set of AISI 4340

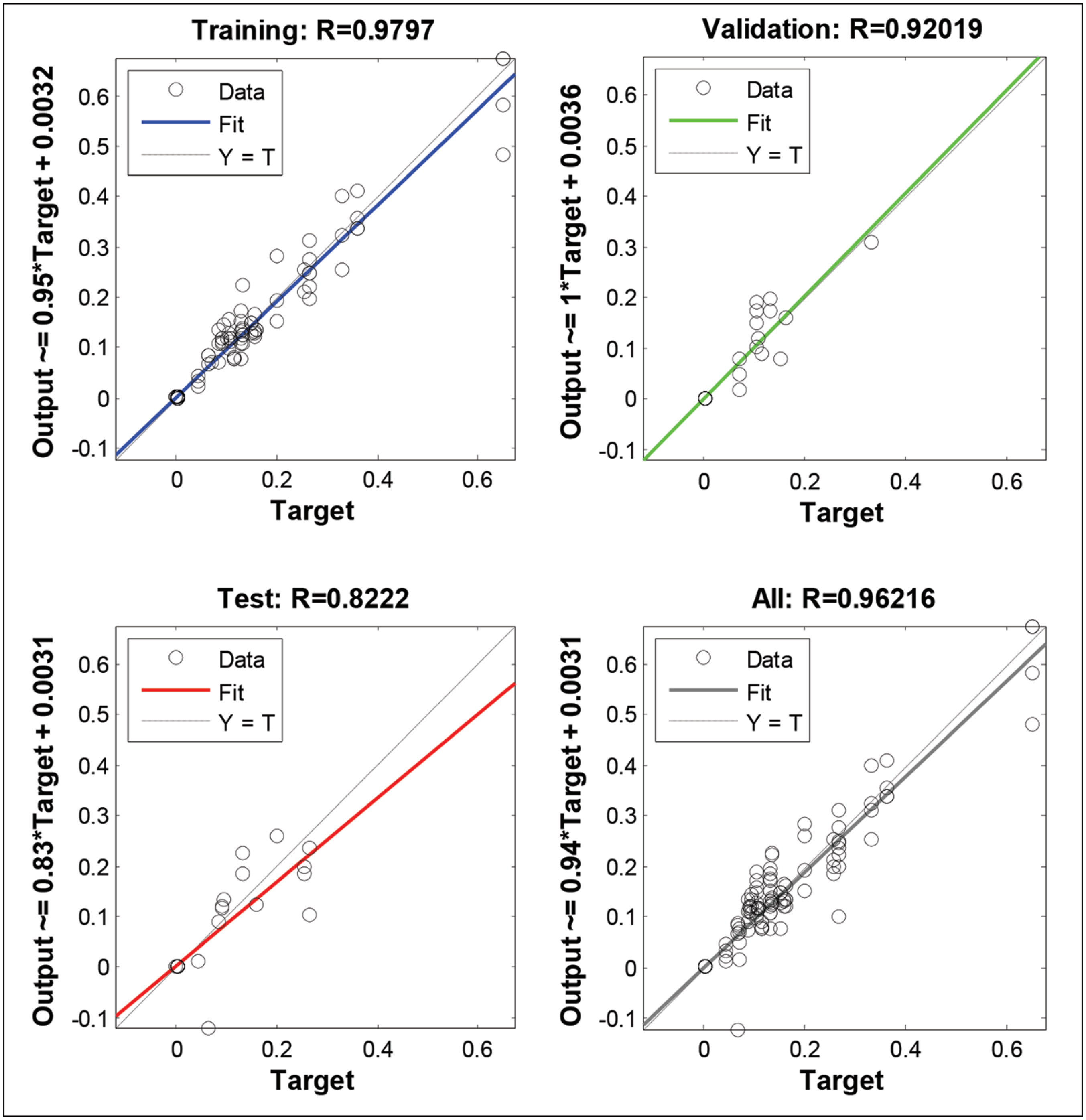

Figure 7: Regression Plot of Expanded Data Set of AISI 4340

Table 7: Predicted values of 20% of Modified Data Set

Sr No	Trial No	Predicted (surface roughness) (mm)	Sr No	Trial No	Predicted (surface roughness) (mm)
1	1	0.0007	14	66	0.0007
2	6	0.0007	15	71	0.0007
3	11	0.0006	16	76	0.0006
4	16	0.0005	17	81	0.0006
5	21	0.0004	18	86	0.0006
6	26	0.0007	19	91	0.0006
7	31	0.0006	20	96	0.0005
8	36	0.0007	21	101	0.0006
9	41	0.0006	22	106	0.0006
10	46	0.0008	23	111	0.0006
11	51	0.0007	24	116	0.0006
12	56	0.0006	25	121	0.0006
13	61	0.0005			

Table 8: Adequacy Check for the Model

Adequacy check	Interpolated readings		Focused Experiment	Confirmation Experiment
	Training (80 %)	Testing (20 %)		
R	0.97	0.82	0.95	0.97

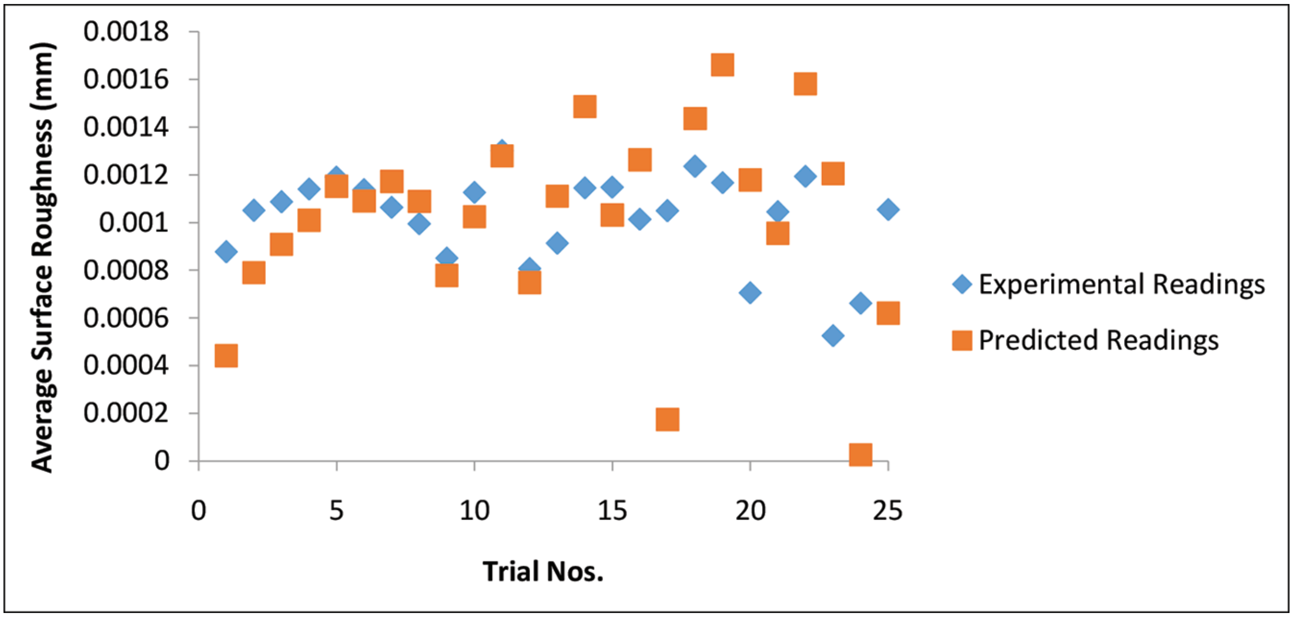

Figure 8: Comparison of 20% of Experimental Values of Surface Roughness Considered for Testing Purpose

4.0 Conclusions

Based on the work presented the following conclusions can be seen:

The primary objective of this research was to predict and develop an neural network model for surface roughness under MQL environment. The model used in this study proved successful with experimental recorded results. The developed model can also be used to forecast the surface roughness.

The smaller data set (25 readings) at primary experimentation level decided on the basis of Taguchi orthogonal array is used in training the network. Sometimes small data set may disturb the results hence the interpolation is performed to expand the dataset (121 readings).

With the many techniques available for training ANN, the backpropagation (BP) training is used to operate as a multilayer fully-interconnected feed-forward ANN. Five inputs with each of five levels, 10 hidden neurons for training of basic dataset, 5 neurons for testing of interpolated dataset found to be the optimum network (architecture as 5-10-1, 5-5-1) for the model in consideration. Based on the R value, different networks are found to be optimum amongst other. The results predicted for the 20% results, not used to develop the model, are found in good agreement with the experimental values. The ANN network is also developed for the interpolated data set to predict the responses simultaneously. In this case also based on R value, various networks are trained and tested. The optimum network amongst other is used. The results predicted for the 20% results, not used to develop model, are found in good agreement with the experimental values.

A good performance of developed neural network has been observed. The R for the 96 readings (80%) out of 121 interpolated readings is = 0.96 (96%) and for the remaining 25 readings (20%) is = 0.96 (96%). This shows that predicted values are in good relation with the observed values

The work presented in this paper, uses five input parameters. They are Quantity of Mixture, Distance of block, Cutting Speed, Feed, Depth of cut and the output parameter studied is surface roughness. This work can be further extended by considering more no. of output parameters.

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