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RESEARCH PAPER

An Artificial Neural Network Approach to Prediction of Surface Roughness and Material Removal Rate in CNC Turning of C40 Steel

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ABSTRACT

The present study is focused to investigate the effect of the various machining input parameters such as cutting speed (v_c), feed rate (f), depth of cut, and nose radius (r) on output i.e. surface roughness (R_a and R_q) and metal removal rate (MRR) of the C40 steel by application of an artificial neural network (ANN) method. ANN is a soft computing tool, widely used to predict, optimize the process parameters. In the ANN tool, with the help of MATLAB, the training of the neural networks has been done to gain the optimum solution. A model was established between the computer numerical control (CNC) turning parameters and experimentally obtained data using ANN and it was observed from the result that the predicted data and measured data are moderately closer, which reveals that the developed model can be successfully applied to predict the surface roughness and material removal rate (MRR) in the turning operation of a C40 steel bar and it was also observed that lower the value of surface roughness (R_a and R_q) is achieved at the cutting speed of 800 rpm with a feed rate of 0.1 mm/rev, a depth of cut of 2 mm and a nose radius of 0.4 mm.

KEYWORDS: *Modelling; Artificial neural network (ANN); Turning; surface roughness; MRR.*

1. Introduction

The basic essential requirement of a customer is the surface quality of a component, which is responsible for the performance of the product and often surface quality is expressed as surface roughness. The surface roughness (R_a) significantly influences the functional performance of mechanical parts such as fatigue strength, wear resistance, and corrosion resistance. surface roughness is influenced by several parameters such as cutting speed, feed, nose radius, depth of cut (doc), tool material, and cutting fluid [1] etc. C40 alloy steel is widely used in industries such as oil and gas pipelines, chemical industries, power plant industries, heat exchangers etc. due to its easy availability, good machinability, and good weldability properties. Unique characteristics of C 40 steel, it does not lose its ductility when heat treated. In recent years, several mathematical studies based on artificial neural network (ANN) have been carried out because of its good predictive ability i.e. reduces the effort, save money, and time for optimal and efficient implementation of any method [2-4]. Yogesh V. Deshpande et al [5] applied the ANN approach to forecast the surface integrity (roughness) of Inconel 718 material during turning operation and they found that the models developed by an artificial neural network to predicting surface roughness having 98% accuracy. S.C. Cagan et al [6] optimized the process parameters of AZ91D magnesium alloy bars in machining operation by artificial neural network technique and they concluded that the usage of ANN models provides for time and cost-saving in experimental studies. Abdullah et al. [7] studied the ANN approach and Taguchi

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technique to determine the surface roughness in the turning process of AISI 4140 steel and it is revealed from their result that neural networks is more effective than predictive regression analysis (Taguchi). Hasan Basri Ulas and Murat Tolga Ozkan[8] compared the ANN results and experimental results of surface roughness and cutting forces of AISI 304, AISI 420, and AISI 2205 material during the turning operation and they concluded that cutting force has been modelled using the ANN technique and ANN results have been found very nearcloser to the experimental results. T. Deepan Bharathi Kannan et al [9] developed an ANN model for drilling process parameters and they compared the predicted value and measured value and it was observed that both predicted value and measured value were fairly closer. Farag Abdallah et al [10] generated an ANN model to predict the surface roughness and cutting tool temperature during hard machining of C45 alloy steel and they concluded that on increasing the rotational speed and feed rate surface roughness decreases and it was also revealed that the ANN model having a reasonable agreement with the experimental results. Farid Boukezzi et al [11] developed an artificial neural network (ANN) model to predict the roughness of C38 steel during the turning process with P20 carbide insert in dry condition and they concluded that the ANN approach is very suitable to predict the relation between predicted and measured value with accuracy. Kuldip Singh Sangwan et al [12] coupled the ANN technique with the Genetic Algorithm (GA) approach to determine the optimal machining variable lead to minimum surface roughness during turning of Ti-6Al-4V titanium alloy and they informed that predicted results by ANN designate a good agreement between the predicted values and experimental values. Abderrahmen Zerti et al [13] used RSM approach and ANN models to predict the surface roughness of AISI 420 MSS during the machining operation and they informed that Surface roughness is strongly affected by the feed rate (f) and they also observe that artificial neural network (ANN) model shows better accuracy. Based on the previous literature of studies it is revealed that artificial neural network (ANN) predicted values are very near to the experimental values and indicate that the developed model can be significantly applied to predict the material removal rate (MRR) and surface roughness (SR) [14-16] and it is also observed that surface roughness and material removal rate is highly influenced by feed rate, slightly influenced by the depth of cut (doc) and nose radius of insert [17-18].

2. Material and Method

The workpiece material used in this experiment work is C40 steel. C40 is medium carbon steel with good tensile strength and is extensively used for various industrial applications such as shafts, gear, bolts etc. Iit is a well-known material that can be easily machined in any condition. The chemical composition and mechanical properties of workpiece material are listed in Tables 1 and 2 respectively.

Tab. 1. Chemical composition of C40 steel

C	Si	Mn	P	S	Fe	Ni	Mo
0.35	0.21	0.78	0.035	0.05	Balance	-	-

Tab. 2. Mechanical properties of C40 steel

Material	Yield strength (MPa)	Tensile strength (MPa)	% elongation	Toughness (J)
C40	440	610	25	30

2.1. Experimental work

In this research article, C40 steel is used for turning purposes. Machining operation was performed on CNC lathe machine of MIDAS 8i of Fanuc controller of 7.5 KW powers of spindle and spindle speed of machine varies from 40-4000 rpm, with CNMG type tungsten coated carbide tool insert. The insert was fixed on a right-hand tool holder. Experimental was used in this process is shown in fig.1. after completing machining process, the roughness (R_a, R_q) of all twenty-seven (27) machined workpieces was measured with portable surface roughness tester (make: Surtronic 3+, Japan). Surface roughness was measured at three points along the circumference of workpiece. Table 3 enlists the machining process parameters and their levels used in this experiment.

Tab. 3. Process Parameters

Parameters	Unit	Level-I	Level-II	Level-III
Cutting speed	rpm	400	600	800
feed	mm/rev	0.1	0.2	0.3
Depth of cut	mm	0.7	1.6	2.0
Nose radius	mm	0.4	0.8	1.2

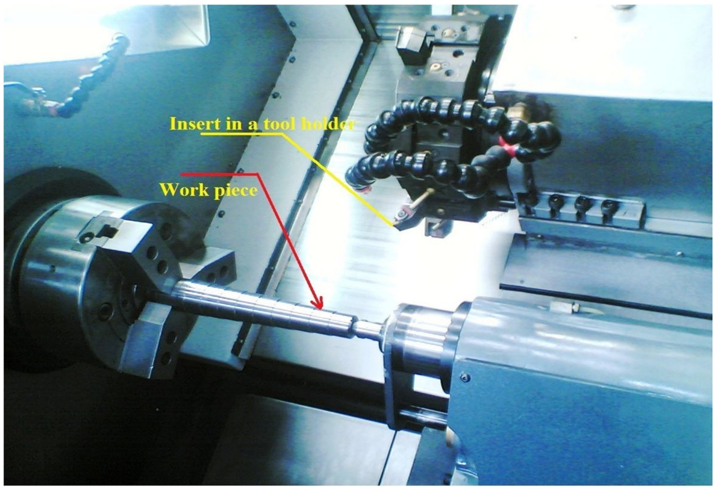

Fig.1. Experimental setup of CNC turning

The experiments were performed with values of cutting speed from 400 to 800 rpm,feed rate from 0.1 to 0.3 mm/rev,depth of cut from 0.7 to 2.0 mm,and nose radius 0.4-1.2 mm. Table 4 shows the experimental result carried out in this experiment. In this experimental work, the Taguchi technique was applied to optimized the process parameters and L_{27} orthogonal arrays DOE was used.

Tab. 4. Experimental result

Trial No	cutting speed	Feed	DOC	NR	R_a Experimental	R_a Predicted	R_q Experimental	R_q Predicted	MRR Experimental	MRR Predicted
1	400	0.1	0.7	0.4	3.72	3.885	4.89	4.965	389	529.053
2	400	0.1	1.6	0.8	3.52	3.551	4.75	4.615	765	765.741
3	400	0.1	2	1.2	3.02	3.146	4.13	4.277	1120	918.013
4	400	0.2	0.7	0.4	4.3	4.392	5.36	5.029	431	1352.270
5	400	0.2	1.6	0.8	5.66	5.279	6.81	6.348	880	444.591
6	400	0.2	2	1.2	3.02	3.217	4.25	4.331	1323	1323.459
7	400	0.3	0.7	0.4	9.02	9.123	10.45	10.78	495	495.647
8	400	0.3	1.6	0.8	3.06	3.102	4.23	4.322	1052	1055.319
9	400	0.3	2	1.2	2.5	2.537	3.67	3.35	1511	1601.498
10	600	0.2	0.7	1.2	6.82	6.553	7.91	7.117	1682	1683.167
11	600	0.2	1.6	0.4	3.2	2.909	4.33	3.985	523	395.422
12	600	0.2	2	0.8	4	3.808	5.17	4.996	1077	1075.387
13	600	0.3	0.7	1.2	4.62	4.882	5.79	5.693	2061	2061.297
14	600	0.3	1.6	0.4	6.36	5.944	7.42	7.96	686	685.201
15	600	0.3	2	0.8	3.86	4.111	4.95	5.279	1386	1620.611
16	600	0.1	0.7	1.2	2.94	3.826	4.11	4.169	2387	2387.490
17	600	0.1	1.6	0.4	2.02	1.953	3.15	3.226	792	791.850
18	600	0.1	2	0.8	3.74	3.792	4.98	4.784	1588	1587.082
19	800	0.3	0.7	0.8	2.68	2.858	3.81	3.775	1805	1804.078

20	800	0.3	1.6	1.2	3.46	3.13	4.86	5.053	2739	2736.296
21	800	0.3	2	0.4	7.1	6.95	8.54	8.825	911	910.439
22	800	0.1	0.7	0.8	2.68	2.51	3.72	3.527	2021	2017.238
23	800	0.1	1.6	1.2	3.3	3.677	4.56	4.847	3269	3532.181
24	800	0.1	2	0.4	1.16	1.194	2.36	2.906	1023	1024.876
25	800	0.2	0.7	0.8	2.04	2.207	3.16	2.923	2351	2350.715
26	800	0.2	1.6	1.2	4.86	4.548	5.99	5.358	3583	3581.569
27	800	0.2	2	0.4	3.38	3.332	4.74	4.481	1120	1119.929

3. Result and Discussion

3.1. Artificial neural network (ANN)

An artificial neural network (ANN) is a mathematical or computational model which is stimulated by biological neurons functional aspects like brain aspect [19]. A neuron is a primary element of the neural network, which is composed of neurons, input, weights, activation function, summation function, and output. The mathematical formula for calculating the net input of the neuron is given by the equation (1) where as equation (2) is used to compute the activation function.

$$\mathrm{NET_i} = \sum_{j=1}^{n} w_{ij}x_j + w_{bi} \quad (1)$$

Where NET_i=weighted sum of the input to the i^{th} processing element

w_{ij}=weight of the connections between the i^{th} processing elements

x_j=output of the j^{th} processing element

w_{bi}=weight of the biases between the layers

n=number of processing elements in the previous layer

$$f(NET_i) = \frac{1}{(1 + e^{-NET_i})} \quad (2)$$

An ANN model was developed by the NN tool of MATLAB software. MATLAB 2017a was used to generate the model. ANN neurons structure containing input, hidden layer, and output layer as shown in fig 2 and fig 4 shows improved an ANN model using MATLAB software.

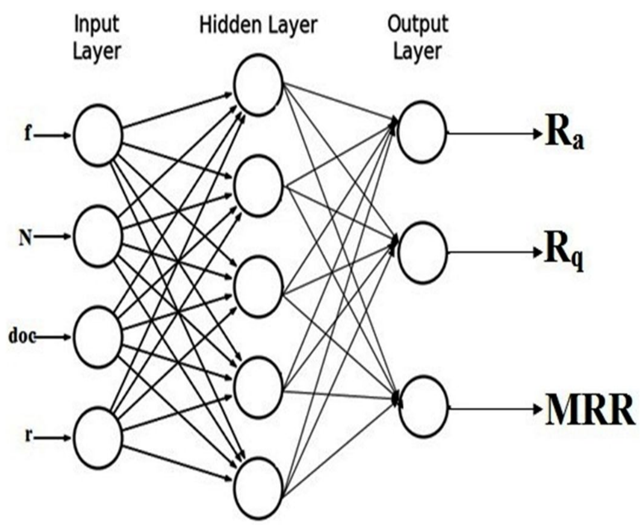

Fig. 2. ANN structure (4-14-3)

The simulated multi-layer ANN structure consists of four neurons in the input layer i.e. feed rate (f), cutting speed (v), depth of cut, and nose radius (r). Three neurons in the output layer represent R_a, R_q and MRR. One hidden layer with 14 neurons was applied between the input layer and output layer as shown in fig 2. In this training process, the artificial neural network structure is set like 4-14-3, i.e. four inputs, one hidden layer (14 neurons), and three put as shown in fig 3. The trial and error method was selected to execute the algorithm which is linked the neuron to recognize the hidden layer and allocate the neuron for all hidden layers. The Artificial Neural Network (ANN) model generated is expressed in fig.3.

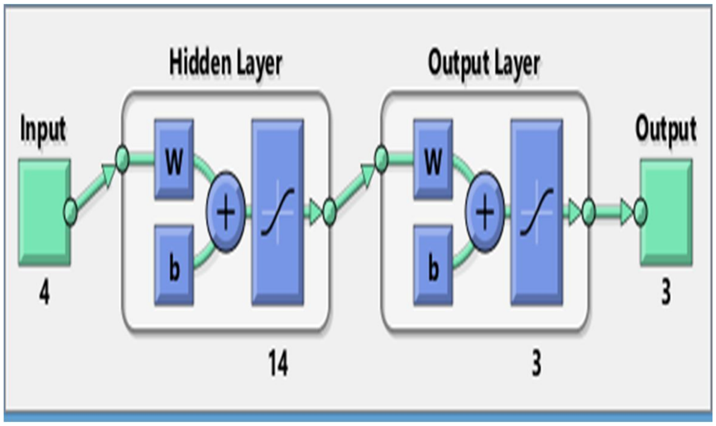

Fig. 3. Artificial neural network (ANN) model

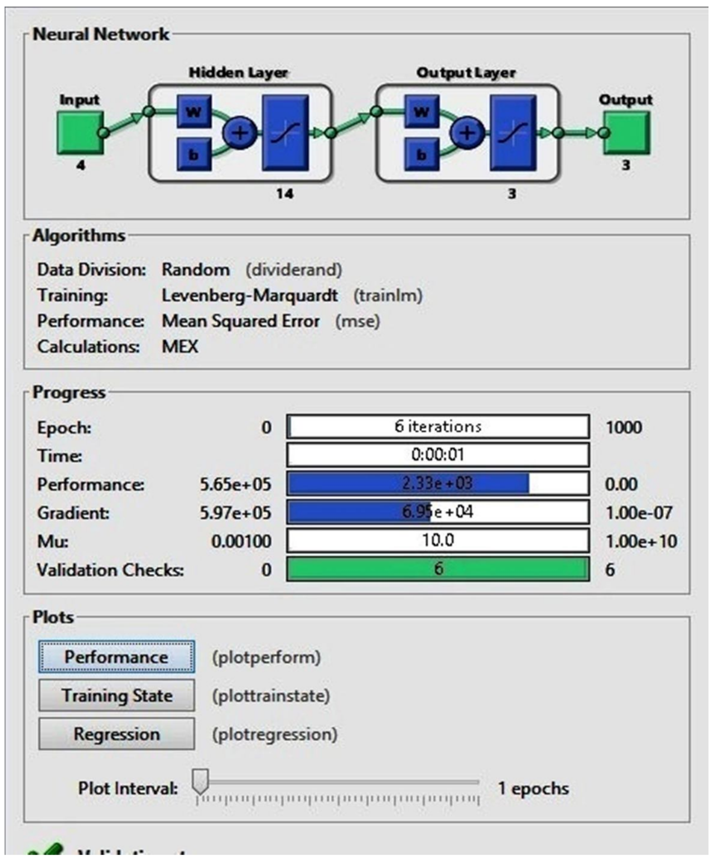

Fig. 4. improved ANN model by MATLAB R2017a

The number of neurons in the first hidden layer was selected by trial and error. Analysis of the graphical functions is demonstrated in fig 5 & fig 6 respectively. Fig 5 & fig 6 shows that the MLP 4-14-3 configuration had the minimum error in the valediction set.

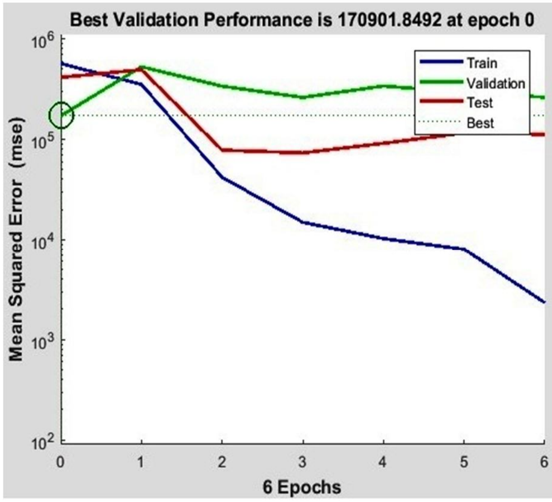

Fig. 5. Best validation of ANN

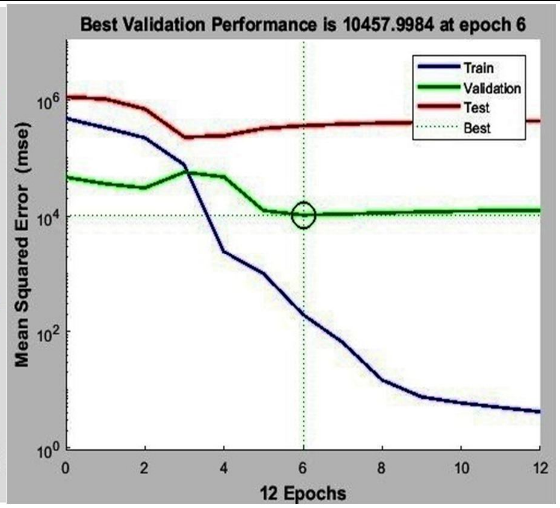

Fig. 6. Best validation of ANN

The performance curve of ANN i.e. regression curve for all patterns, training, validation and testing are summarised in fig.7. For surface roughness (R_a, R_q) and MRR respectively. For a perfect fit, the data should fall along a 45^o line (dash line) as shown in fig 7. The dotted line in fig 7 indicates the best line fit whereas the solid line indicated the perfect fit. The regression coefficient for training and validation was noted at 0.99987 and 0.96555 respectively, which is very closer to 1. As the value of the testing coefficient is 1, which shows that the trained model is best fitted for testing the data and it is also observed that prediction is relatively accurate as surface roughness predicted point lie very near to the experimental values [20].

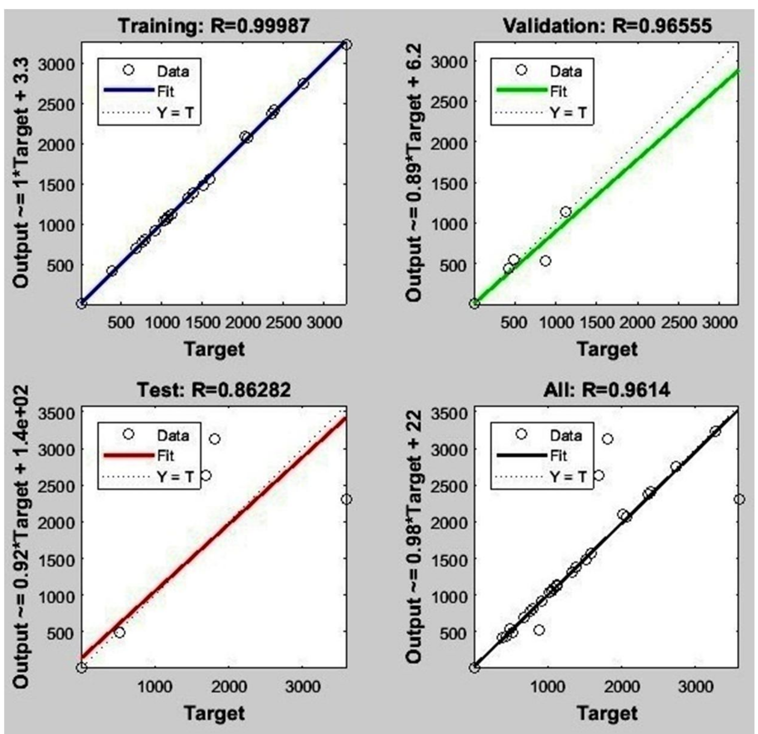

Fig. 7. Network model regression analysis for a. training dataset, b. validation dataset, c. testing dataset and d. combined datasets.

Compression of experimental data and predicted data of three out for twenty seven (27) experiments are listed in fig 8 and fig 9 respectively. Fig. 8 show the surface roughness R_a and R_q values and from figure it was observed that there is a good agreement between predicted data and experimental data. Results of this study validates with the previous work [21] as the graph of surface roughness almost is same.

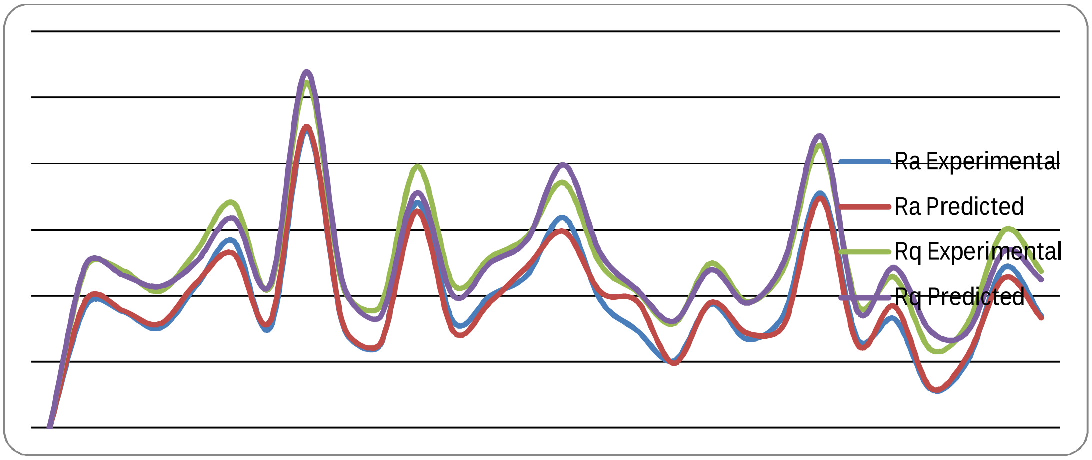

Fig. 8. comparison of experimental and estimated surface roughness (R_a and R_q)

Fig. 9 showed the results of prediction and actual data for the material removal rate of the machined parts. However, the deviation at run 3 and 4 were observed. Fig 9 depicts that error is within the limit, and hence ANN technique can be effetely applied to predict the MRR and the pattern of the graph is like the horn of bovine [22-23]. However, the accuracy of the MRR prediction is within acceptable range. There for, it can be suggested that model is acceptable.

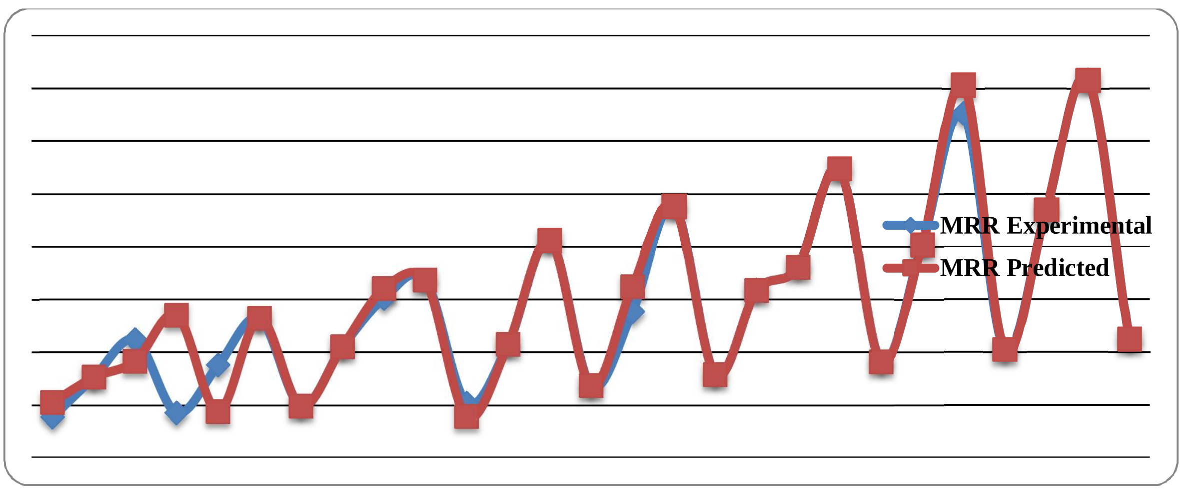

Fig. 9. comparison of experimental and estimated material removal rate (MRR)

4. Conclusion

Based on the theoretical knowledge and practical experience with ANN approach, development and training, authors have been observed that ANN approach can be applied to predict the surface roughness and MRR and from the present study, the following important conclusions have been drawn

1) An ANN model of 4-14-3 structure, found best suitable for this study.
2) An ANN model has been designed to predict the surface roughness and MRR in turning of C40 steel.
3) Lower the value of surface roughness (R_a and R_q) is achieved at the cutting speed of 800 rpm with a feed rate of 0.1 mm/rev, a depth of cut of 2 mm and a nose radius of 0.4 mm.
4) Higher rate of material removal rate is achieved at the cutting speed of 800 rpm with a feed rate of 0.2 mm/rev, a depth of

cut of 1.6 mm and a nose radius of 1.2 mm.

5) From result it was also observed that there is an excellent agreement between the two patterns i.e. experimental and predicted value hence the ANN model is a very reliable model to predict the surface roughness and material removal rate (MRR).

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