Research Article

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Prediction of output parameters in wire electrical discharge machining of EN-31 steel by artificial neural networks

Chetan Raj Singh* **and Rudra Pratap Singh**
Department of Mechanical Engineering, GLA University, Mathura, Uttar Pradesh, India

Abstract
The objective of this work is to predict the effect of input parameters on output parameters using artificial neural network in wire electrical discharge machining. The input variables considered are peak current, pulse on time, flushing pressure of dielectric, pulse off time, wire tension and wire feed rate. The output variables taken into consideration are dimensional deviation and material removal rate. Workpiece used in the study is of EN-31 steel. Wire electrical discharge machining is a thermal cum electrical process and uses the electrical and thermal energy for cutting materials. Wire electrical discharge machining is utilised for cutting electrically conductive materials, which are difficult to machine with conventional machining methods. This process uses discrete electrical discharges between continuously travelling wire (tool) and the workpiece for cutting the workpiece. In this work, artificial neural networks are used for prediction of output parameters. Artificial neural networks have a highly connected set of nodes or processing elements that operate in parallel. Artificial neural networks can be trained using input and output data and can be used to predict data for new input values.

Keywords
Wire electrical discharge machining, EN-31, Effect of input parameters, Output parameters, Artificial neural networks.

1.Introduction
Wire electrical discharge machining (WEDM) is a unconventional process of machining. It is utilised in conditions where workpiece is very hard to cut by conventional machining processes. This process machines electrically conductive materials [1]. The machining is carried out by controlled electrical sparks in a dielectric medium [2]. No stresses are developed in this process because there is no physical contact between the tool and the workpiece. When potential difference is applied between the tool and the workpiece the dielectric breaks down allowing the flow of spark, which causes erosion on workpiece and on tool also. The magnitude of erosion is more on the workpiece than on the tool (i.e. constantly travelling wire). Wire electrical discharge machining is a complex process owing to the number of variable that control the process.

Different parameters have different degree of effect on the output parameters, which makes the selection of parameters cumbersome for the machine operators. This in turn affects the efficiency with which machining can be done. *Figure 1* shows the block diagram of wire EDM machine.

Artificial neural networks (ANNs) have a number of highly interconnected processing units called as neurons [3]. The overall behaviour of ANNs is analogous to the human brain [3]. ANNs can be trained using data sets. From these data sets they can learn and generalise the underlying relationship between the input and output data. ANNs can be utilised where the relationship between input and output data is hard to establish by conventional statistical methods. These networks are trained using already available data in the form of inputs and outputs, ANNs then use this data to train themselves, which can then be used to predict the data for a different set of values. Artificial neural networks can also handle inexact and noisy data. *Figure 2* shows the layout of artificial neural network.

Singaram Lakshmanan et al. optimized the surface roughness using response surface methodology for EN-31 tool steel [4]. Arunkumar et al. investigated the process parameters for machining EN-31(air-hardened steel) [5]. Harpuneet Singh investigated the effect of different electrodes on EN-31[6]. Malhotra

*Author for correspondence

et al. studied the material removal rate for EN-31 on EDM [7]. Singh et al. investigated the effect of different electrode materials on EN-31[8].

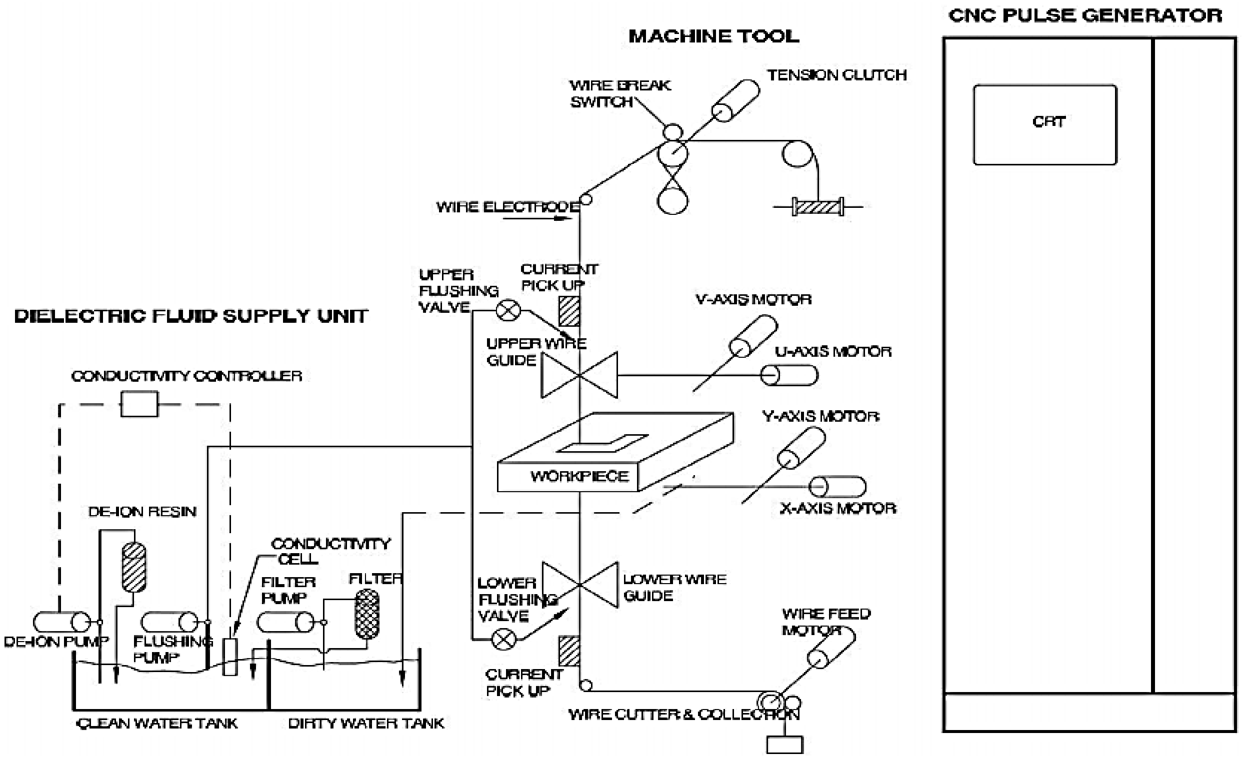

Figure 1 Block diagram of wire EDM machine [Source: Technological Manual of Electronica Sprintcut Wire-cut Electrical Discharge Machine]

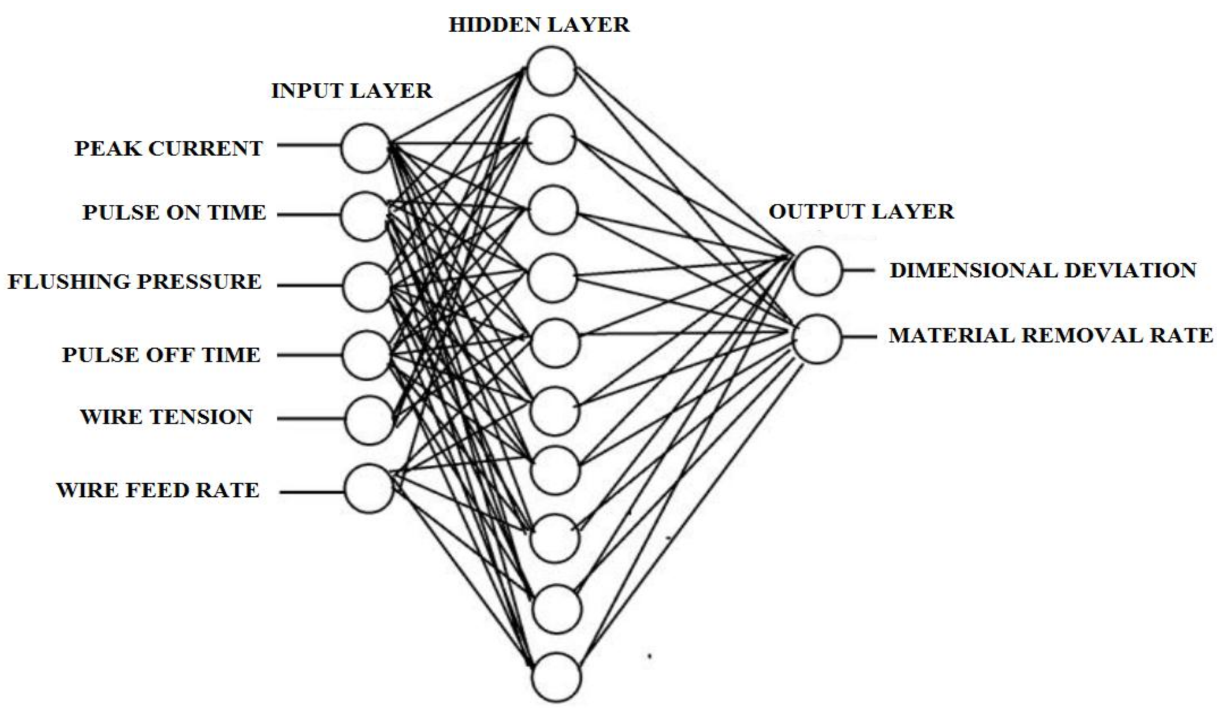

Figure 2 Layout of artificial neural network

2.Workpiece material

Material used in experiment was EN-31 steel. Contents of EN-31 steel are shown in *Table 1*.

Table 1 Contents of EN-31 steel

Component	Weight %
Manganese	0.30-.75
Silicon	0.10-0.35
Sulphur	0.040 max
Phosphorus	0.040 max
Carbon	0.90-1.20
Chromium	1-1.60
Iron	Remaining

3.Artificial neural networks specifications

Number of inputs: 6
Number of outputs: 2
Number of neurons in hidden layer: 10
Network type: Feed foreword back propagated
Transfer function used: Tansig and Purelin
Error Function: Mean squared error
Learning Scheme: Supervised learning
Artificial neural network toolbox of MATLAB R2013a was used. The topology of the model is shown in *Figure 3* below.

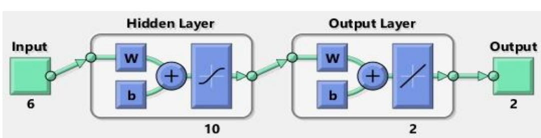

Figure 3 Topology of ANN model

4.Experimental procedure

The work pieces of 50 mm length were obtained from the long blank of 25*25 mm^2 cross sectional area. These pieces were ground on surface grinder so as to remove the little rust on surface and to make surfaces at right angles to each other. From these work pieces, sample of 3 mm thickness were parted off to study the dimensional deviation and material removal rate. Tool used was brass wire of diameter 0.25mm. Surface roughness tester used was Carl Zeiss Handysurf E-35A with least count of 0.01 µm. Weighing machine used was Shimadzu AUW220D with least count of 0.1mg. Dimensions were measured using micrometer of least count 0.01mm. Experiments were carried out on Electronica Sprintcut Wire EDM with Generator ELPULS-40 A DLX. The factors taken into consideration are six input parameters, which are peak current, pulse on time, flushing pressure of dielectric, pulse off time, wire tension and wire feed rate. The units of these are as per the machine settings. The parameters of peak voltage, servo voltage and servo feed were kept constant at 2, 20 and 2100 units respectively. One parameter at a time was varied and its effect was observed.

5.Observations

Experiments were performed by changing one parameter at a time and keeping the other parameters constant and thus to study the effect of that parameter on dimensional deviation and material removal rate (MRR).Firstly, the value of peak current (Ip) was varied to observe its effect on Dimensional deviation and MRR. The *Table 2* shows the variation of Dimensional deviation and MRR with I_p .The *Figure 4* shows the plot of dimensional deviation versus peak current and *Figure 5* shows the plot of material removal rate versus peak current. The other parameters were kept constant as: pulse on time at 118 units flushing pressure of dielectric at 1 unit ,pulse off time at 60 units, wire tension at 10 units and wire feed at 3 units.

Table 2 Variation of dimensional deviation and MRR with I_p

Serial number	I_p	Dimensional deviation (%)	Mrr (Mm^3/S)
1	230	-1.33	0.135
2	220	-1	0.133
3	210	-1	0.133
4	200	-0.66	0.133

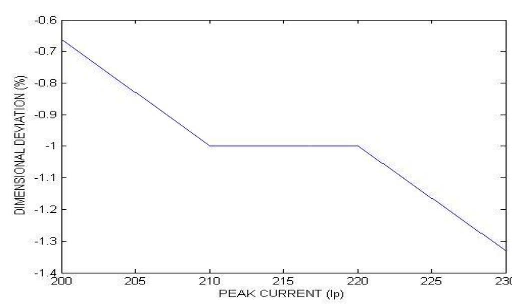

Figure 4 Variation of dimensional deviation with I_p

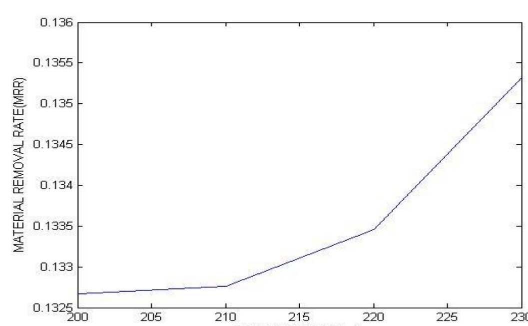

Figure 5 Variation of MRR with I_p

Secondly, value of pulse on time (T_{on}) was varied to observe its effect on MRR, dimensional deviation. *Table 3* shows the variation of dimensional deviation, MRR with T_{on}. The *Figure 6* shows the plot of dimensional deviation versus pulse on time and *Figure 7* shows the plot of material removal rate versus pulse on time. The other parameters were kept constant as: peak current at 230 units, flushing pressure of dielectric at 1 unit, pulse off time at 60 units, wire tension at 10 units and wire feed at 3 units.

Table 3 Variation of dimensional deviation and MRR with T_{on}

Serial number	T_{on}	Dimensional deviation (%)	Mrr (Mm^3/S)
1	131	-1.66	0.197
2	125	-1.66	0.174
3	120	-2	0.156
4	115	-2	0.117

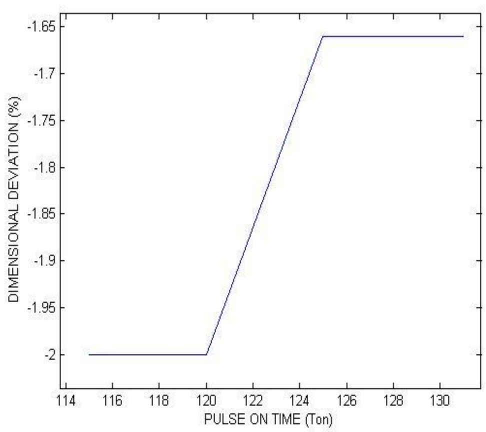

Figure 6 Variation of dimensional deviation with T_{on}

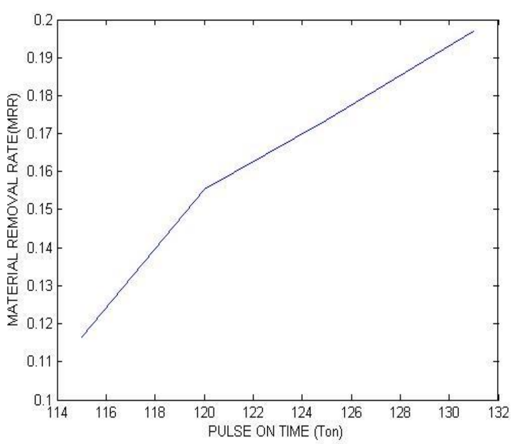

Figure 7 Variation of MRR with T_{on}

Then the value of water pressure (W_p) was varied to observe its effect on Dimensional deviation and MRR. The *Table 4* shows the variation of Dimensional deviation and MRR with W_p. The *Figure 8* shows the plot of dimensional deviation versus water pressure and *Figure 9* shows the plot of material removal rate versus water pressure. The other parameters were kept constant as: peak current at 230 units, pulse on time at 118 units, pulse off time at 60 units, wire tension at 10 units and wire feed at 3 units.

Table 4 Variation of dimensional deviation and MRR with W_p

Serial Number	W_p	Dimensional deviation (%)	Mrr (Mm^3/S)
1	0	-2	0.130
2	1	-1.66	0.135

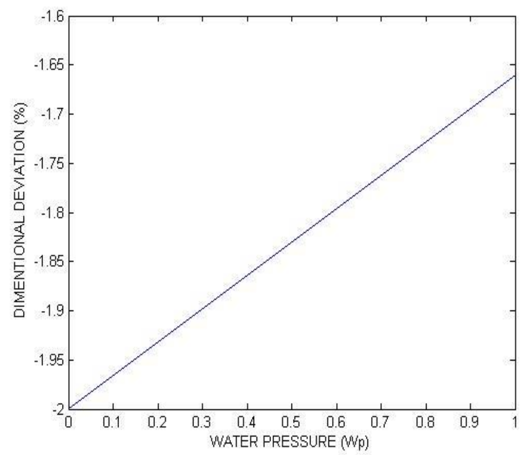

Figure 8 Variation of dimensional deviation with W_p

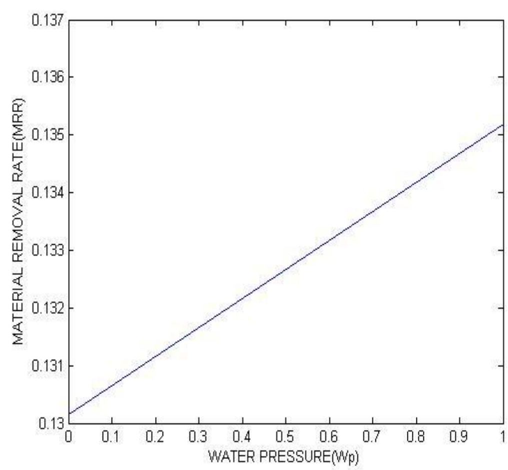

Figure 9 Variation of MRR with W_p

Then the value of pulse off time (T_{off}) was varied to observe its effect on Dimensional deviation and MRR. The *Table 5* shows the variation of Dimensional deviation and MRR with $T_{off.}$ The *Figure 10* shows the plot of dimensional deviation versus peak pulse off time and *Figure 11* shows the plot of material removal rate versus pulse off time. The other parameters were kept constant as: peak current at 230 units, pulse on time at 118 units flushing pressure of dielectric at 1 unit, wire tension at 10 units and wire feed at 3 units.

Table 5 Variation of dimensional deviation and MRR with T_{off}

Serial number	T_{off}	**Dimensional deviation (%)**	**Mrr (Mm^3/S)**
1	63	-1.33	0.129
2	61	-1	0.120
3	59	-1	0.147
4	56	-0.66	0.163

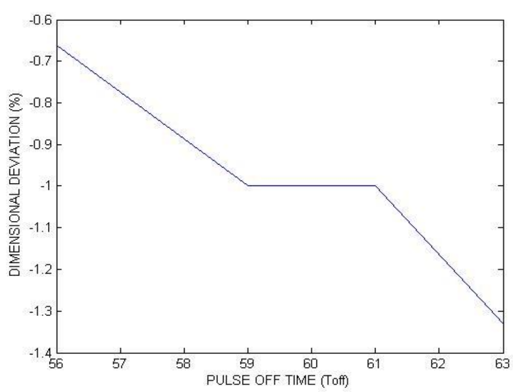

Figure 10 Variation of dimensional deviation with T_{off}

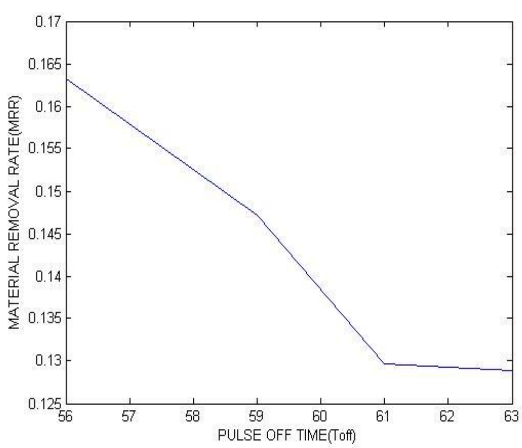

Figure 11 Variation of MRR with T_{off}

The value of wire tension (W_t) was varied to observe its effect on Dimensional deviation and MRR. The *Table 6* shows the variation of Dimensional deviation and MRR with W_t. The *Figure 12* shows the plot of dimensional deviation versus wire tension and *Figure 13* shows the plot of material removal rate versus wire tension. The other parameters were kept constant as: peak current at 230 units, pulse on time at 118 units flushing pressure of dielectric at 1 unit, pulse off time at 60 units, and wire feed at 3 units.

Table 6 Variation of dimensional deviation and MRR with Wt

Serial number	W_t	**Dimensional deviation (%)**	**Mrr (Mm^3/S)**
1	15	-0.66	0.1390
2	13	-1.33	0.140
3	11	-1.66	0.136
4	10	-1.66	0.135

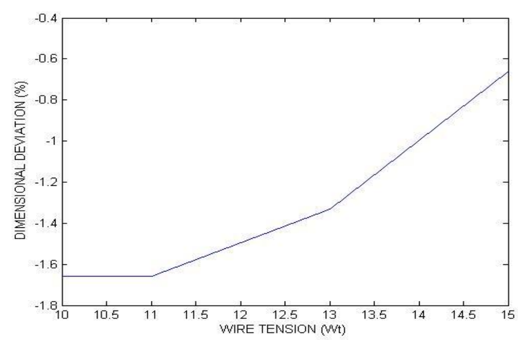

Figure 12 Variation of dimensional deviation with W_t

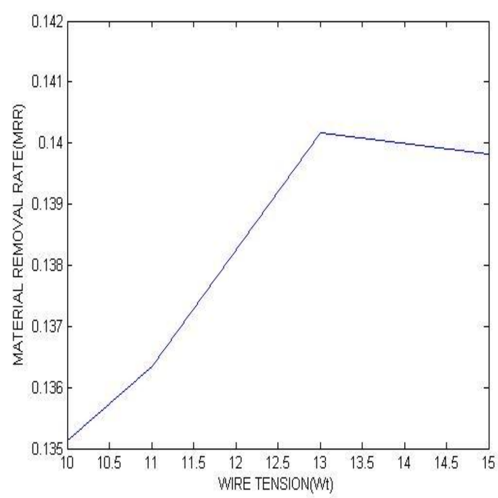

Figure 13 Variation of MRR with W_t

Lastly the value of wire feed (W_f) was varied to observe its effect on Dimensional deviation and

MRR. The *Table 7* shows the variation of Dimensional deviation and MRR with W_f. The *Figure 14* shows the plot of dimensional deviation versus wire feed and *Figure 15* shows the plot of material removal rate versus wire feed. The other parameters were kept constant as: peak current at 230 units, pulse on time at 118 units flushing pressure of dielectric at 1 unit, pulse off time at 60 units and wire tension at 10 units.

Table 7 Variation of dimensional deviation and MRR with W_f

Serial number	W_f	Dimensional deviation (%)	Mrr (Mm^3/S)
1	15	2.66	0.12891
2	13	2.33	0.12881
3	11	2.33	0.12275
4	9	1	0.11979

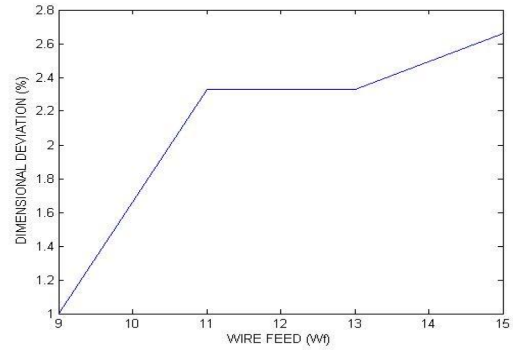

Figure 14 Variation of dimensional deviation with W_f

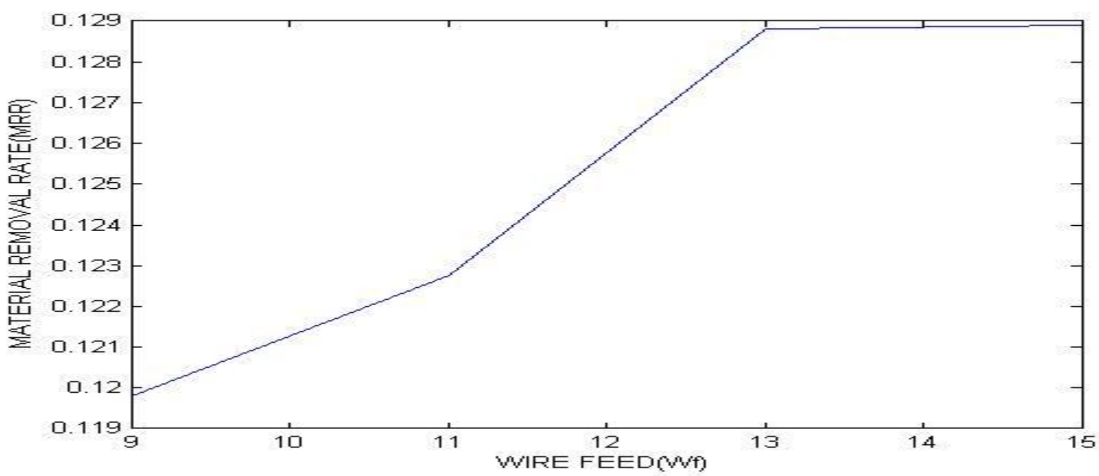

Figure 15 Variation of MRR with W_f

6.Results and discussions

Artificial neural network was able to predict the output data from the data set provided to it. Data set as shown in *Table 8* below was given as input and the output parameters were noted. *Figure 16* shows the variation of MSE with epochs. It indicates that the network is trained and the error is decreasing. From *Figure 17* we can see that the overall value of correlation coefficient (R) is 0.9858 which shows that there is a good relation between inputs and output data sets.

Table 8 Prediction by artificial neural network

I_p	T_{on}	W_p	T_{off}	W_t	W_f	Dimensional deviation	Mrr
230	117	1	62	10	3	1.35	0.1245
220	120	1	60	9	5	1.08	0.1420

7.Confirmation test

Confirmation tests with the input parameters as shown in *Table 8* were carried out. The value of the dimensional deviation attained was 1.42 % and 1.12 % and material removal rate was 0.1198 mm^3/s, 3.92 0.1403 mm^3/s which is very close to the value predicted by artificial neural networks.

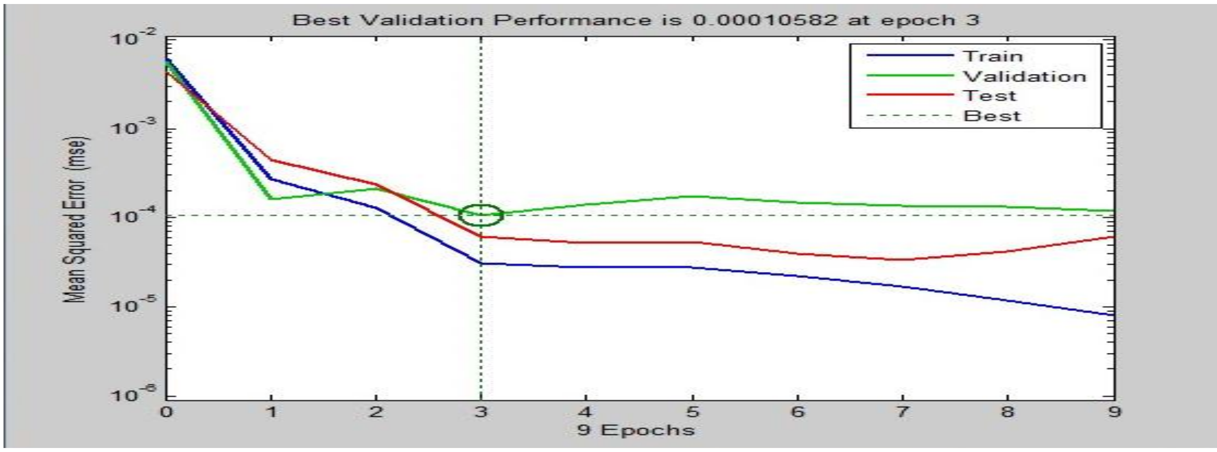

Figure 16 Variation of mean square error with epoch

Table 9 Error % in dimensional deviation

Value of dimensional deviation predicted by ann	Actual value	Error %
1.35	1.42	4.92
1.08	1.12	3.57

Table 10 Error % in MRR

Value of Mrr predicted by ann	Actual value	Error %
0.1245	0.1198	-3.92
0.1420	0.1403	-1.21

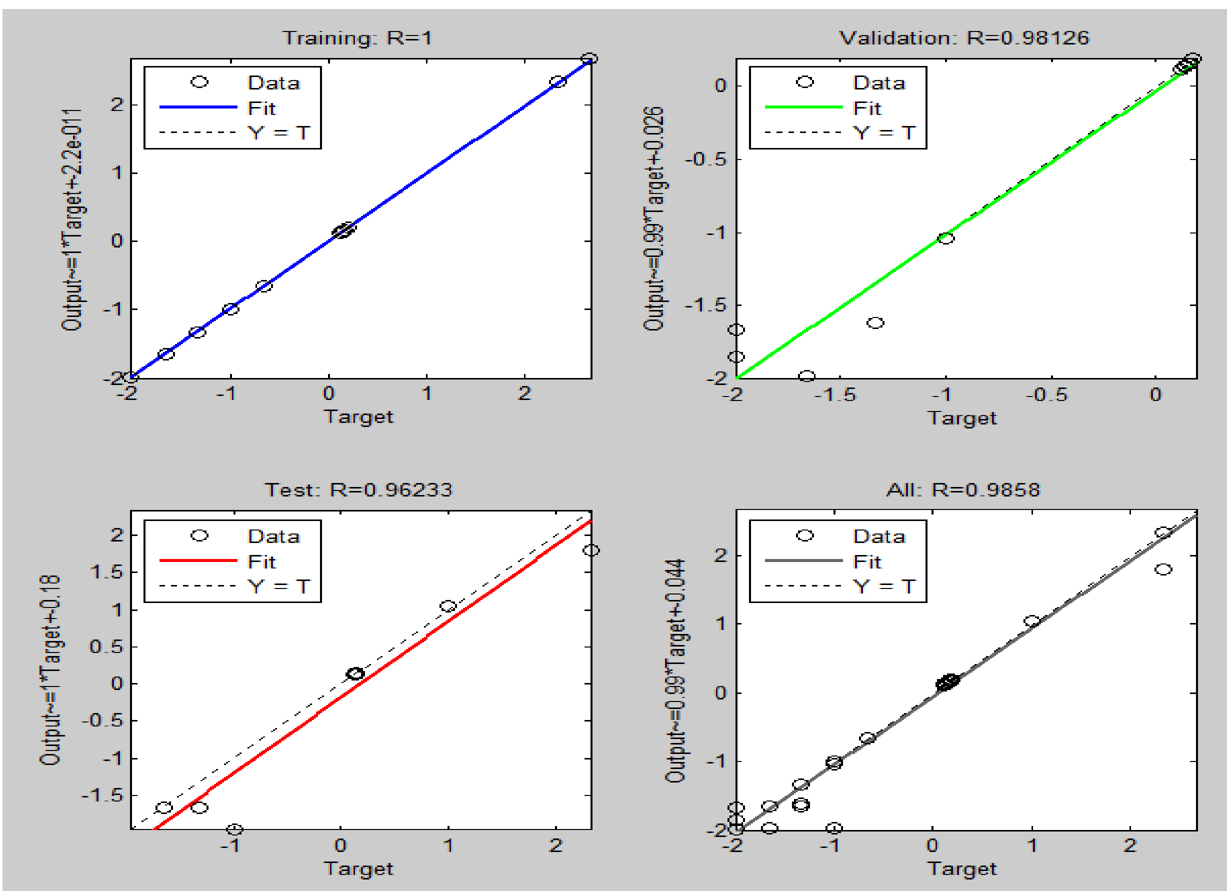

Figure 17 Values of correlation coefficient (R)

8.Conclusion

Artificial neural network is able to predict from the data provided to it with very less error. The results of ANN are reliable which is observed from the error *Tables 9 and 10.*

Acknowledgment

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Conflicts of interest

The authors have no conflicts of interest to declare.

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Chetan Raj Singh is currently a student of Master of Technology in GLA University, Mathura, Uttar Pradesh, India. He completed his Bachelor of Engineering degree from Sant Longowal Institute of Engineering and Technology, Sangrur, Punjab and Diploma in Engineering from Aligarh Muslim University, Aligarh, Uttar Pradesh. He has a consistantly good academic record and secured first division throughout. He has attended two national conferences in institutes of repute. He has also been awarded scholarship by GLA University and by Army Welfare Education Society twice.
Email: chetanrajsingh1989@gmail.com

Dr. Rudra Pratap Singh is currently serving as Associate professor in GLAUniversity, Mathura, Uttar Pradesh, India. He has over sixteen years of teaching experience. He has also worked in industry for over six years. He completed his Ph.D from U.T.U. Dehradun in February 2015. He has also held the position of Program coordinator of Mechanical Engineering department in GLAITM Mathura, Hostel warden in GLAITM Mathura, Class advisor and counselor for many classes. He has published more than thirteen papers in international journals of repute and has attended many national and international conferences.